Myopic Optimisation of Generation and Storage Investment for Long-Term Electricity System Planning

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Myopic Optimisation of Generation and Storage Investment for Long-term Electricity System Planning

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Summary

Power system planning is a strenuous exercise for both people and computers. As carbon goals and geopolitical complexities intensify, the number of scenarios for electricity system development is limitless. In search of robust policy and profitable investments, policymakers and investment managers rely on long-term electricity system simulation models. Those seeking to simulate myopic investment behaviour in systems reliant on intermittent generation, batteries and seasonal storage then encounter a computational barrier. The sole model detailed enough to conduct such simulations – MIDO (Myopic Investment Detailed Operational) – takes over 12 hours to run a 20-year scenario. Exploring avenues to cut back computational time is key to unlocking the potential to meaningful scenario analyses. Also, due to its novelty, many of its assumptions and modeling choices were not validated with stakeholders. Research into methodologies to reduce the computational burden at an acceptable compromise to model behaviour thus holds merit.

To this end, this methodological thesis explores myopic optimisation, developing the MODO methodology: Myopic Optimisation, with Detailed Operational analysis of system performance. We have realised an 85% improvement in computational efficiency with a sufficient degree of accuracy for it to be considered as an alternative to MIDO. The essence of our approach is the replacement of an iterative investment loop with a single optimisation. In doing so, we transfer insights from the field of agent-based modeling into the field of myopic optimisation, potentially enabling the revitalisation of a research area which has seen little activity in recent years.

MODO has been implemented as a modular toolkit in Linny-R, in such a way that users need not have any technical modeling knowledge to be able to construct their own system and/ or analyse their own scenarios. The implementation in Linny-R greatly enhances model transparency and usability.

We create a projection for the state of the Dutch electricity system by 2030 and use MODO to simulate the transition path from 2030-2050. Preliminary results suggest the significant potential of both seasonal (hydrogen) and battery (lithium-ion) storage to lower electricity prices below 2030 levels, bringing down annual consumer spending to EUR 15 bn annually in a scenario with mid-range commodity price forecasts. Additionally, results affirm the functionality of MODO in more complex electricity systems.

We identify three exciting avenues for future research. The risk of contemporary investment decisions is largely mitigated through long-term contracting, such as bilateral power purchase agreements or forward ENDEX markets. Ideally, academic work would converge to the point where a first model simulates a range of potential portfolio choices based on long-term contracting, after which - based on risk appetite - the upside potential of offering excess capacity on spot markets is assessed with a methodology such as MODO. However, as the data on such long-term contracting is often kept secret, research into ways to approximate the data or work with it using 'black-box' models could prove fruitful. Secondly, researchers could choose to build upon this work by leveraging it to conduct large-scale exploratory analyses. The case studies in this work illustrate the potential of MODO, but only provide a preliminary insight into system development. Whilst model development has been informed by a stakeholder consultation, the scenarios analysed have not. This is simplified by the highly accessible nature of MODO's implementation in Linny-R. Lastly, we suspect that qualitative research into the empirical applicability of power system simulation models might prove invaluable. Research that treats decision-makers and policy analysts as clients to discover their modeling needs could result in a roadmap for the participatory development of power simulation models in order to better foster their adoption, and that of their findings.

Acknowledgement

The weekend before completing this thesis, I visited the Dutch National Military Museum. As my mind wandered off to all the research that remains to be done in relation to this thesis, the tour guide spoke of planes designed with guns that shot holes in their own propellers and tanks equipped with cannons so powerful the recoil from a fired round would flip the entire vehicle on its side. A take-away: innovation is an ongoing process, and finished products are rarely perfect.

I'm therefore glad to have been able to build upon the work of my good friend Yasin, and to be able to leave my finished product in the capable hands of Roos. Master theses at our faculty being a short six months, I've found this 'relay' of thesis research to be a great motivator and highly fulfilling. I'm excited to see where it goes.

The research wouldn't have been where it is today if Yasin hadn't picked up the baton about a year ago, passing it to me in the form of high-quality work half a year later. And whilst I have been the one doing all the running for the past half year, it has been invaluable to have such a close friend cheer me on and be a sparring partner at the same time.

Pieter, thank you for ensuring that the passing of the baton was paired with a significant expansion of Linny-R's functionalities, and for your continued dedication to its development. Your proactive and receptive attitude to novel requirements and suggestions have definitely made Linny-R a force to be reckoned with. Moreover, your critical questions and suggestions never fail to trigger new ideas or challenge my established thinking.

Laurens, your courses on electricity markets motivated and enabled me to conduct this research, and your insights and guidance gave me the much needed reminders that there is still a lot that I don't know. I admire the nuance and perspective you have contributed to my thinking.

All in all, this thesis has definitely been a team effort and I am happy to leave the finished product in good hands so that it may be built upon and adapted to further innovation in electricity market design.

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Nomenclature

μ_j Energy conversion efficiency of technology type j

$c_{i,j}$ Construction time of standard asset i of technology j

d Day

$d_{j,y}$ Depreciation period for technology type j in year y (Years)

$dec_{i,j,y}$ Decommissioning of standard asset i of technology j in year y (binary)

$f_{j,y}$ Fixed cost of technology type j in year y (EUR/MW/y)

$f_{j,y}^{O\&M}$ Fixed operation and maintenance cost for technology type j in year y

$g_{i,j,y,t}$ Power output of asset i of technology type j in year y at time t (MWe). Note that this may take negative values when charging storage.

$G_{j,y}$ Installed generation capacity of technology type j in year y, i.e. total size of an asset stack

h Hour

i Standard asset in an asset stack.

$I_{j,y}^{annuity}$ Annuity for an investment in technology j in year y (EUR/MWe/y)

$I_{j,y}^{CapEx}$ Capital expenditures for technology type j in year y (EUR/MWe)

$I_{j,y}^{markup}$ Markup for an investment in technology j in year y (%)

$inv_{i,j,y}^{investor}$ Investment in standard asset i of technology j in year y as determined by ex-post profitability analysis, from an investor perspective (binary)

$inv_{i,j,y}^{solver}$ Investment in a standard asset i of technology j in year y as determined by the solver (MWe)

j Type of technology

$l_{i,j,y,t}$ Storage level of storage asset i of technology type j in year y at time t

$L_{y,t}^{markup}$ Load in year y at time t (MWh)

la Look-ahead year for investors in LA

LB Set of all look-back years for investors

lb Look-back year for investors in LB

$ll_{y,t}$ Lost load in year y at time t (MWh)

$n_{i,j,y}^{inv}$ Number of installed generators i of technology j in year y, i.e. total size of an asset stack during an investment simulation

$n_{i,j,y}^{reg}$ Number of installed generators i of technology j in year y, i.e. total size of an asset stack during a non-investment simulation

$NPV_{i,j,y}$ Net present value of asset i of type j in year y

$P_{i,j,y}$ Profitability of asset i of technology j in year y

$P_{i,j,y}^{threshold}$ Profitability threshold required to make an investment in technology j in year y

$p_{y,t}$ Market price in year y at time t

$s_{i,j,y}$ Standard asset size of asset i of technology type j in year y, i.e. total size of an asset stack (MWe)

$s_{i,j,y}^{storage}$ Standard asset size of storage asset i of technology type j in year y, i.e. total size of an asset stack (MWe)

$s_{i,j}$ Standard generation capacity of assets i with technology j

$Stack$ Set of all standard asset stacks of the same asset type.

$stack$ Standard asset stack.

t Time unit (e.g. hours or days)

$v_{j,y}^{fuel}$ Fuel price of technology type j in year y (EUR/MWth)

$v_{j,y}^{O\&M}$ Variable operational and maintenance cost of technology type j in year y at time t (EUR/MWh)

$VoLL$ Value of lost load (EUR)

W_d The weight of representative day d

$WACC_{j,y}$ Weighted average cost of capital for technology type j in year y

y Year

1 Introduction

The need for a carbon-neutral power sector by 2050 has forced policymakers across the European Union (EU) into the driver's seat, despite their intention for the invisible hand to steer investment in electricity generation and storage [39]. The complexity of the electricity sector's ongoing overhaul stands in stark contrast to the relative predictability of the original system. Unencumbered by carbon emission constraints, the electricity system used to be relatively straight-forward as it was characterised by predominantly thermal generation, a stable policy environment and predictable demand. The transition toward net zero has introduced novel degrees of freedom which substantially complicate portfolio choices. Variable renewable energy sources (vRES), thermal assets with carbon capture and sequestration (CCS) and storage solutions are now additional components of any serious revenue forecasting, as well as varying scenarios for Power-to-X (P2X) demand and a broader spectrum of climate policy uncertainty. The increased complexity and decreased predictability exacerbate the bounded rationality of both investors and policymakers. Hence, the European Commission's efforts to foster more market-based investment in the power sector whilst achieving decarbonisation objectives must account for myopia.

Novel simulation methodologies are required to facilitate the analysis of myopic investment decision-making on the path toward Net Zero, primarily because the current state-of-the-art either lacks detail or is too computationally intensive. Most notably, the Myopic Investment Detailed Operational (MIDO) methodology, recently proposed by Sagdur, has been the first to enable the consideration of (seasonal) storage and extreme weather scenarios in myopic investment simulations, but requires 12 hours to simulate 20 years on a high-end personal computer[1] [56]. For purposes of future robustness analyses, usability and interoperability with other market simulation models, a methodology incorporating MIDO's level of detail at a more favourable computational cost is a fruitful research avenue and the primary focus of this thesis.

More fundamentally, little has been reported on validation amongst stakeholders of the manner in which their empirical myopia is represented in myopic simulation methodologies. MIDO too, has been developed without surveying relevant parties despite existing debate on the degree to which myopic simulations represent real-world investment behaviour [47]. Therefore, the secondary objective of this thesis is to compare and contrast real-world myopia with myopic simulation models by means of a stakeholder consultation.

Pragmatically, as the power system's increased complexity is intensifying interactions between stakeholders, especially between public and private parties, the need for simulation models to be transparent has become ever more important [38]. MIDO is quite difficult to work with. Thus, the tertiary objective of this thesis is to ensure transparency and usability of our model.

This introductory chapter first elaborates on investment decision-making in the EU's liberalised power sector in section 1.1. Section 1.2 further introduces the role of myopia and myopic simulation methodologies. We motivate our research objectives and approach in sections 1.3 and 1.4 respectively, before outlining this document's structure in section 1.5.

[1] Intel i7-10700K, 32GB RAM, Nvidia RTX3070

1.1. Investment in Electricity Generation and Storage

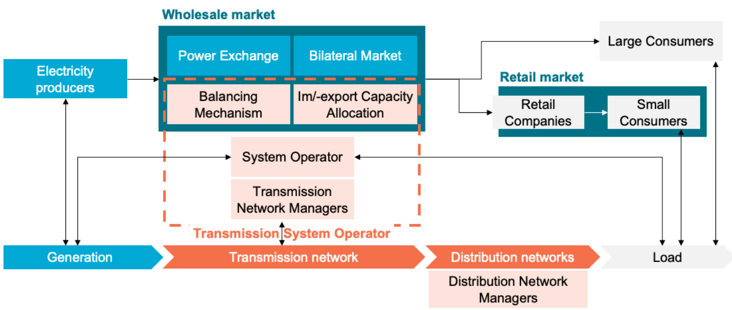
Due to the transition from a straight-forward, predominantly fossil-fueled electricity system toward a more complex renewable design, investment in electricity generation and storage is subject to increased uncertainty. The purpose of this section is to elaborate upon the development and motivate the need for novel decision support methodologies and models.

1.1.1. Liberalised EU Electricity Markets

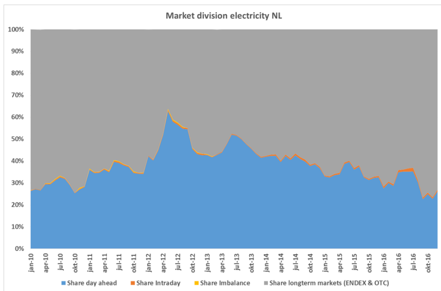
From 1990 to the mid-2000s, the EU's electricity markets were unbundled to reallocate investment decisions from public utilities to the private sector. Ensuing competitive wholesale markets confirmed aptness of the new market design. Figure 1.1a displays the market structure, in which electricity producers, large consumers and retail companies meet on power exchanges and bilateral markets. Transmission System Operators (TSO) procure balancing services from, and arrange cross-border capacity allocation for, producers, consumers and retailers alike.

Power exchanges and bilateral markets are the primary arenas for competitive wholesale market dynamics. Their combined market share by volume is nearly 100% (figure 1.1b). In a theoretically optimal free market context, the invisible hand should bring about an economic welfare optimum as competition amongst energy producers induces efficiency.

However, market structures as they exist were designed with technologies of a 20^{th} century system in mind, i.e. one dominated by fossil-fueled thermal generation, hydropower and nuclear baseload [30]. Even in today's energy only markets, where competition reigns and generators are not directly compensated for available capacity, three concerns require the attention of policymakers. Foremost are greenhouse gas emissions, of which the global power sector emitted 25% in 2021 [65]. Their reduction is the principal public policy argument for the promotion of variable renewable energy sources (vRES[2]) [5]. In turn, vRES investments supply electricity at a marginal cost of (near) zero, thus reducing the full-load hours of existing assets and diminishing profitability across the board[3]. This provides a precarious situation where the future profitability of assets is highly dependent on public policy regarding climate targets, such as carbon prices or offshore wind concessions. Third, current wholesale market prices are capped to prevent the exercise of market power, but the ceiling may prove to be too low if vRES further reduces full-load hours of generators to secure sufficient investment [39]. In sum, the carbon externality has significantly complicated electricity market dynamics due to its need for regulation.



(a) Electricity market structure, adapted from [15].



(b) Market share by volume, blue = day-ahead, grey = Bilateral PPAs & 1-5 year ENDEX. Imbalance and intraday markets in between. From: [13].

Figure 1.1: Electricity market structure and divison

1.1.2. Increased Uncertainty

As electricity market dynamics have become more complex, uncertainty has risen amongst policymakers and investors alike.

The Investor Perspective In the contemporary context, investors are facing a much vaster scenario space for market development. The uptake of vRES and storage add complexity to revenue forecasts and demand growth rates which used to be predictable are now heavily dependent on electrification agendas of industries

[2]Intermittent, non-dispatchable and non-synchronous generation are interchangeable with the term *vRES*.
[3]This is commonly referred to as the merit-order effect.

otherwise reliant on other energy sources. Moreover, the necessary intervention of government heightens uncertainty as both the political context and the need to stay adaptive to the results of carbon monitoring reports in relation to policy targets add a layer of complexity atop free market dynamics.

The Policy Perspective In face of these deep uncertainties and market imperfections, predominantly risk-averse investors cannot be relied upon to deliver satisfactory results independently [38]. Policymakers thus need to design interventions in order to shape markets to deliver on the three well-established, competing societal objectives for electricity markets: reliability, sustainability and affordability [37]. Overextending on one objective will endanger another.

In doing so, policymakers are up against uncertainty as well. On the one hand, it is difficult to assess market performance on the societal objectives in absence of their regulation. In turn, devising the right policies is a complex task as their effects often cannot be definitively known. On the other hand, policymakers must be transparent and committed, for else they become a source of uncertainty themselves, further impeding free market dynamics.

All in all, the transition toward a competitive, decarbonised electricity market has become a complex coordination issue co-dependent on concrete regulation and the invisible hand.

1.1.3. Power System Planning

Power system planning is the exercise of deciding on the upgrading and greenfield construction of power system elements to satisfy future loads [27, 57]. The contemporary dilemma therein is evident: policymakers want to leave planning decisions to the private sector as much as possible, but climate policy requires them to set targets and award concessions.

Conventional planning approaches which sufficed in straight-forward, stable, concentrated fossil electricity systems are insufficient in navigating today's challenges. They relied on historical trend projections and a handful of scenarios to make strategic planning decisions [21, 59]. The ongoing overhaul of the electricity system has accompanied - and will continue to present - unforeseen circumstances and face choices between a plethora of different routes toward its final organisation.

Two implications for modern planning approaches ensue. Firstly, modern planning requires a participatory process, involving actors with diverging views, into a process that couples qualitative stakeholder engagement with quantitative modeling. Secondly, modern approaches should rely on exploratory thinking, i.e. analysing a much wider range of scenarios than has hitherto been customary [33, 34]. In sum, modern decision-making must be pro-active and aim at informing robust strategies by facilitating the analysis of many scenarios and doing so in a way that incorporates stakeholder input.

1.1.4. Quantitative Decision Support Methodologies

To support power system planning activities, academics, policymakers and investors rely on quantitative simulation models. The breadth and depth of models available for long-term power system simulation has been extensively reviewed in recent years [4, 14, 17, 20, 31, 56, 60][4]. Hitherto, work could be segmented into two categories. Long-term simulation models provide insight into possible energy scenarios without examining technologies in detail. In doing so, they have a large time horizon (>5 years) and are concerned with transmission expansion planning, policy development and investment decisions during that period [27]. Traditionally, short-term simulation models have dealt with more operational planning issues, such as unit commitment, economic dispatch and day-ahead markets [26, 27].

Increased intermittency as a result of vRES has posed a challenge to the applicability of long-term simulation models. Their significant size and time horizon force limitations on temporal detail in face of computational (time) constraints. Hence, they are prone to overlook the impact of intermittent generation assets, which has been shown to lead to an undershoot of investments in peak generators, an underestimation of carbon emissions and an unacceptable amount of lost load hours [1]. As a consequence, novel approaches either include more operational details in long-term simulation models, or couple models with complementary temporal resolutions [27]. This convergence unlocks the opportunity to account for short-term vRES and flexibility implications in long-term planning. Alas, doing so increases computational time and provides a challenge to conducting robust analyses.

[4] None of them predate 2018 and most were published in 2020 or later.

Academic work is at the point where these trade-offs are being explored through various modeling strategies. Work on myopic simulation models appears especially alluring in the contemporary context, as they are suspected to have the potential to realistically simulate investment behaviour in complex electricity systems at [47, 56]. However, existing methodologies are either too computationally intensive [56], or fail to represent investment behaviour realistically [47].

1.2. Simulating Myopic Investment

In face of increased uncertainty and a more complex system, our methodological research into the simulation of myopic investment stands to achieve two aims at once: reduce simulations' computational burden by representing the real-world bounded rationality of investors.

1.2.1. Myopic Decision-Making

The dictionary definition of myopia in the non-medical sense is the "lack of foresight or intellectual insight". When decision-making is myopic, one is said to be short-sighted, or "unable to see what the results of a particular action or decision will be" [43].

The practical implications of myopia are twofold. Firstly, decisions are made with imperfect information, resulting in satisfising rather than optimal choices. Secondly, myopia may foster a bias toward the short-term, especially in policy arenas where elected officials hold office for a limited period of time [3].

Analysis of myopic investment decision-making in electricity systems has become ever more relevant because of the increased uncertainty investors are facing in today's complex system. As the long-term development of the electricity system has become significantly less predictable, myopia amongst investors and policymakers has inevitably increased. Also, an additional driver to myopic investment decision-making has re-emerged as political decision-making has regained importance in electricity system development.

1.2.2. Need to Advance Myopic Investment Simulation Methodologies

The current state-of-the-art in myopic investment simulation is the Myopic Investment, Detailed Operational (MIDO) model. Inspired by the methodology underpinning the Energy Modelling Laboratory (EMLab) [68], MIDO is the first methodology to facilitate the inclusion of (seasonal) storage and extreme weather years in the analysis of myopic investment [56]. However, on a high-end personal computer - running on an Intel i7-0700K with 32 GB RAM - the average runtime of a 20-year period is 12 hours. The bottleneck to MIDO is that its investment decision algorithm is iterative, requiring the repeated dispatch of a unit commitment model for each asset that is considered to be invested in.

The bottleneck might be overcome with myopic optimisation (MO), which would be conceptually similar to MIDO's iterative process at a much higher computational efficiency. Poncelet et al. review the literate on MO and find that it is indeed argued to be a promising method to model myopic investment decision-making at an attractive computational cost [47]. However, based on their own analysis of an MO model they identify that MO might not reflect investment behaviour realistically. In sum, further research into myopic optimisation and its validity is warranted.

1.3. Objective: Modeling Myopic Investment Behaviour

1.3.1. Research Objectives

Bringing insights from the previous paragraphs together, myopic investment simulation methodologies aimed at supporting decision-making in policy and corporate arenas would benefit from a reduced computational effort and warrant additional validation. Therefore, the first two research objectives of this thesis are:

- To reduce the computational burden of the MIDO methodology by replacing the iterative investment loop with an optimisation. Therewith, the objective is to create the Myopic *Optimisation* Detailed Operational methodology (MODO).
- To further the literature's conceptual understanding of empirical myopia in investment decision-making, so that this may either be embedded in methodologies – MODO or otherwise – or be used to place methodologies and model results in perspective.

Additionally, MIDO is quite difficult to work with due to its cumbersome – yet effective – multi-model implementation. Hence, the third research objective is to ensure model transparency and usability of MODO.

Synthesising these objectives, our overall objective is to create a model that enables the long-term simulation of myopic investment in EU energy-only electricity markets with high intermittency, batteries and seasonal storage, in a way that is transparent and computationally efficient.

1.3.2. Research Questions

Three supporting research questions structure our research effort toward the methodological objective:

1. What conceptualisation captures the dynamics of myopic, private generation and storage investments in liberalised EU electricity markets?
2. What are the requirements for the myopic optimisation detailed operational model?
3. What formalisation incorporates the requirements in a way that is transparent and suitable for use by other academics, investors and policymakers?

Finally, we add a fourth question to illustrate potential use of the model in future research efforts:

4. Does the model produce plausible results when simulating the transition of the Dutch electricity system from 2030 to 2050?

1.4. Research Approach

There are two focal components to this thesis. The conceptualisation and elicitation of requirements lean on findings from a literature review and stakeholder consultation. The development of the transparent MODO model is underpinned by the use of Linny-R, a graphical language for the specification of (mixed) integer linear programming models [6].

1.4.1. Deliverables

O7ur research results in three deliverables:

- This document, which is written to suffice as a stand-alone, reproducible account of our research;
- The MODO modeling toolkit with which users can easily create their own systems and scenarios in Linny-R;
- An explanatory video of working with MODO, which enables those without any knowledge of modeling in Linny-R to nevertheless conduct their own experiments.

All deliverables can be freely accessed and downloaded from this shared Google Drive folder. Please reference appropriately.

1.5. Document Outline

This document is structured as follows. Chapter 2 conceptualises myopia in electricity sector investment and presents the requirements for MODO. Chapter 3 further conceptualises MODO and formalises the methodology mathematically, after which is is implemented in Linny-R in chapter 4. Chapter 5 elaborates on the use case for the demonstration of MODO, the results of which are presented in chapter 6. Chapter 7 concludes, followed by a reflection in chapter 8 and discussion in chapter 9.

2

Myopia in Electricity Sector Investment: Conceptualisation and Model Requirements

The objective of this chapter is twofold:

1. To conceptualise the transition dynamics of myopic, private generation and storage investments in liberalised EU electricity markets;

2. To establish the requirements for the myopic optimisation detailed operational model.

2.1. Theoretical Myopia

Recall the dictionary definition of myopia as the "lack of foresight or intellectual insight", i.e. being "unable to see what the results of a particular action or decision will be" [43]. In itself, this definition is too opaque to be useful to our research. In this first section we explore the theoretical concept of myopia further, identifying two related but distinct components: a purposeful short-term focus by actors and the inevitable bounded rationality of actors in electrictiy markets.

2.1.1. Bounded Rationality and Satisficing Behaviour

Chi and Fan succinclty summarise the theoretical foundation of investment myopia:

> "Optimization of investment decisions in an uncertain and dynamically evolving environment is difficult due to the limitations of the decision-maker's cognitive capacity. Thus, actual investment decisions may deviate from the dynamically optimal decision rule." [11, p.27]

In economics, the limited cognitive capacity is often referred to as bounded rationality, and the sub-optimal investment decision-making is satisficing behaviour [35].

In other words, the first theoretical component of myopia is the limited availability of information when making decisions. A key activity in our exploration and conceptualisation of myopic investment decision-making must therefore be the identification of which information is available.

2.1.2. Short-Term Managerial Focus

Less evident from the dictionary definition is the account that Holden and Lundstrum provide on managerial myopia:

> "The managerial myopia theory predicts that a variety of short-term pressures, including inadequate information on long-term projects, cause asymmetrically-informed corporate managers to underinvest in long-term projects." [28, p. 126]

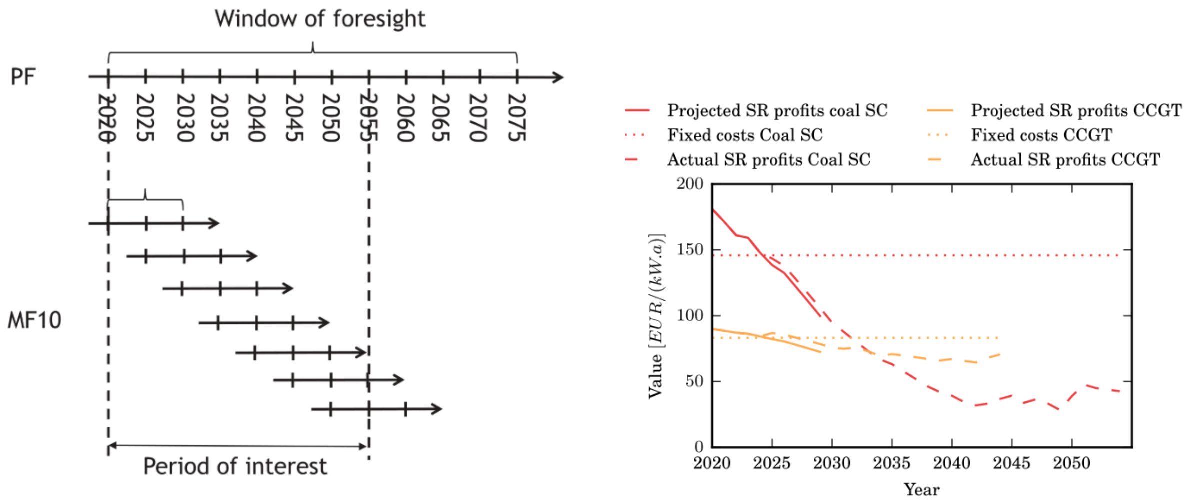
In other words, the bounded rationality available for long-term projects creates a context of pressure for decision-makers to focus on the short-term.

All in all, there exists a strong theoretical basis for why investment decision-making simulations should include myopia. The next section presents our literature review, investigating how these concepts have hitherto been operationalised in simulation methodologies.

2.2. Simulated Myopic Investment Decision-Making

2.2.1. Myopic Optimisation

In *Myopic Optimization Models for Simulation of Investment Decisions in the Electric Power Sector*, published in 2016, Poncelet et al. review the literature and define myopic optimisation models to be those models "in which the foresight is restricted to a certain period." [47, p. 1] To illustrate, consider figure 2.1a, which displays the difference between perfect foresight (PF) and myopic foresight, limited to a period of 10 years (MF10). The vertical dashes on the arrows indicate years during which investment decisions are made.



(a) Perfect Foresight (PF) vs Myopic Foresight limited to a 10 year period (MF10) [47, p. 2]

(b) SR profits in MF10 window versus actual SR profits after reconsidering investments every 5 years. From Poncelet et al. [47, p. 7]

Figure 2.1: Figures on myopic optimisation from Poncelet et al. [47].

On the Theoretical Advantage of Myopic Optimisation The primary argument for the use of myopic optimisation models is that they "account for the limited foresight and the short-term focus of investment decision-makers, which should lead to more realistic results" [47, p. 2]. Myopic models assume perfect information for a *window of foresight*, consisting of a limited number of years, and assume no information is available outside that period. This reflects the highly uncertain character of model inputs, such as fuel prices or policy interactions.

Another advantage of myopic models is a reduced computational cost due to the shorter time horizon, as a result of which temporal, geographical and/ or technical detail can be increased. This is considered a crucial advantage in order to enable the modeling of challenges related to increasing penetration of intermittent generation [46, 48].

On the Drawbacks of Myopic Optimisation In their analysis of myopic optimisation models, Poncelet et al. conclude that a major limitation is that the approach does not extrapolate the trends of projected short-run (SR) profits found within the window of foresight into the future [47]. In figure 2.1b the full lines present the SR profit projections at the time of decision-making. The dashed lines show SR profits when the investment would be reconsidered every 5 years. Dotted lines show annualised fixed costs. Based on the negation of these trends by the model, Poncelet et al. conclude that the investment decision-making process in myopic models might not be reflective of reality [47]. They recommend further research into simulating investment decisions using optimisation models.

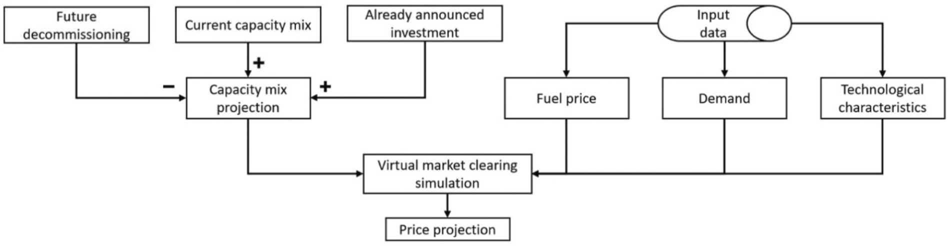


Figure 2.2: The *myopic agents* price projection method. Figure from [60, p. 7].

2.2.2. Myopic Agent-Based Models

The agent-based literature offers a more promising view on adopting a myopic perspective in simulation models. In *Review and analysis of investment decision making algorithms in long-term agent-based electric power system simulation models*, published 2021, Tao et al. identify a price projection method which they call *myopic agents* [60]. In it, "agents project the capacity mix in a given future year by starting from the existing capacity mix and adding the already announced or built new capacities (i.e., the investment decisions made by other agents during the course of the simulation) and subtracting the capacities reaching life expectancies before that given year." [60, p. 6] Figure 2.2 presents the conceptualisation. A notable difference to myopic optimisation is that in this agent-based methodology, agents take turns in making investment decisions, without knowing what the others have decided on in that specific round. Since agents do not make assumptions about their competitors' investment decisions during the round, as they look further into the future, they will over-estimate their potential revenues [60].

Interestingly, if the look-ahead horizon is set to 5 years, the *myopic agents* price projection method approximates the long-run equilibrium (figure 2.3). The reason is that a 5-year look-ahead means that the observed scarcity on which agents base their investment decisions is the recent decommissioning, and that agents consider no future information. Pertaining to this result, Tao et al. state: "In a perfectly competitve market, the profit-maximizing agents will make investment decisions that fill the gap in a system cost-minimizing manner." [60, p. 10]

From this we deduce that if we apply myopic optimisation not with a *window of foresight*, but rather to a *year of reference 5 years into the future*, we could be able to reduce computational time whilst also approximating the long-run equilibrium. This approach is familiar from EMLab and MIDO [16, 56].

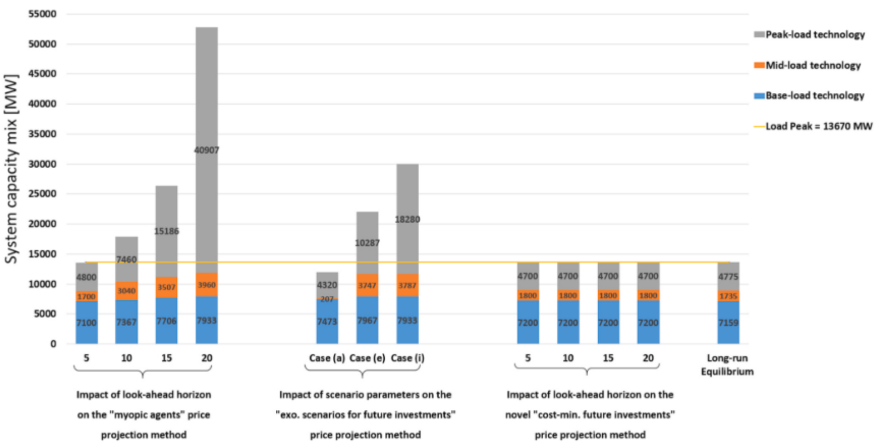


Figure 2.3: Results from the comparison of price projection methods by Tao et al. [60, p. 11]

2.2.3. MIDO: Myopic Investment Detailed Operational model

Sagdur does not provide a definition of myopic investment behaviour in developing the *myopic investment, detailed operational (MIDO)* methodology, but he i) builds upon the methodology used in EMLab, which is akin to the *myopic agents* methodology as Tao et al. identified it, and indeed ii) assumes a single year in the future as a reference point for making investments, however iii) this reference point lies 7 years in the future

[56] and iv) investors are aware of investment decisions made by competitors before they decide on their own investments. The degree to which the 7 years is significantly different from the 5 years is beside the point. The key take-away from this section is that we have established that Sagdur's greedy iterative investment loop can indeed be replaced by a cost-minimising myopic optimisation model, assuming that investment decisions are made based on a reference year 5 years into the future. We will refer to this methodology as *myopic optimisation, detailed operational (MODO)*.

On the MIDO Conceptual Framework Having established that from an academic perspective, transforming MIDO into MODO is a promising avenue of research as it is set to bring down the computational burden without conceptual drawbacks, we first address the conceptualisaion of MIDO – and MODO alike, if we were to make no changes – here. After having done so, we will move on to our stakeholder consultation to validate and nuance the conceptualisation. At the end of this chapter, we conclude with the final conceptualisation of MODO.

The MIDO methodology has two segments to its conceptualisation. The first being *Myopic Investment (MI)*, the second being *Detailed Operational (DO)*. In figure 2.4, the DO component is incorporated in the *Present Price Model*, and the MI component is incorporated in *Investment Decision Model* and *Future Price Model*. In MIDO, these segments interact. We discuss the key conceptual choices embedded in this conceptual design here.

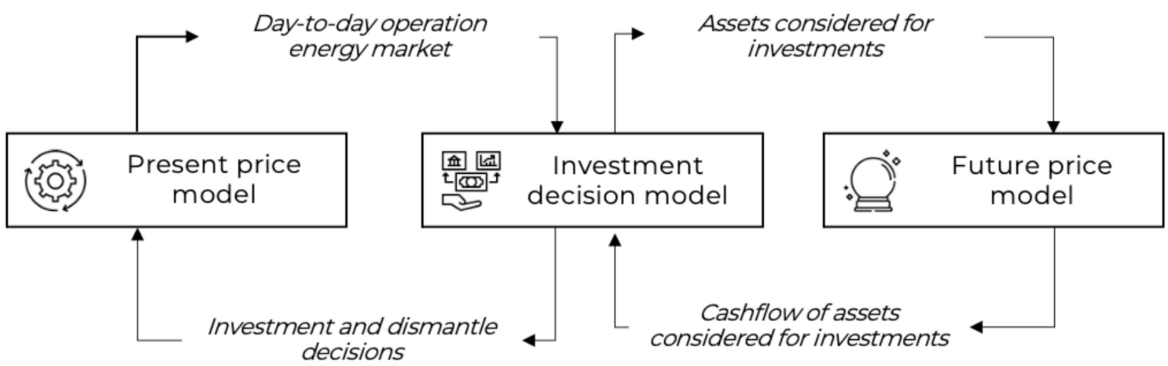


Figure 2.4: Conceptualisation of the MIDO model developed by Sagdur [56, p.9].

On the Markets that are Modeled MIDO relies on simulating day-ahead spot market dispatch with perfect foresight on demand and weather patterns to serve as a proxy for the total revenues an asset is able to obtain in the markets. There are no imbalance, long-term, or bilateral markets. The MIDO methodology does offer a capacity market module.

On the Present Price model The present price model offers spot market dispatch at an hourly resolution. Its primary objective is to analyse key performance indicators (KPIs) on the performance of the system and the assets at a high temporal resolution to account for intermittency and storage. It thus simulates a full year: 8760 hours.

On the Future Price model The future price model assesses the same KPIs, but does so based on information in the look-ahead year of the myopic investor, and uses a shorter temporal resolution with representative days. Its inputs are defined as per the previously discussed *myopic agents* method in figure 2.2.

On the Investment Decision model The investment decision model decides on investment and dismantle decisions. Its iterative nature in having to repeatedly run the future price model to find the assets with the highest NPVs until no budget is left, or there are no more profitable investment options, is what we seek to replace with the myopic optimisation in MODO.

On Dismantle Decisions The key dynamic of the dismantlement component is that MIDO assumes that assets are dismantled if they are unprofitable for five continuous years, there is no support scheme to change this and the supply ratio is not low enough to justify keeping the asset operational in hopes of it becoming profitable again in the near future.

Another more self-evident component is that assets are dismantled as they reach the end of their technical lifespan.

On the 'Day-to-day operation of the energy market' The reason for this link between the present price and investment decision model is that the investment decision model uses the data to analyse the profitability of installed power plants and assess whether any should be decommissioned according to the decision rule discussed above.

The following subsection presents the stakeholder consultations in which we explore real-world myopic investment behaviour and validate/ nuance this conceptual approach, before we present a final conceptualisation of MODO.

2.2.4. Real-World Investor Perspective

Having established the basis for our conceptualisation, this section is aimed at comparing and contrasting it with the real-world investor perspective. We conduct semi-structured interviews with all stakeholders. In the interviews focused on acquiring insight into investment rationales we focus on two themes: *i)* the empirical myopic investor perspective *ii)* the reflection on the conceptualisation of MIDO, and decision rules therein, and *iii)* acceptability and applicability of myopic simulation models power system planning[1]. To this end, we prepared the following broad pointers and were flexible in their order and form, except for the final question which we would always ask last:

1. What criteria must be met before making an investment[2]?
2. What do you perceive to be the most significant obstacles to determining the degree to which those criteria are met?
3. In your view, what are the core uncertainties and risks accompanying an investment in electricity markets?
4. How do you analyse and mitigate those uncertainties and risks?
5. Following a brief explanation of the "myopic agents" price projection paradigm: Would such a model have added value to your operations - lobbying, planning or otherwise - and if so, what would the requirements be for you to adopt it?

We checked the following assumptions through closed-form questions:

1. What are the criteria for dismantling an asset before it has reached the end of its technical lifetime? (MIDO assumes dismantlement after 5 consecutive years of losses).
2. How realistic is a 5-year look-ahead period after which all timeseries and inputs (e.g. fuel prices, electricity demand) are assumed to remain constant?

On Empirical Myopic Perspectives Recall that the *myopic agents* price projection methodology (figure 2.3) which many models, including MIDO rely upon, is heavily dependent on the look-ahead period. Beyond the look-ahead, modeled investors assume parameters stay level [47]. The idea feels arbitrary to those unfamiliar with modeling, their intuitive descriptions of what should be done tends very much toward the novel method proposed by Tao et al. [60] (figure **??**), i.e. assuming system development based on the cheapest additional MWh and investing based on that. Those with experience in power market modeling recognise the challenge when seeking to model path-dependence in face of uncertainty.

On the one hand, investors without in-house power market modeling capabilities rely on external consultants to supply them with estimates for the coming 10-15 years. They will then model three scenarios for themselves - low/medium/high -, generally dependent on electricity demand (recall the importance of the electrification agenda we described in section **??**), and invest if the worst-case scenario is satisfactory. On the other hand, investors with in-house modeling capabilities (one incumbent IPP described having a team of 10 employees dedicated to modeling and fundamental market analyses), balance their own projections with

[1] In the broad sense; within the firm and in planning activities between government and the private sector.
[2] Note that 'making an investment' means different things to different firms, e.g. direct investment versus loans.

those from external parties. Their analyses will inevitably be more detailed than those made by someone using the "myopic agent" price projection methodology. To illustrate with an example, consider how in figure 2.5 an investor would make a different investment decision based on having information of the full future, versus being limited to the single final look-ahead year. The light blue line (bottom) displays an NPV based on a single look-ahead year. The dark blue (top) line is an NPV based on information about the entire period. One year after the look-ahead period of the light blue (bottom) line, an asset is dismantled, which it does not account for whilst the dark blue (top) line does. Hence, the difference in NPVs (using a 10% discount factor).

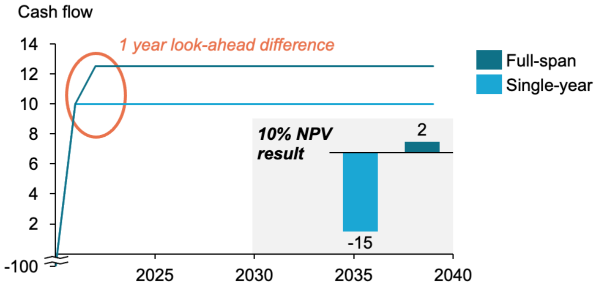


Figure 2.5: NPV results illustrate the difference between information about a single year versus multiple, e.g. due to dismantlement.

Our rationale for accepting less accurate representation of investment behaviour is harboured in the quest for combining short-term storage, seasonal storage and intermittent generation in a model that is computationally feasible. We feel adopting an MO approach based on a single look-ahead year is best aligned with these requirements at this time. MO is the evident choice given its computational efficiency as opposed to the iterative agent-based methodology [47, 60]. Also, Tao et al. write they will be working on expanding the methodology they proposed to also include intermittent generation and storage. As such, our avenues of research are complementary to each other, allowing the results - regarding both output and computational time - to be compared.

Investment Drivers General consensus is that post-liberalisation, two factors have driven investment for competitive investors. Initially, replacement CapEx was a core driver. More recently, investments have been heavily incentivised by feed-in tariffs in several countries. Provided the availability of land and access to a grid connection, capital allocation to these projects has been an easy decision across the board. In markets without such feed-in tariffs or similar schemes, high demand for long-term power purchase agreements (PPAs) by sufficiently reliable counterparties characterised the landscape. For example, the early 2010s were characterised by investments in gas-fired plants and renewables, many of which relied on 20-year PPAs. Nevertheless, several gas-fired generators also took on spot market risk. Capital was - and still is - widely available as long as risks are properly hedged through PPAs.

The role of feed-in tariffs as vRES investment driver is increasingly being replaced by the attractiveness of renewable power to corporations looking to boost their image and secure supply at the same time. This point was mentioned explicitly with regard to the Dutch SDE++ subsidy. Amazon taking a significant stake in a Dutch wind farm to secure renewable power is an example. Also recall figure **??**, showing the significance of long-term and bilateral contracting.

Financing Solutions We identified two investment drivers: replacement CapEx for thermal plants and high availability of feed-in tariffs or similar guaranteed cash flows for vRES. The former are mainly financed from the balance sheets of incumbent IPPs because they can borrow money at extremely attractive rates, as an investment manager employed by one confirmed. The latter has seen a mix of project-finance-based and corporate-finance-based developments over the past few years, as the favourable terms have opened up the market to smaller players as well. Assets relying on project financing will be fully hedged with feed-in tariffs, PPAs or likewise solutions, whilst incumbent IPP-owned generally play a bit more on electricity markets.

Spot Markets Spot market gaps have not been a key driver to investment, except when the replacement of power power plants being taken out of commission created a clear market gap. A noteworthy degree of spot market risk is generally adopted only when there is a clear grid-scale gap in the market (hence the importance of replacement CapEx). These investment decisions are closely linked to corporate strategy departments, who usually direct investment departments to analyse financial feasibility of investments. The business case for conventional thermal assets is argued to be broken. Some argue that the decrease in operating hours and increase in start-stop cycles will not sort itself out and requires some sort of capacity mechanism or investment guarantees. This argument is supported by the fact that very few investment decisions are taking place nowadays, barring wind farms in the North Sea at guaranteed prices. A more nuanced rationale is presented by others, who argue that whilst the market is indeed very dependent on government, it is more so for clarity than a significant monetary support. The planning element arises here, where the interviewees mentioned offshore wind as an example of something going well because of the clear concessions and timely preparation of plans for 2030, rather than focusing on the feed-in tariffs.

Core Uncertainties Risks identified by stakeholders are well-aligned with risks described in literature, listed in figure 2.6. A relatively novel one is global commodity prices for renewables, such as the material required to produce solar PV panels. Skyrocketing prices have led certain planned projects to become infeasible. In some countries, this issue is amplified by scarcity of qualified technicians driving up labour prices for these installations.

On the other end of the value chain, the electrification agenda is the largest uncertainty. Stakeholders indicate that planning is key and investments take long to materialise. Thus, timely communication of clear plans to which the government is in some way committed are beneficial to both parties.

Technology	Capital size per unit	Lead time	Capital cost share	Fuel cost share	CO_2 cost	Fuel price risk	Regulatory risk on construction cost
Gas turbine (100 MW)	Very low (€20 million)	Very short	Low	Very high	Medium	High	Low
CCGT (400–600 MW)	Low (€100–200 million)	Short	Low	High	Medium	High	Low
Coal (2× 700 MW)	Large (€700–1000 million)	Long	High	Medium	High	Medium	High
Nuclear (1500 MW)	Very large (€2–3 bn)	Long	Very high	Low	Nil	Low	High
Renewables (wind farm/200 MW)	Medium (€300 million)	Medium	Very high	Nil	Nil	Nil	Medium

Figure 2.6: Cost and risk characterisation of generation technologies, from [25, p. 161].

The Underestimation of Risk-Averse Portfolio Decisions by Most Simulation Models In terms of the myopic investor perspective there are two stories to be told. The first is one of assets structured through project finance. Whether or not a project materialises is a function of whether the contracts are there to make it profitable. There is little to no place for spot market risk. The question then becomes how these prices are determined and negotiated. Whilst a novel simulation methodology presented recently by Tao et al. [60] does indicate negotiation of bilateral contract negotations as an opportunity, we find that literature pays little attention to the interaction between the two in long-term electricity system planning.

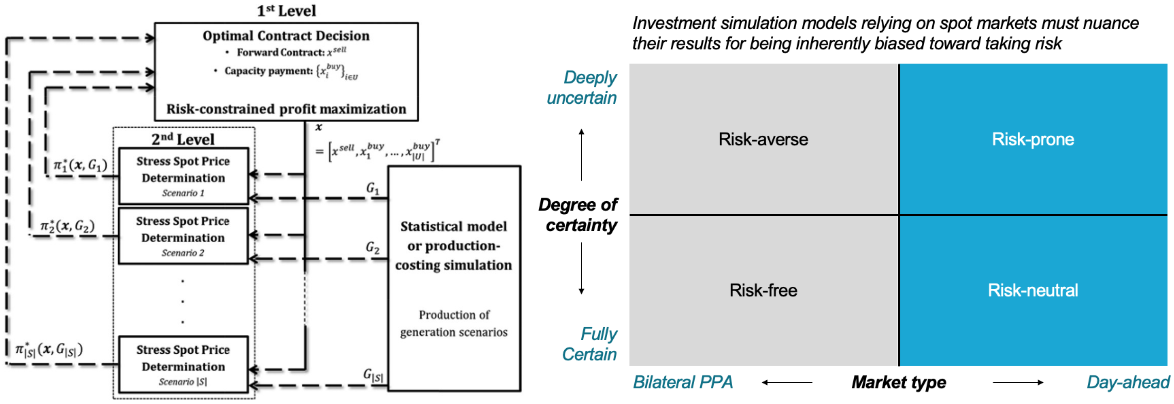
Besides the aforementioned work, Falbo & Ruiz [23] develop a model to find the optimal sales mix and generation plan, but do not focus on long-term development of systems. An article titled *Medium-term power planning in electricity markets with pool and bilateral contracts* [36] is more in line with this characteristic of power system planning. However, the topic appears to have little attention as the paper has only been cited thrice[3]. Most models have little regard for the bilateral component, as does ours.

The key reason for the absence of such models is data unavailability. Prices of long-term contracts generally remain undisclosed, hence modeling efforts are difficult to calibrate and validate.

Myopic Investment Decisions Based on Spot Market Dispatch Limiting ourselves to spot market dispatch is a justifiable approach nonetheless. Consider the already exorbitant amount of time it takes to analyse runs based on spot-market dispatch in current state-of-the art models such as MIDO [56] and consider the limited literature available on MO. As our work reduces the time it takes to simulate myopic investments based on spot markets, we open the door to its extension or pairing with capabilities or models respectively, that account for long-term forward contracting. Our focus is on developing the 2nd level in figure 2.7a in a way that accounts for myopic perspectives in long-term electricity system development. In turn, the 1st level may be developed with a similar focus, so that a simulation approach may become available in addition to the stochastic approach developed by [24]. As for why we have opted to develop the 2nd level, we argue it to be the logical next step given the momentum that work in this area has, the MIDO model being the most

[3]and it is referenced 5 times, according to https://ideas.repec.org/a/eee/ejores/v260y2017i2p432-443.html

recent. Limited time prevents us from developing both.



(a) Stochastic approach to portfolio optimisation for Energy Trading Companies from [24, p. 1831]

(b) Our understanding of the required nuance for investment simulation models relying on spot markets.

Figure 2.7: Portfolio choices for energy trading companies related to investment simulation modeling.

On Models and Intuition The key barrier to the acceptance and adoption of models identified by interviewees is the ability to intuitively understand what is going on. Especially when working with market advisors who do the modeling, the source of the results is too much a *black box*. Some argue that intuition will not give way to models, especially when the final decision rests with a more senior executive who is not necessarily an expert on the topic.

Nevertheless, some making this point also state that there is room for a whitelabel easy-to-understand low-maintenance model. From this, we deduce that for our model to have impact in the field, we must make it as elegant and intuitive as possible.

Criteria for non-end-of-life dismantlement In addition to the universal need to consider end-of-life dismantlement, several existing models make choices regarding dismantlement based on continued unprofitability. For example, MIDO dismantles assets if they lose money five years in a row [56]. Interviewees expressed never having had to make such a decision and not being aware of commonplace decision rules. Their intuitive feedback on the assumption brought forward the point that the model should look ahead to whether the asset stands to make money in the years to come. Another option would be to dismantle the asset 50% of the time and give it another couple of years otherwise. Lastly, it would be acceptable to leave the asset in the mix, considering the cost of decommissioning and CapEx when making a wrong decommissioning decision. Further supporting the latter argument, consider how Dutch shut-down gas-fired power plants suddenly became profitable again after four years of non-activity due to a sudden policy decision to shut down coal plants, paired by a capacity shortage in Belgium. Aligned with our aim to keep the model as simple and elegant as possible, we find this latter argument to pack enough punch and opt not to dismantle assets due to year-over-year losses. Naturally, we do analyse performance ex-post. In sum, assets are only dismantled if they reach their end-of-life.

2.2.5. Conclusion

The consultation regarding both inplace methodologies and our proposed approach highlights important nuances. Contemporary long-term simulation models cannot allocate risk in a way that aligns with empirical investor considerations, but those same investors - and commercial modelers supporting their decisions - recognise that computational effort makes such limitations inevitable. Additionally, an inevitable limitation is that academic research must rely on spot-market based models in investment simulations because the data required to calibrate and validate models that would otherwise simulate long-term contracting is unavailable. Nevertheless, feed-in tariffs and government support schemes can often be modeled adequately, but in terms of commercial PPAs or ENDEX markets, there generally is an inevitable abstraction in models.

Additionally, we have identified a need for models which have a lesser 'black-box' effect, i.e. that are easily accessible as a basis for planning discussions in the industry. Given the emphasis several interviewees have put on the need for clear visions from government to then be acted upon by industry, such models might contribute to the acceptance and communication of such visions. Here it is important to recognise that modeling of wicked problems as is done today - especially in participatory processes - is a relatively novel concept, especially to those who have left the academic world long ago but are in charge of important investment decisions today.

In conclusion, our participatory effort has yielded an affirmation of the value-add of our proposed approach, improved our understanding of myopic investors' perspectives and stressed the need for elegant modeling.

Additionally, we feel comfortable adopting the same conceptualisation used in MIDO, as per figure 2.4, with the following three alterations:

- We replace the iterative investment loop with an optimisation;
- We assume no dismantlement takes place based on assets being unprofitable for extended periods of time;
- We assume a five-year look-ahead.

The next section translates the progress of this chapter into a set of concrete requirements for our modeling effort.

2.3. Requirements

Based on our literature review and stakeholder consultation, our view on the next step to be taken is encompassed by the requirement breakdown structure (RBS) in figure 2.8. The figure contains the objectives we have discussed, and therewith also represents the trade-offs addressed. Overall requirements 1 through 4 were similarly defined to structure the construction of the MIDO model. As we have established, we will be making trade-offs in reducing the accuracy obtained by MIDO for requirements 1 through 3 - pertaining to the degree of detail of UC and the optimisation of profits - so as to achieve better performance on requirement 4 - computational efficiency. Lastly, as the stakeholder review has laid bare the need for more transparent modeling, we have added a fifth requirement to tackle just that.

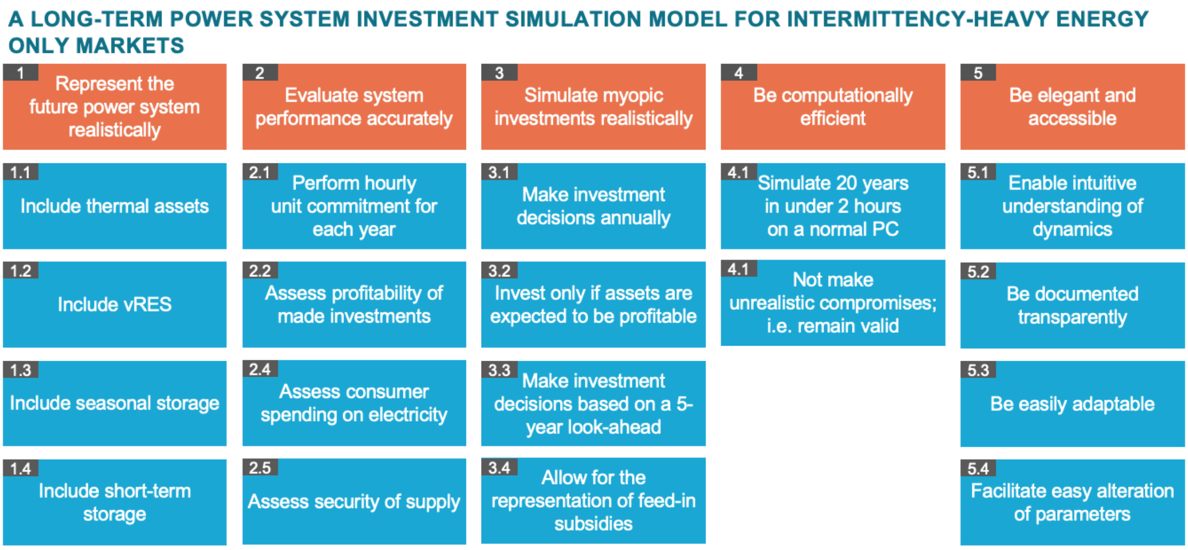


Figure 2.8: Requirement Breakdown Structure (RBS) to structure our modeling effort.

3

MODO: Myopic Optimisation Detailed Operational

3.1. Introduction

Having established the requirements for our model, this chapter is concerned with its formalisation. In doing so, we have two objectives:

1. Formalise the model logic and its mathematics so that it may be reproduced by those wishing to do so;
2. Simultaneously conducting this formalisation in a way that is aligned with the manner in which we have implemented the model in Linny-R, so that it is well-aligned with the following chapter on our implementation of the model.

3.2. Conceptualisation of Stages and Timescales

MODO relies on a similar multi-stage multi-timescale conceptualisation as MIDO, which is required to keep the model computationally feasible [56]. The two stages are the Myopic Optimisation (MO) and Detailed Operational stages (DO) (figure 3.1). The structural electricity market, unit commitment model itself is universal across all stages, only the temporal settings and input data differ.

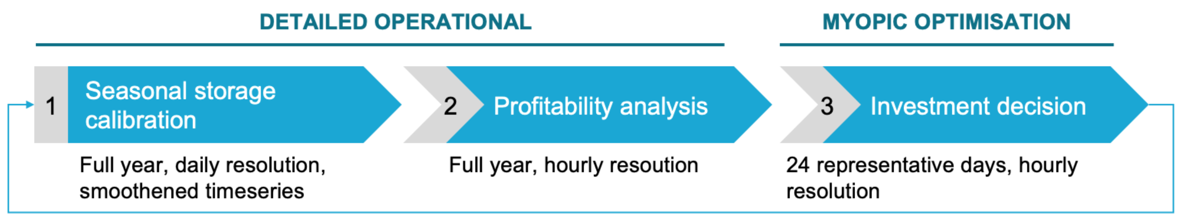


Figure 3.1: Multi-year, multi-timescale conceptualisation, adapted from MIDO [56].

The purpose of the Myopic Optimisation stage is to make myopic investment decisions. Because the analysis of investment decisions adds significant complexity to the unit commitment (linear optimisation) problem, the time period it is able to simulate at an acceptable computational cost is limited. Hence, the myopic investment optimisation relies on representative days.

To assess the performance of investment decisions and the system as a whole, the Detailed Operational stage solves a unit commitment problem for a full year with an hourly temporal resolution. To enable the inclusion of seasonal (hydrogen) storage, the full year, hourly analysis is preceded by a seasonal storage calibration phase. The purpose of this stage is to ensure realistic simulation of the seasonal storage by filtering out intermittency in the dispatch. To this end, the seasonal storage calibration stage uses smoothened timeseries with a daily temporal resolution. Data of its behaviour is subsequently input into the hourly, detailed run to ensure its seasonal storage role is properly simulated. The next section provides a more detailed account of this conceptualisation.

3.3. Model flow

Figure 3.2 offers a flowchart accompanying this section, but the text should suffice in providing an intuitive understanding of MODO's modus operandi. For each simulated year, MODO has four stages with complementary objectives. They all use the same structural model, only changing input parameters and optimisation settings between them. The first two revolve around seasonal storage, the second provides a detailed hourly market dispatch and the final is the invesment run.

Stage 1 determines a suitable initial level for the seasonal (hydrogen) storage assets in stages 2 and 3. Because the asset mix is novel (almost) every time this stage is initiated, we cannot assume a fixed value. Nor would it be realistic to start the later, 'proper' UC dispatch operations with a value of zero as the year starts on the first of January, i.e. mid-winter. Because the storage is seasonal and long-term approximations of weather and demand patterns would also suffice in reality, we solve the UC with daily time steps and assume perfect foresight. We simulate 1.5 years so that the solver refrains from emptying the storage just before January first, and save the storage level at the end of the year to input it into stage 2.

Stage 2 is solved with the same settings and parameters as stage 1, the only difference being the initial level. The output we are looking for are the seasonal storage levels of every 72nd hour, because this concurs with the look-ahead period for which weather can generally be adequately forecasted in reality [56]. This is so that we can peg these in the detailed, hourly simulation to ensure the seasonal effects are not lost there.

Stage 3 is an hourly UC model which we use to evaluate system and asset performance. Because the investments are made using representative years, we require hourly runs to evaluate whether those investments yield any fruit in terms of profitability, system benefits or both. Because we omit any strategic market bidding or forecasting errors, ideally we would optimise over all 8760 hours in a year as the seasonal storage levels have already been pegged and highly intermittent battery behaviour will not differ much unless the look-ahead is set to a minimal number of hours, which would in turn significantly increase the computational burden. 8760 hour blocks may not always be possible, but even for more complicated models, half-year blocks with a small look-ahead to prevent storage assets from emptying themselves at the end generally suffice.

Stage 4 is the investment model, based on representative days. Here we co-optimise installed assets with assets that can be invested in. This is also where we employ our heuristic to ensure assets are only installed in when they yield a profit. The next section will explore this heuristic, and the other phases, in more depth.

3.4. Modeling choices for computational efficiency

We choose to ignore all technical constraints, such as ramping and network congestion, except for the maximum capacity of assets. This enables us to reduce the number of decision variables in the model, which alleviates the computational burden. Like Sagdur [56], we model installed generation capacity as a single decision variable by stacking the capacities of individual assets atop each other as in 3.3a. This applies to all assets.

Also, seasonal storage assets are regarded as integrated investments (figure 3.3b). Modeling hydrogen markets is not the scope of this research, investments in the electricity sector are; we thus consider the role of hydrogen assets in a vacuum, pertaining only to their role in the electricity system. The business case for electrolysers and hydrogen turbines is otherwise highly complex and does not rely on seasonal storage [64]. Thus, we seek to study it solely in relation to the business case for seasonal storage so that analyses of its merit are not disturbed.

3.5. Mopic Optimisation with Profitability Constraints

This section formalises the approach we take to unify myopic optimisation and profit-seeking investment. Subsections 3.5.1 and 3.5.2 contain standard unit commitment operations. Subsections 3.5.3 and 3.5.4 explain the ex-post profitability heuristic we propose to ensure profitability of investments.

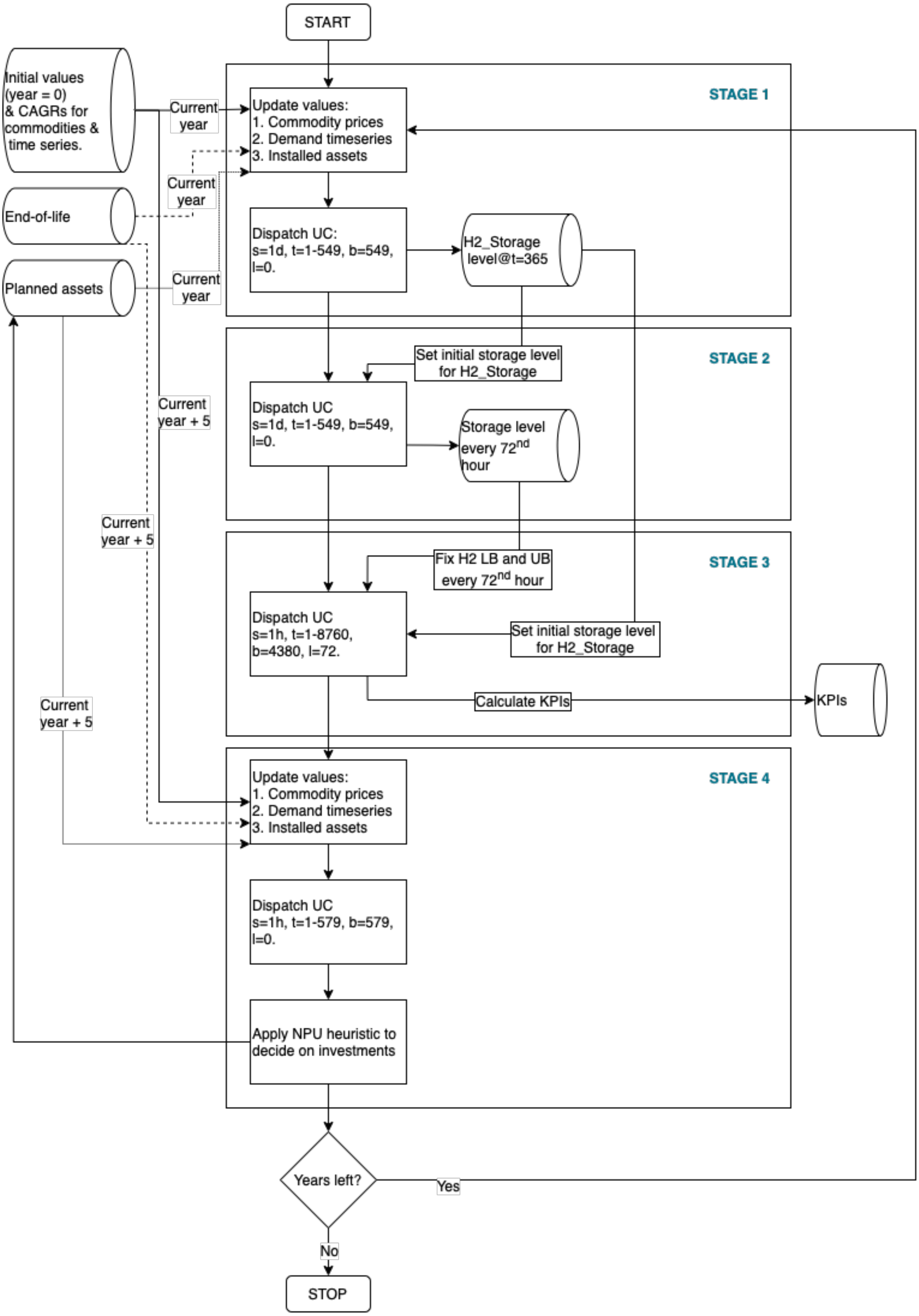
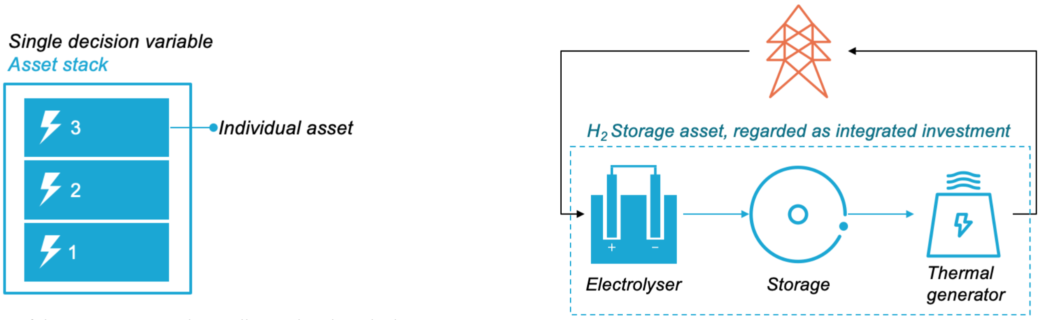


Figure 3.2: Myopic Optimisation Detailed Operational (MODO) logic. In UC dispatch operations, 's' = time step, 't' = simulation period, 'b' = block length, 'l' = look-ahead.



(a) Assets of the same type are identically sized and stacked to form a single decision variable.

(b) Storage assets are regarded as an integrated investment.

Figure 3.3: Conceptual visualisations of asset stacks and seasonal hydrogen storage.

3.5.1. Objective function

For stages 1 through 3, we seek to minimise the societal cost of electricity production, i.e. minimise the cost of i) dispatch of already installed assets and ii) loss of load (equation 3.1):

$$minimise \sum_y \sum_t \left(\left(\sum_i \sum_j g_{j,i,y,t} \cdot (v^{fuel}_{j,t} + v^{O\&M}_{j,y,t}) \right) + VoLL \cdot ll_{y,t} \right) \tag{3.1}$$

Note that the domain for t differs between stages, and is defined in figure 3.2.

Stage 4 requires us to first co-optimise investment opportunities and already installed assets. The investment opportunities will be committed in dispatch if the savings to the system as a whole supersede the investment cost (equation 3.2). Note that this does not mean definitive installation, for which we will describe the heuristic later in this section.

$$minimise \sum_y \sum_t \left(\left(\sum_i \sum_j g_{i,j,y,t} \cdot (v^{fuel}_{j,t} + v^{O\&M}_{j,y,t}) \right) + VoLL \cdot ll_{y,t} + I^{annuity}_{j,y} \cdot inv^{solver}_{i,j,y} \right) \tag{3.2}$$

In the objective we have opted for an annuity[1] as investment threshold, which we formalise in equation 3.3:

$$I^{Annuity}_{j,y} = \frac{I^{CapEx}_{j,y}}{\dfrac{1-(1+WACC_{j,y})^{-d_{j,y}}}{WACC_{j,y}}} \tag{3.3}$$

3.5.2. Constraints

At each moment, generation (including VoLL and negative generation from charging storage) must meet demand (equation 3.4):

$$\sum_{i=1}^{I} \sum_{j=1}^{J} (g_{i,j,y,t}) + ll_{y,t} = L_{y,t} \quad \forall i \in I, \forall j \in J, \forall y \in Y, \forall t \in T \tag{3.4}$$

Generators cannot exceed their standard generation capacity (equation 3.5):

$$g_{i,j,y,t} \leq s_{i,j,y,t} \quad \forall i \in I, \forall j \in J, \forall y \in Y, \forall t \in T \tag{3.5}$$

Storage levels must not fall below zero or rise above the storage capacity (equation 3.6):

$$0 \leq l_{i,j,y,t} \leq s^{storage}_{i,j,y} \tag{3.6}$$

[1] Our problem formalisation assumes an annuity as investment barrier. It may naturally be replaced with another type of barrier.

3.5.3. Heuristics for Profitability in Face of Standard Asset Capacities

As the solver seeks to minimise total investment cost, it might invest in assets to fill a gap when the standard size of the asset would be larger than that gap. As a consequence, the investment would price itself out of the market. In other words, the lumpiness of investments leads to situations where the solver over-invests form an investor's perspective, whilst the investment is attractive from a societal welfare perspective. We must thus evaluate whether a committed investment would be sufficiently profitable before definitively adding it to the (planned) generation mix:

Firstly, for all assets, their profitability is defined by 3.7:

$$P_{i,j,y} = g_{i,j,t,y} \cdot (p_{y,t} - \frac{v^{fuel}_{j,y}}{\mu_j}) - s_{i,j} \cdot f_{j,y} \tag{3.7}$$

Where $p_{y,t}$ is defined as the highest marginal cost price of all generating assets in equation 3.8:

$$p_{y,t} = \max_{\forall i,j} \left(\left(\frac{v^{fuel}_{j,y}}{\mu_j} + v^{O\&M}_{j,y,t} \right) \cdot \min_{\forall i,j} (g_{i,j,t,y}; 1) \right) \tag{3.8}$$

Profitability Heuristic for Standard Asset Sizes For assets in each stack proposed by the solver, investors invest in the maximum of the number of profitable assets, or else the stack size subtracted by 1 (equation 3.9).

$$inv^{investor}_{i,j,y} = \max(\sum_s P^{investment}_{i,j,y,stack} \cdot inv^{solver}_{i,j,y,stack} \geq P^{threshold}_{j,y}; \sum_s P^{installed}_{i,j,y,stack} - 1) \quad \forall i \in I, \quad \forall stack \in Stack \tag{3.9}$$

3.5.4. Installed capacity

For phases 1 through 3 the number of installed assets is equal to the already installed assets and the number of investments made in the number of years ago equaling their construction time, subtracted by assets taken out of commission (equation 3.10):

$$n^{regular}_{i,j,y} = n^{regular}_{i,j,y-1} + \sum_i (inv^{investor}_{i,j,y-c_{i,j}} - dec_{i,j,y}) \quad \forall j \in J, \forall y \in Y, \forall c \in C \tag{3.10}$$

For phase 4 the number of installed assets equals the number of installed assets in the previous runs - and is thus dependent on equation 3.10 - plus the number of assets invested in but not yet deployed period, minus the assets that will be decommissioned during the look-ahead period (equation 3.11):

$$n^{invest}_{i,j,y} = n^{regular}_{i,j,y} + \sum_i \sum_{lb} \sum_{la} (inv^{investor}_{i,j,y-lb} - dec_{i,j,y+la}) \quad \forall j \in J, \forall y \in Y \tag{3.11}$$

4

Implementing MODO in Linny-R

4.1. Introduction

Our expert & stakeholder consultation has highlighted the need for long-term simulation models to be transparent and easily adaptable in order for them to be accepted by stakeholders and usable for power system planning exercises. The task ahead is therefore to implement MODO in a way that meets these requirements (therefore complying with our requirement breakdown structure as defined in figure 2.8). Hence, the objectives of this chapter are threefold:

1. Implement MODO in a way that is elegant and transparent, i.e. robust to future use;
2. Document MODO's implemenation to support objective 1 and mitigate 'black box' objections as much as possible;
3. Verify the working of MODO to foster acceptance and transparency.

4.1.1. Rationale for the use of Linny-R

We opt to implement MODO in Linny-R, a graphical modeling language well-suited for modeling unit commitment problems [6]. Our main motivation is the transparency Linny-R offers. The graphical representation of process levels and flows - such as power supply from a plant to the grid at a certain time step - empowers users to follow system behaviour step-by-step.

Linny-R is thus aptly designed to deal with a core attribute of human decision-makers: intuition. Any model can affirm intuition when results are in line with expectations. Linny-R's transparency makes it perfectly positioned to also have its results accepted when they counter intuition, because users – both modelers and those purely interested in running scenarios without doing any modeling themselves – are able to visualise where the model behaviour deviates from their expectations.

Arguments against the use for Linny-R also exist. The tool has seen a lot of development in recent years and, whilst open source, is currently being maintained and developed by a single person. As has been the case during this thesis, users of these novel features are likely to encounter bugs. This is well-compensated by prompt replies to bug reports, often within the same day.

Also, documentation is a work in progress. No formal articles have been published on Linny-R yet. However, there is a wiki-style website available, which is also hosts all files and information required to install Linny-R[1]. Therefore, we have made certain that features relevant to this thesis are well-covered on the site where necessary.

Overall, if MODO is to become a transparent decision-support tool for long-term electricity simulation planning, the transparency and elegance of Linny-R more than counterbalance drawback in terms of occasional bugs and lack of extensive documentation.

4.1.2. Reading guide

We structure this chapter so that *i)* readers may understand the implementation and accept the model logic, and *ii)* those seeking to use the model are empowered to do so without needing to undertake any modeling.

[1] linny-r.info

MODO has been designed and implemented as a modular toolkit, which empowers users to construct their own electricity systems – including all components of the MODO methodology – at the press of a few user-friendly buttons. Subsequently, all that remains for the user to be done is to input their own assumptions and refine the selection of output criteria. We have created a 10-minute video which explains and showcases this modular use of MODO to foster transparency and usability. The video, as well as all other required resource are available through this shared Google Drive folder (same as linked in the introduction).

The first segment of this chapter guides the reader through MODO's modular design, verifying behaviour along the way. The second component of this chapter applies MODO to a relatively simple system for verification and illustrative purposes. For any questions that remain, contact details are available in the Drive Folder as well. Please feel free to reach out.

4.2. Modular MODO Toolkit

The MODO toolkit consists of five components:

1. The MODO framework, to which all other modules connect;
2. A module for thermal generation;
3. A module for vRES;
4. A module for batteries;
5. A module for seasonal hydrogen storage in salt caverns.

In the case of MODO, adding a module means adding an asset class which can be defined by the user, e.g. importing a vRES module requires the user to specify the details that make the asset class solar PV or offshore wind, a.o. through the specification of weather-dependent generation output timeseries.

Imported modules already include all datasets that need to be specified for the user to successfully run the model. There is a select number of relatively straight-forward steps the user needs to take in order to be able to run the model, such as specifying model output as relevant output to the experiment that is to be executed. These steps are straight-forward and a step-by-step guide is provided in both the video and in the yellow sticky note in the framework.

Additionally, all modules are annotated. The blue 'information' button in Linny-R will highlight annotated model components in blue, which means that selecting them (by holding shift when hovering the mouse over) will reveal additional comments/ explanations/ remarks.

4.2.1. Key Linny-R Concepts

Three core visual components underpin modeling in Linny-R:

- Products can be produced and/ or consumed by a process. They can be tangible, such as fuels, or intangible, such as information. Four variations of a default product exist, mostly for visualisation purposes. Figure **??** provides an overview.
- Processes represent the transformation of some product(s) into some other product(s).
- Links connect entities, such as products and processes. Figure **??** shows how the three components come together; we have built our first power plant transforming fuel into electricity.

We can now transfer this knowledge into constructing the framework.

4.2.2. MODO Framework Module

The MODO framework module is the point of departure for any myopic investment simulation with the MODO methodology. As depicted in figure 4.3, it includes the core components to the electricity system:

- The product 'Electricity_Grid' is where all generation is fed into, in turn supplying it to the process 'Electricity_Final_Consumption' or 'Curtailment'.
- The process 'Electricity_Final_Demand' is constrained by a lower bound to represent final demand.

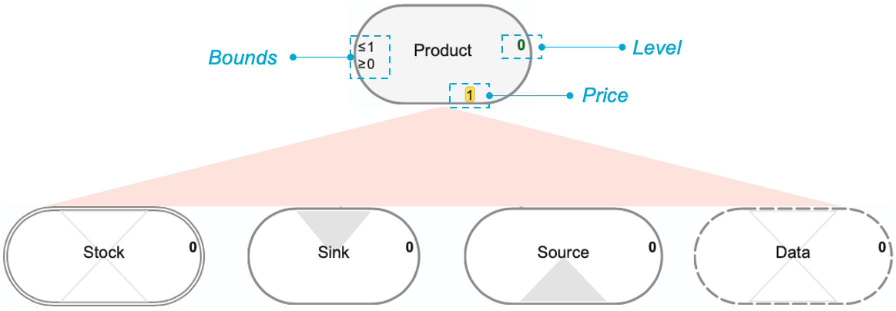


Figure 4.1: A default product and its four variants. Apart from stocks, the sole difference is the visual representation.

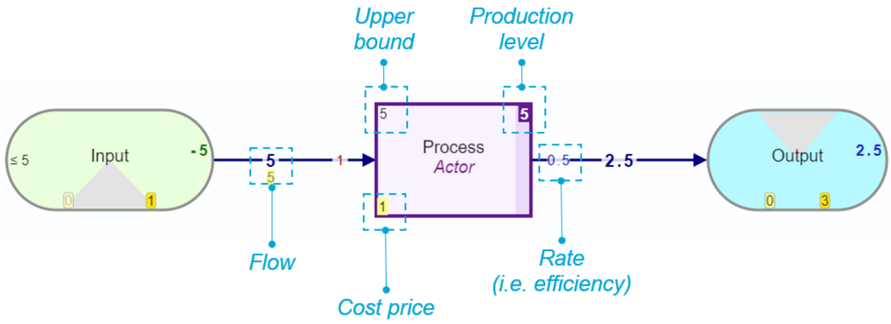


Figure 4.2: A process transformign an input product into an output product. Entities are connected with links.

- The capacity of the ’Loss_of_Load’ process is infinite so that the model remains feasible when maximum generation levels are met, at the same time accounting instances of lost load and setting the grid price to the value of lost load through the ’VoLL’ data product (Price in yellow, bottom-right of the product).
- The EU Emission Trading System (ETS) credits are simulated using a stock with a maximum capacity which generators will feed into. If the stock is full, generators emitting carbon will not be able to generate any more.
- The price of ETS credits is set through a data product.
- All investments will be linked to the ’CapEx’ product, where each CapEx ’unit’ will be attributed a cost of 1 through the ’CapEx_Accounting’ data product. The ’Cumulative_CapEx’ stock allows for easy data processing.
- The yellow ’100%’ on the link from ’Loss_of_Load’ to ’Electricity_Grid’ means that 100% of the Cost Price of the loss of load process is attributed to the electricity grid, i.e. its ’weight’ in the average cost price of the grid product is 1.

When importing modules, all modules will link to the products:

- ’Electricity_Grid’;
- ’CapEx’.

Only thermal generators which emit carbon will link to the products:

- ’EU_ETS_Credits’;
- ’EU_ETS_Price’.

The yellow sticky note describes the linking process in detail for those seeking to work with MODO. Hence we omit a detailed guide here.

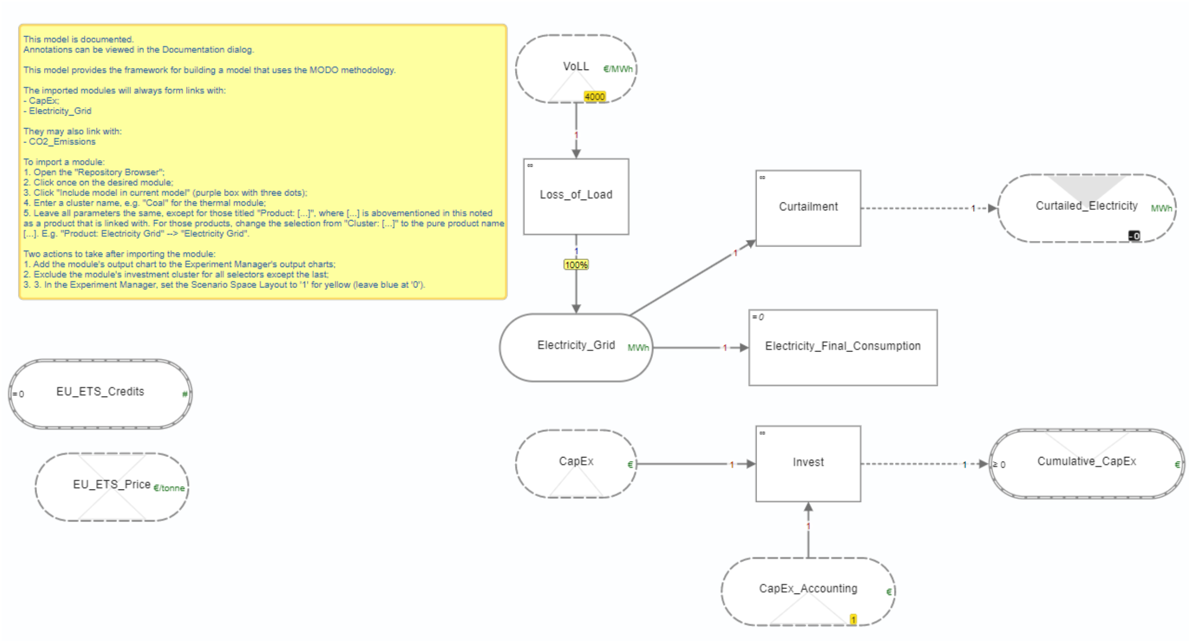


Figure 4.3: MODO Framework Module

4.2.3. Thermal Module

The 'top' (main/ first) cluster of the thermal module is depicted in figure 4.4. We observe the following:

- The large box with a shadow is a 'cluster', which helps visually organise the model. Processes can only be part of a single cluster, but products can be visualised across clusters (whilst remaining a unitary entity: changing its parameters in one cluster will alter it in the others).
- Additionally, entire clusters can be excluded during user-specified runs within an experiment, enabling these runs to be processed much faster as entire groups of otherwise demanding decision variables can be ignored.
- When the module is imported to the framework, all processes are imported by default, prefaced by a prefix attributed by the user (e.g. 'Coal: Installed_Stack').
- When the module is imported to the framework, the user has the ability to determine what happens to the underlined products. They can either be linked to existing products in the framework (as is the intention with 'Electricity_Grid', or they may be imported in a similar manner as products. In this latter case, they would be unique products, whereas in the case of the former the imported product would be 'morphed' with the identically named product in the framework, only leaving one product.

Opening up the 'Investments' cluster, we find figure 4.5 and observe the following:

- Investment options are linked to CapEx with a special link type (dashed with an asterisk). This indicates a first commit link. The value on the link represents the investment barrier. The first commit functionality now ensures that if the solver decides to activate the process during an investment run, the CapEx is paid upon first activation and no more thereafter.
- The same first commit link is used to link investment options to the stock 'Invested_Assets_Count', which then allows for easy data processing.

More importantly, we note that investment asset stacks are linked to the 'Output_Invested_Assets' product rather than directly to the grid. The product aggregating their output feeds their cumulative generation into the 'Feed_In_Output_Invested_Assets' process. The benefit of modeling it this way is twofold.

Firstly, an investment in the assets spikes their cost price due to the CapEx payment. If the assets were directly connected to the 'Electricity_Grid', the simulated cost price of electricity would include this price

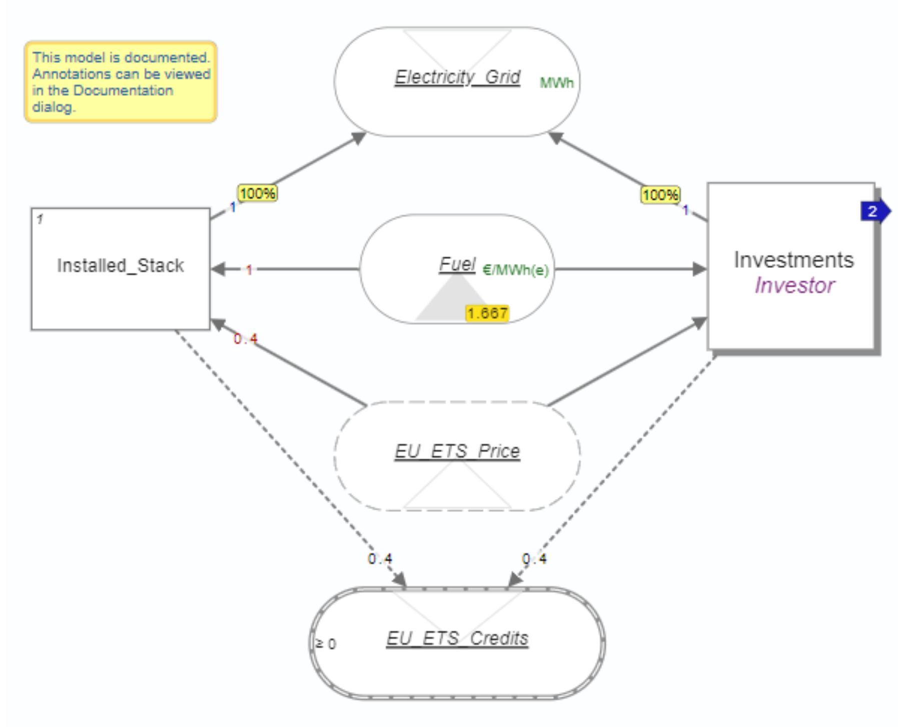


Figure 4.4: Top cluster of the thermal module.

spike, distorting model behaviour and output data. Routing the generation through the additional product and process prevents this from happening.

Additionally, the single process reduces computational cost by reducing the number of times the computationally intensive *Number of Profitable Units (NPU)* formula we use to implement our heuristic for profitability in face of lumpy standard asset capacities (equation 3.9 in the previous chapter). Rather than calculating the NPU for all investment options, we calculate it once. The following subsection elaborates on the NPU and explains why this is effective.

4.2.4. NPU: Number of Profitable Units

To determine whether we commit all of the investment options committed by the solver or all but one (in accordance with equation 3.9 if the solver decides to invest but the investment prices itself out of the market due to its lumpiness, we choose to withdraw it), we need a way to calculate the number of profitable standard assets in an asset stack. This also goes for the profitability analysis of installed assets.

The challenge is that the calculation must take place within Linny-R, between model runs, and that the multiplication of the timeseries of the electricity price with that of the level of the installed stack would require the number of if-statements equal to the number of assets in the stack to properly allocate revenues to the right stack. If-statements are computationally intensive and are best avoided, especially with the knowledge that stack sizes can be sizeable.

Hence, we worked together with the creator of Linny-R, Pieter Bots, to develop the Number of Profitable Units (NPU) algorithm. To calculate the number of profitable units, it takes as input:

1. The process (i.e. relevant asset stack);
2. The standard asset size;
3. The marginal cost;
4. The electricity price;
5. The threshold before an asset can be considered profitable;
6. An optional sixth argument to analyse the NPU per time step, rather than over the run as a whole.

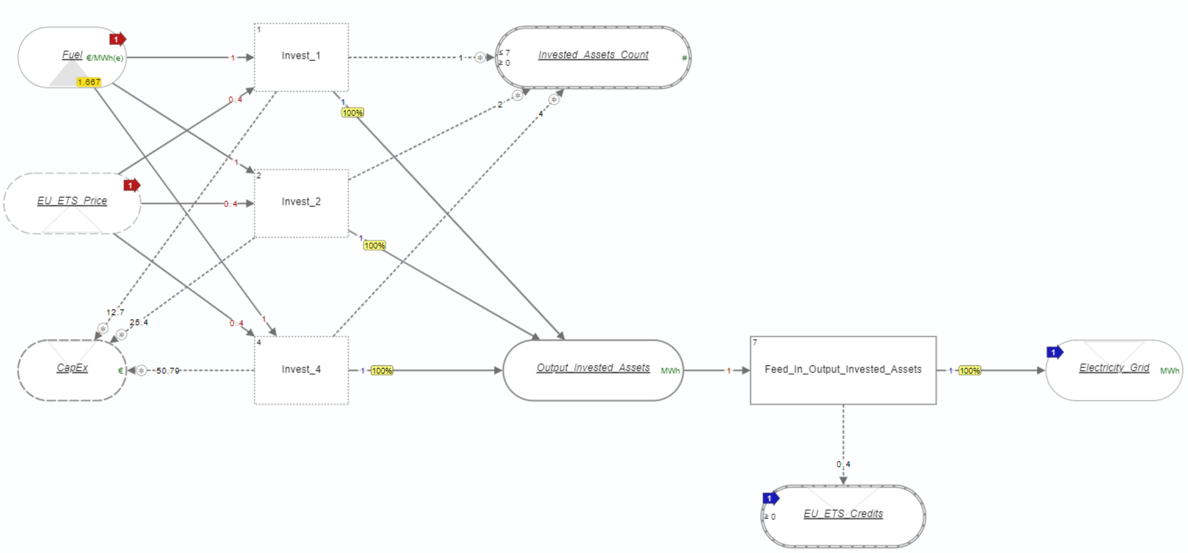


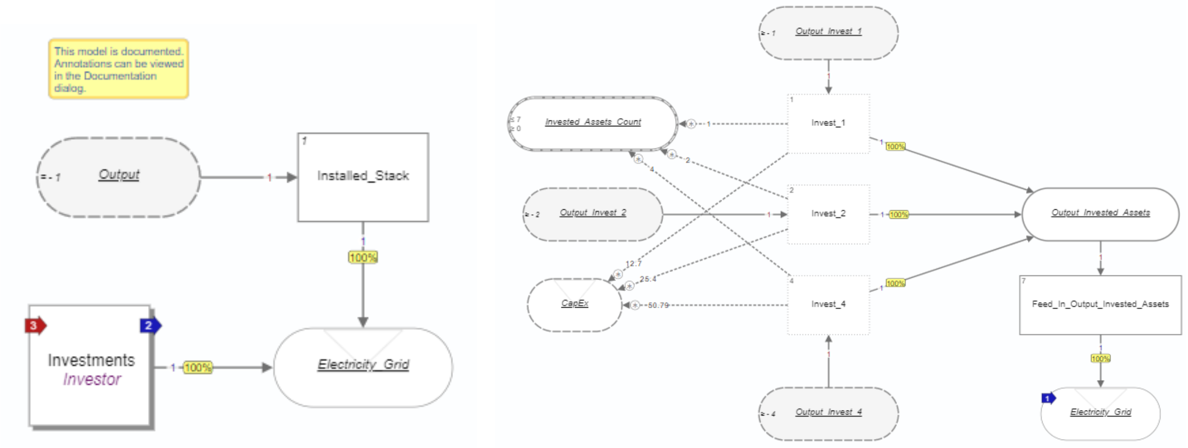
Figure 4.5: Thermal module investment cluster.

For all units that are committed, the NPU algorithm multiplies their production level (relative to the standard assets size) with the difference between the electricity price (i.e. the highest cost price of the 'Electricty_Grid' product) and marginal cost of generation, and evaluates whether its sum exceeds the specified threshold.

Because the NPU formula is also quite computationally intensive, yet much less so than having many if statements, calculating it only once in the aggregate process is beneficial over individual calculations for each asset stack.

4.2.5. VRES module

The VRES module (figure 6.10) is not much different from the thermal module. Notably, it excludes carbon-related products, and includes one additional product: 'Output'. The output product is constrained to always produce the weather-dependent timeseries. In the investment cluster, this constraint is multiplied for each output product by the size of the investment stack.



(a) VRES module top cluster.

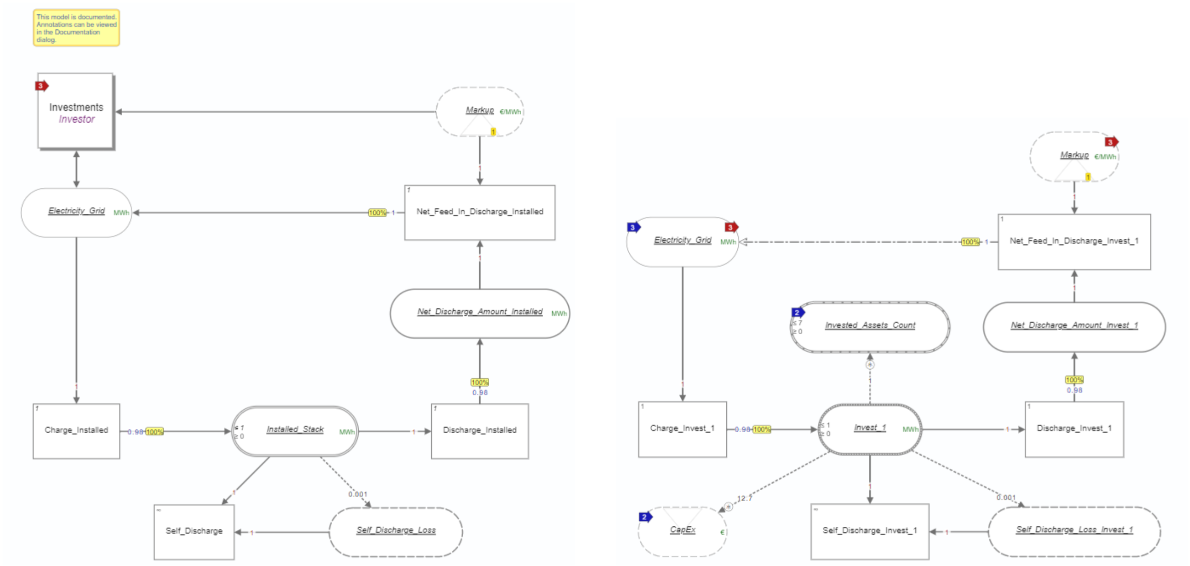
(b) VRES module investment cluster

Figure 4.6: VRES module

4.2.6. Battery Module

On the battery module, visualised in figure 4.7, we note the following:

- The battery self-discharges at a user-specified percentage of its stock level;
- The user may specify a mark-up for battery discharge, which may also be zero;
- The mark-up price requires the modeling of the process delivering the net infeed, because the markup can only be charged on actually supplied electricity;
- The investment cluster displayed in figure 4.7b is one of mulitple identical investment clusters, apart from the difference in stack size amongst them.



(a) Battery module top cluster

(b) Battery module investment cluster

Figure 4.7: Battery module

4.2.7. Seasonal (Hydrogen) Storage Module

The seasonal storage module is quite similar to the battery storage module. Besides obvious differences such as efficiencies, we note the following:

- As the next chapter will motivate, we assume infinite storage capacity in salt caverns. Hence, we model a single stock which is also utilised by the investment assets to simulate the need for investment in electrolysis and thermal hydrogen conversion rather than additional storage, as shown through figures 4.8 and 4.9;
- Instead, hydrogen storage has a marginal cost associated with it, represented by the 'Storage_Fee' product.
- We assume no self-discharge for hydrogen storage.

4.2.8. Implementing non-structural components

Having addressed the structural composition of the model, we turn to the non-structural components as we have defined it in the previous chapter (figure 3.2). Data processing in Linny-R is quite intuitive and well-documented, so we abstain from elaborating on basic matters such as working with datasets and equations here. We do address the following topics as they concretely pertain to the implementation of our proposed methodology:

1. The implementation of standard asset capacities;
2. Implementing the four stages and their temporal settings;
3. Implementing our profitability heuristic.

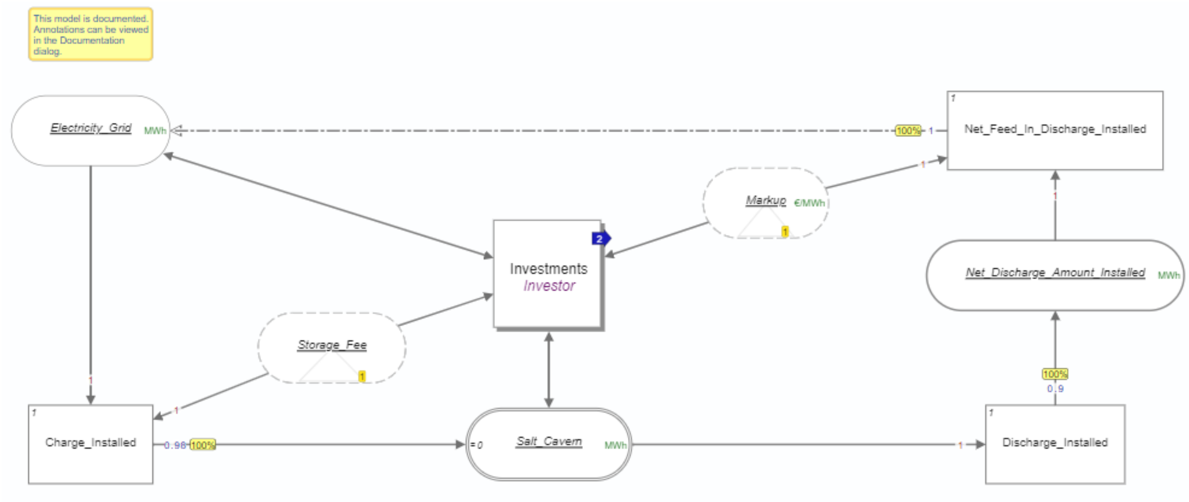


Figure 4.8: Seasonal storage module top cluster

Standard asset capacities as we conceptualised them in figure 3.3a reduce the computational burden of the model because they reduce the number of decision variables. In Linny-R, we have implemented this by having the upper bound of, for instance, the plant in figure 4.5 be the product of the number of installed plants and the standard plant capacity.

To implement the four stages in terms of temporal settings we rely on a combination of the dataset manager and the experiment manager. In the dataset manager, we define the selectors [0, 1, 2, 3] to refer to identify the four stages in respective order. Each variable dependent on the stage should utilise these selectors. In the experiment manager, it is now possible to select the selectors as experiment dimensions. Then, in the model settings dimensions, we specify the temporal settings for each run, following the notation in figure 3.2.

To ensure investments can only be made during stage four, we leverage Linny-R's functionality of ignoring entire clusters during the run of selectors. When selectors 0, 1 and 2 are run, all investment clusters are excluded from the unit commitment problem. Not only does this ensure the adequate behaviour of the invesment decision-variables, it also significantly reduces the computational burden of the runs during which the investment clusters are ignored.

The actor settings in Linny-R allow the creation of rounds. For each round, it is possible to designate which actors may or may not change their production levels. In the *Experiment manager*, we can link rounds to selectors. Whilst we make no use of the actors, the investment rounds help to distinguish which stage the model is in - and reference back to those stages in expressions - efficiently.

4.3. Verification and Validation of MODO

The goal of this section is to verify that MODO functions as expected and is thus properly implemented. At the same time, the limited size of the models we will analyse allows for the opportunity to grasp model behaviour so that we can better form hypotheses and explain behaviour of the more complex model in the next chapter.

4.3.1. Validation

Firstly, we validate basic investment behaviour by means of a very simple model. Into the framework we import a thermal module and change nothing, apart from the standard asset size – which we set to 300 MWe – and the number of installed assets – with which we conduct our experiments.

Firstly, we investigate whether the solver's investment behaviour is rational. The maximum electricity demand, based on representative timeseries for the Dutch energy system from the Quintel Energy Transition Model, also used by Sagdur [49, 56] is 23,239 MW during the investment run. At a standard asset size of 300 MW, 23,239/300 = 77.5 assets would be required to supply peak demand. Figure 4.10 shows the number of

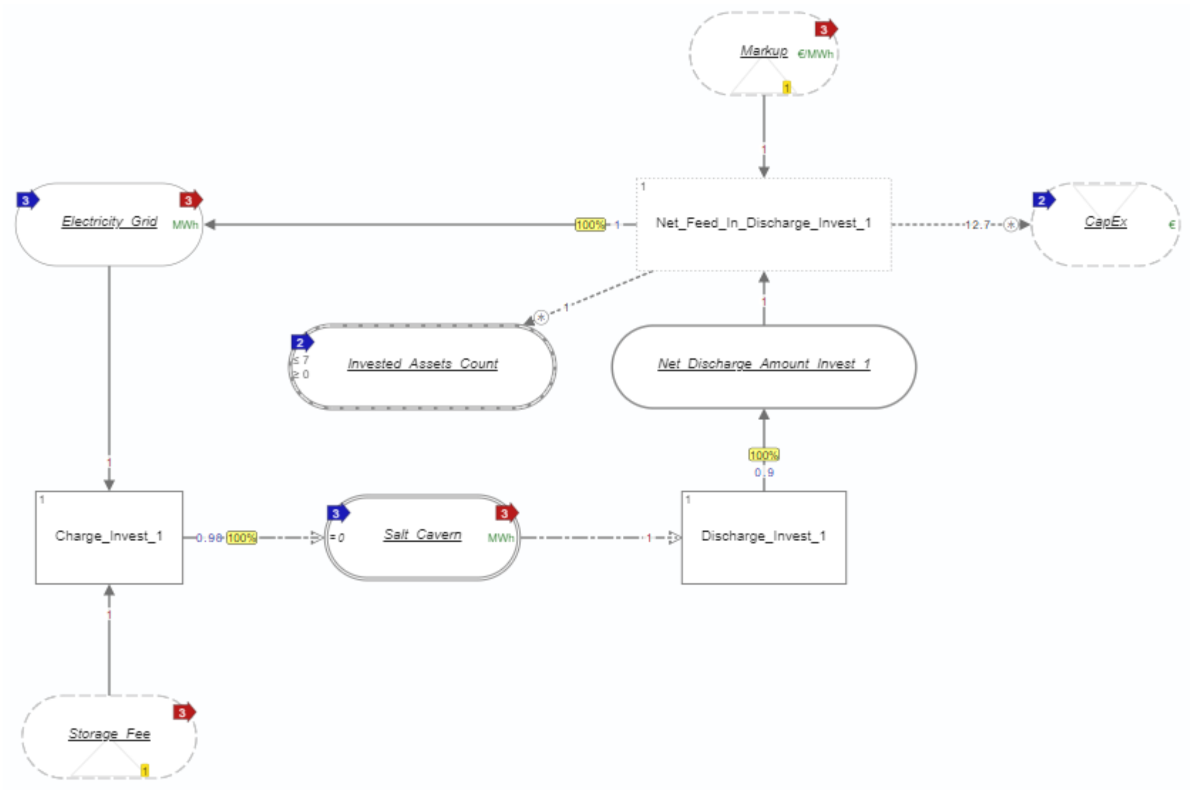


Figure 4.9: Seasonal storage module investment cluster

standard assets the solver invests in dependent on the number of assets that are pre-installed. The maximum number the solver can invest in is seven assets. Hence we witness the same maximal investment number for 69 and 70 pre-installed assets. After, we witness the number of assets invested in by the solver decrease by one with each additional pre-installed asset, which indicates consistent decision-making.

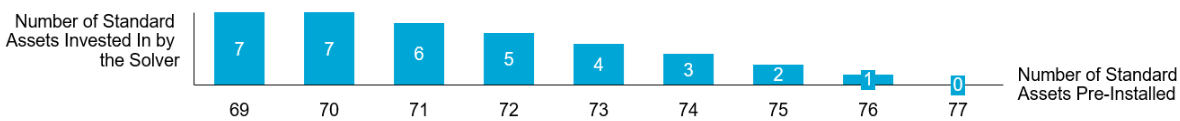


Figure 4.10: Investment behaviour of MODO with a single thermal asset.

Next, we investigate the financial rationale. Figure 4.11 shows that the solver rightly decides to invest in order to reduce total system cost, but that the remaining annual loss of load is insufficient for the investment to be profitable to an investor. Therewith, the figure is a clear showcase of the implication of the lumpiness of investment. Additionally, we rightly see the solver refrain from investing in an additional asset as the remaining loss of load does not outweight the investment cost.

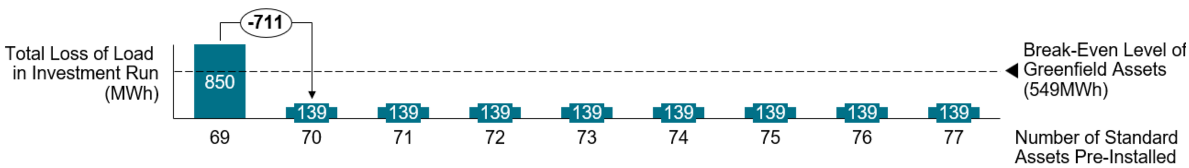


Figure 4.11: Loss of load in MODO with a single thermal asset.

We validate the NPU algorithm in figure 4.12. In line with the previous paragraph, we find that during the detailed, hourly analysis the number of profitable units equals the number of installed units as long as the number is smaller than 77. At 77 assets, insufficient loss of load remains for the assets to be profitable.

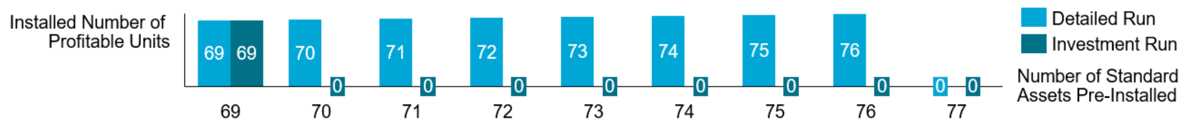


Figure 4.12: Validation of the NPU algorithm in MODO with a single thermal asset.

Now, we investigate whether our profitability heuristic works as expected. If it does, it should counter the 77th investment. Figure 4.13 shwos that it does: the invested number of profitable units is 7 when 69 assets are installed and 0 thereafter, resulting in 76 installed assets (figure 4.14), which are all profitable.

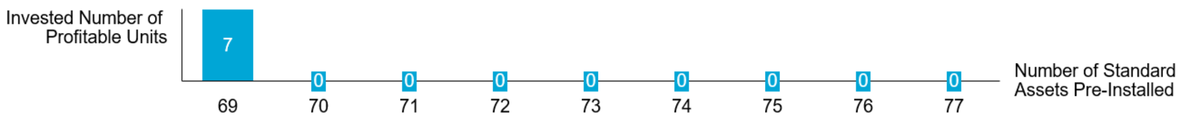


Figure 4.13: Validation of the profitability heuristic in MODO with a single thermal asset.

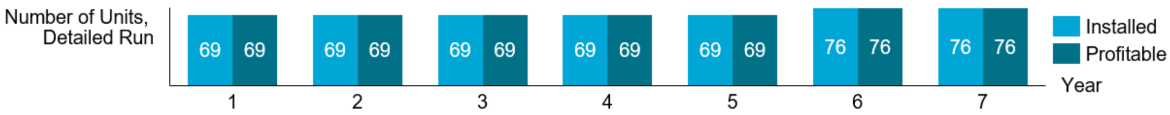


Figure 4.14: Validation of the number of installed units in MODO with a single thermal asset.

Lastly, figure 4.15 shows the simulation of the EU ETS certificate scheme to be functional, as a cap reduces the generation of the thermal assets by the same amount it brings about an increase in loss of load.

Having validated the basic functioning of MODO, the next section elaborates on a model incorporating all asset classes.

4.3.2. Input data and hypotheses

Figure 4.16 shows the model we use to validate the behaviour of MODO when all asset classes are included.

We assume straight-forward input data, displayed in tables 4.1 and 4.2. We fix all parameters at their initial levels. Therefore, we should see the model converge toward an equilibrium state after which no change occurs. Our hypotheses are as follows:

- Because total installed capacity amounts to 100 MW whilst average demand is 155 MW, we should see investments taking place to profit from the value of lost load during lost load hours.
- We should see one or two investments in vRES; with average demand at 155 and vRES standard asset size at 60 MW, vRES will saturate the market for its operational hours at approximately 2.5 times its asset size. We should see the solver wanting to invest in order to be able to store excess production, but this would yield no profit for the investor and should therefore be negated.
- We should see lost load hours drop significantly until there are just enough left for the gas-fired plant to recuperate its investment cost[2].
- As capacity increases, we should see the use of seasonal storage increase alongside. This should be twofold. One, seasonal storage should start to pick up excess vRES, but this role will be limited as we have hypothesised that vRES will not fully saturate its own production hours, thus leaving few shortage moments. More importantly, we should expect storage to trade gas against loss load hours. The solver optimises over the whole timespan, so the objective function will have storage drawing in gas-fired power in times of excess gas supply, to sell it later when there is a supply shortage, in order to reduce the number of lost load occurences.

[2] We have not modeled any additional profitability markups for this verification experiment, but a priori that has no impact as the heuristic must still assess operational profits, only less thereof

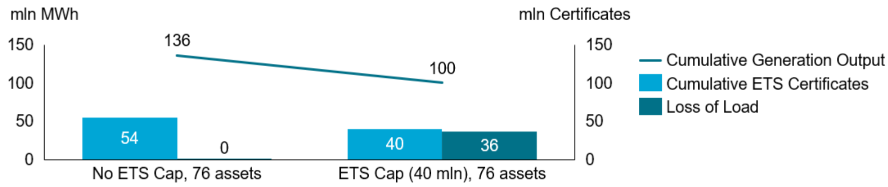


Figure 4.15: Validation of the EU ETS stock in MODO.

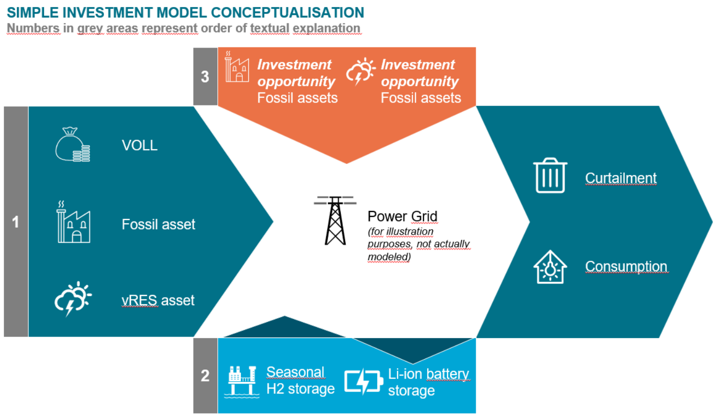


Figure 4.16: Conceptualisation of the more complex validation model.

Table 4.1: Technology input data for MODO_Verification_1

	Unit	Gas	vRES	Li-ion storage	Hydrogen storage
Initial Number	#	1	1	1	1
Standard Capacity	MW	40	60	12	infinite
Storage Capacity	MWh	-	-	50	1000
Depreciation period	years	20	20	-	-
Efficiency	%	50%	100%	81% + variable losses of 0.1%/hour * level	49%
CapEx per MW	€	600.000	600.000	-	-
OM as % of CapEx	%	5%	5%	-	-
Number of investments allowed per annum	#	2	2	-	-
Investment delay	years	1	1	-	-

Table 4.2: Financial, demand and look-ahead inputs for MODO_Verification_1

	Unit	Value
Look-ahead	years	5
Gas price	€/MWh	90
VoLL	€/MWh	4000
WACC	%	8%
Average electricity demand	MWh	155

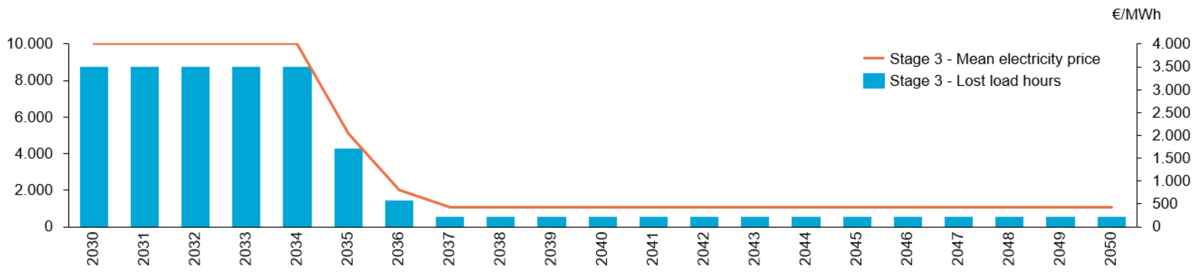
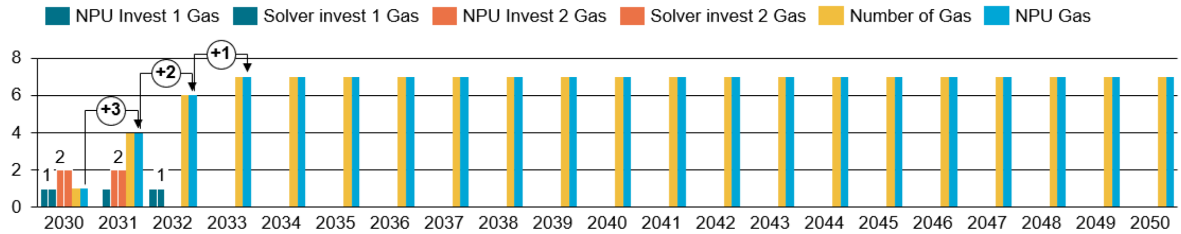
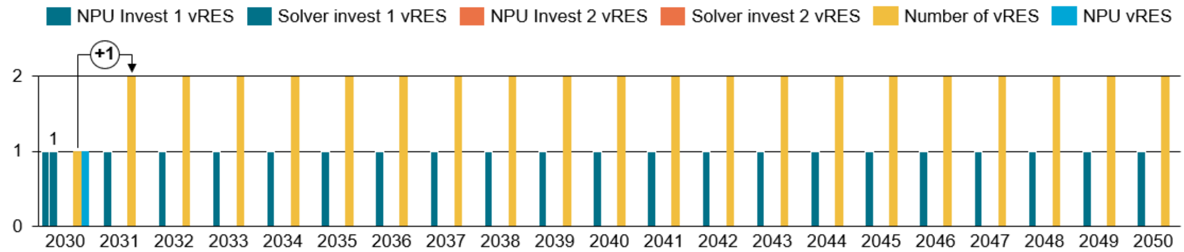


Figure 4.17: Investments are leading to a clear equilibrium as average electricity prices and the number of lost load hours initially drop as investments are made to then stabilise. For reference: cost of 1 MWh_e from the gas-fired plant is €180.



(a) Gas investment decisions follow our heuristic. Investments consistently amount to the number of assets profitable to both the investor and the solver. 2031 shows that the solver wants to invest, but that it would not be profitable to the investor and thus the investment is not made.



(b) VRES investment decisions show the merit of our heuristic: in 2030 both the solver and investor can justify an investment, which accordingly takes place. After, the solver wants to invest, but the investor would not make a profit. The investment is rightfully not made.

Figure 4.18: Investment patterns clearly adhere to our heuristic and reach an expected equilibrium.

4.3.3. Investment behaviour

We witness a significant reduction in lost load hours and - accordingly - the average electricity price in figure 4.17. This should inevitably be brought about by profit-seeking investors who find an opportunity to profit from the significant initial lost load hours due to a capacity shortage.

Indeed, figure 4.20 shows rapid investment by both the solver and the investor. Here too, the chart conveys clear convergence toward a stable equilibrium. Moreover, we find that our heuristic functions as expected. Investments are only made if they themselves are profitable to the solver and to the investor, and if they do not diminish the profitability of already installed assets in their asset class. We provide a more detailed account of how this logic is followed in the figures' captions. We also witness the expected investment behaviour: one vRES asset is installed as it is profitable to both the solver and the investor. Afterward, the solver invests in an additional asset every year, but our heuristic cancels the investment as it would not be profitable to make for the investor. Meanwhile, gas plants are installed until neither the solver nor the investor deem an asset desirable anymore.

4.3.4. Storage behaviour

To start with, seasonal storage behaviour clearly displays behaviour in line with our hypothesis. Figure 4.19 shows how the initial level is correctly transferred from t=365 in Stage 1 to t=1 in Stage 2, after which Stage 3 adopts 72-hourly pegs - in the form of fixed lower and upper bounds every 72nd hour - and adheres to them. Stage 4 also utilises the seasonal storage. It does so more ambitiously than the other stages. Reason being that the figure displays year 2036, in which the solver invests in an additional vRES asset which is not adopted by the investor.

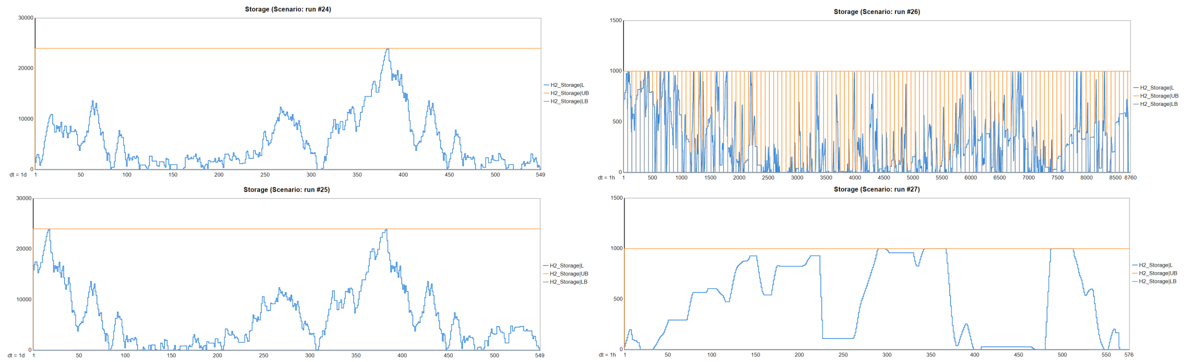
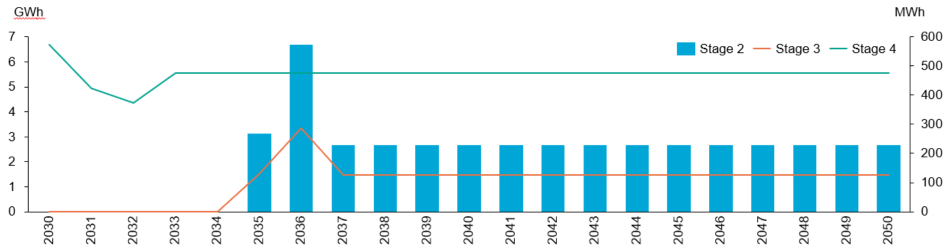
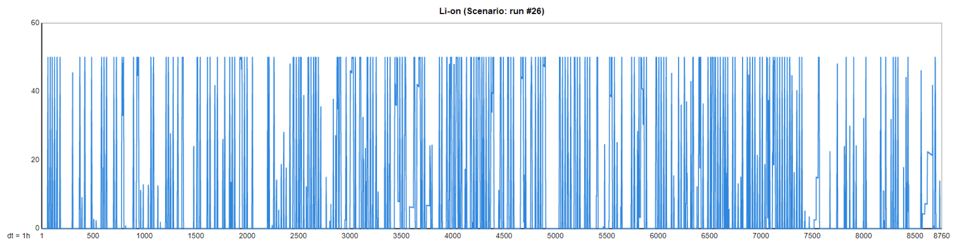


Figure 4.19: Seasonal hydrogen storage behaviour as expected. Charts show storage level in blue, upper bound in orange and lower bounds in grey. Stage 1: top left. Stage 2: bottom left - adequately adopting the initial storage level. Stage 3: top right; accurately following the 72-hourly 'pegs' (note that this chart displays 1 year, the two before 1.5). Stage 4: behaviour during representative days run. Year in simulation: 2036.



(a) Average seasonal storage levels for stages 2 through 4. Note that stage four has a look-ahead of five years, which is the installation delay of assets. Point of this chart is the bowl curve for Stage 4 in the initial years, versus the dome curve in stages 2 and 3 five years later (i.e. pertaining to the same years, accounted for look-ahead). The solver invests in additional wind, reducing the amount of gas needed to be stored to prevent lost load hours. Our investment heuristic cancels this.



(b) VRES investment decisions show the merit of our heuristic: in 2030 both the solver and investor can justify an investment, which accordingly takes place. After, the solver wants to invest, but the investor would not make a profit. The investment is rightfully not made.

Figure 4.20: Investment patterns clearly adhere to our heuristic and reach an expected equilibrium.

This latter point is a trade-off to our methodology: the fact that investments made by the solver may be disregarded by the investor ex-post has implications for all other assets that are invested in during Stage 4. We visualise this to better facilitate the explanation in figure 4.20a. The chart shows how solver-dominated Stage 4 follows a different pattern tho investor-dominated stages 2 and 3 as the solver will assume the investment in assets when they are not actually made following our ex-post heuristic.

Lithium-ion storage is doing exactly what it is supposed to do: trade heavy and trade fast. Observe the lack of a pattern in figure 4.20b: the battery is trading quickly, reducing system cost as much as possible. Recall the mark-up we have modelled, ensuring that these cycles are profitable to the battery as well.

4.3.5. Conclusion

We conclude that we have adequately implemented our proposed methodology in Linny-R. System behaviour is aligned with our hypotheses. Most importantly, we have been able to confirm the functionality of our proposed heuristic. Additionally, storage behaviour works as expected, which is key to modeling future power systems.

5

Applying MODO to 2030-2050 Dutch Electricity System Development

5.1. Introduction

In this chapter we explore whether MODO is fit for purpose in more complex power systems. We therefore apply the methodology to the Dutch electricity system, analysing its development from 2030-2050. In this chapter we will consider the system to be an island grid, ignoring imports and exports of electricity and hydrogen.

The Netherlands lends itself well to a first application of MODO, as it is becoming increasingly reliant on intermittent electricity generation and has ample opportunity for hydrogen storage in the North Sea. In the Dutch Climate Agreement, parties have agreed to a target of 70% electricity generated by offshore wind, onshore wind and (large-scale) solar PV [52].

5.2. 2030 Start Scenario

In this section we survey the present Dutch system as a point of departure for our subsequent forecast of the 2030 system. We deem it necessary to dive into some detail on the forecast due to recent, impactful announcements by the Dutch Cabinet regarding progress toward the future capacity mix. The 2020 Climate and Energy Exploration report by the Netherlands Environmental Assessment Agency serves as basis for the validation of our forecasting assumptions [45].

5.2.1. Context: System Overview

Dutch electricity generation has hitherto relied upon a significant share of natural-gas fired power plants paired with a lesser share of baseload coal. Figure 5.1 offers context on the Dutch system and its status quo as of April 2022. It is the physical point of departure as we work toward our 2030 base scenario.

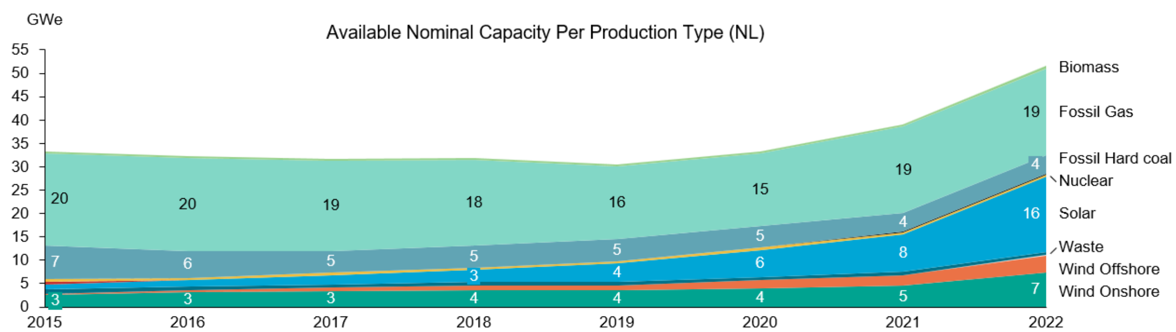


Figure 5.1: Available nominal capacity development from 2015 to 2022. Data from ENTSO-E Transparency Platform [22].

5.2.2. Installed Generation Capacities by 2030

The totals overview is presented in figure 5.2. The headings below provide a detailed account for the choices.

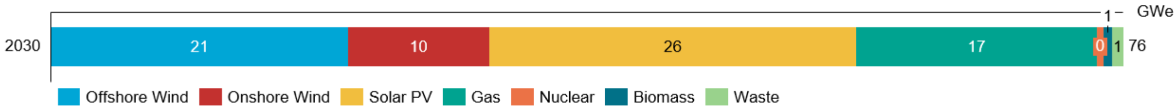


Figure 5.2: Installed capacity by 2030 as assumed in this thesis.

Coal-fired power plants will be out of commission by 2030 at the latest, by order of government [53]. We thus need not account for any.

Gas-fired power plant levels will decrease by 1.7GWe. TenneT's (the Dutch TSO) outlook toward 2027[1] states that official communication with energy companies indicated no plans for greenfield large-scale thermal power, as well as planned decommissioning of 1.4GWe of gas-fired generation [61]. Atop that, Eneco has committed to decommission its Merwede plant by 2030 [41], increasing total planned decommissioning by approximately 0.3GWe [70] to 1.7GWe.[2] Rounding off, we assume a total of 17GWe installed by 2030, closely in line with the PBL prognosis.

Additional nuclear power generation is being explored by the Dutch government. With no investment decision having yet been made, we disregard additional capacity from this scenario. However, we do recognise that the existing nuclear power plant, Borssele, is allowed to remain operational for a longer period of time, beyond 2033 [40]. We thus leave its capacity (485MWe) intact for our base scenario.

Biomass and waste capacity are closely related as biomass is often (co-)fired in waste incinerators. Standalone biomass generation capacity has been difficult to pin-point; the Dutch Central Bureau for Statistics has not been able to do so [8]. In addition to co-firing with waste, biomass is co-fired in coal-fired generators, combined heat-power plants (CHPs) and biogas installations. Recognising that: i) coal-fired generators will have been decommissioned by 2030, ii) the government has stopped subsisidising biomass installations when their sole purpose is the generation of electricity and iii) biogas is expected to become a scarce commodity post-2030 [50], we will assume biomass and waste to stay level post-2022, assuming the same figures as in 5.1: 0.8GWe for waste and 0.6GWe for biomass (rounded).

Offshore wind capacity will be 21GWe by 2030 if recently announced public policy goals are met. The initial Climate Accord target was 11GWe, but in March 2022 the Cabinet announced three additional offshore wind farms [42]. We will thus assume 21GWe in this thesis.

Onshore wind capacity development is uncertain. Total installed and planned capacity amounted to 7.9GWe in 2020, 1.2GWe of which will be realised post-2023. To forecast, we note that over 2014-2020 1.7GWe was realised, about double of which was required to achieve the 2020 goal of 6GWe total installed capacity [72]. With seven years to go beyond 2023, we extrapolate this trend to project a total installed capacity of 10GWe by 2030 (7.9GWe + 1.7GWe, rounded up). This exceeds the PBL prognosis by approximately 4GWe.

Solar PV capacity will amount to 26GWe by 2030, according to the Netherlands Environmental Assessment Agency (PBL) [45]. We have not identified developments requiring the alteration of their findings.

5.2.3. Available Storage Capacities by 2030

The totals overview is presented in figure 5.3. The headings below provide a detailed motivation for our choices.

Grid battery capacity will amount to 1-1.5 GWe if policies remain unchanged, a 2021 study by CE Delft found [9]. However, the business case supporting those numbers is underpinned by the profitability of imbalance

[1] Published: 2017

[2] Whilst figure 5.1 shows post-2017 gas capacities already dropped (figure) by more than 1.4GWe to then be build back-up again, the chart represents the available capacity rather than the installed capacity. An unfavourable operational climate for gas-fired plants led to their shutdown over the course of four years, until their operation became attractive once again by 2021 [67].

Figure 5.3: Installed storage capacity by 2030 as assumed in this thesis.

(FCR and aFRR) markets, supported by congestion management revenues. Conversely, a grid battery optimising its deployment over day-ahead, intraday and congestion markets will not be profitable by 2030. Neither will will smaller-scale 'neighbourhood batteries' doing so. Batteries accompanying solar farms will not be profitable regardless of the market mix they optimise over.

As the battery dispatch in our model would represent spot market trading (day-ahead/ intraday markets would be theoretically approached), we should thus not expect any capacity to be present given current policy.

However, in its investment plans, TenneT is counting on 2.6-15.4GWe to be available [62]. And whilst CE Delft findings on the unprofitability of grid batteries are highly robust to capital costs and grid tariffs, policy choices such as investment subsidies are not unthinkable in the eight years to come. Therefore, we will assume such policies will originate but do so conservatively, as we adopt the lower bound of TenneT's forecast, rounded up: 3GWe of installed grid batteries. Furthermore, we assume their full dedication to the spot markets.

As a rule of thumb, based on CE Delft's data, we multiply the (dis)charge capacity of 3GWe by 4 to arrive at 12GWh(e) installed storage capacity.

Seasonal hydrogen storage capacity demand will vary between 42-475GWh(th) by 2030 [63]. Approximately 3-4GWe electrolyser capacity will be available [54]. However, the core purpose of these assets is to supply the transport and industrial sectors. From that perspective, the demand curve is flat and flexibility/ storage need limited, and most gas will be produced by converting national gas coupled with CCS [63]. Since we are only interested in analysing the feasibility of seasonal storage in relation to the supply of electricity demand, we will assume the availability of 0.5GWe electrolyser capacity, as well as 0.5GWe in hydrogen-fired CCGT capacity. We assume injection capacity is amply available – which we will account for later with a marginal cost for injection – due to the parallel hydrogen market developments and assume infinite storage capacity (GWh(e)), given the ample availability of salt caverns and their significant size, paired with the same parallel hydrogen market developments.

5.2.4. Investment costs

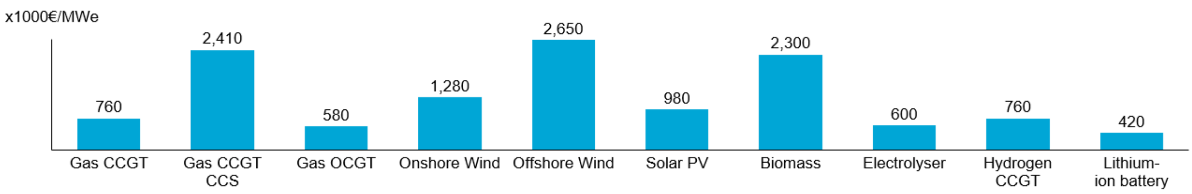


Figure 5.4: Overnight cost for the generating technologies included in our model, based on empirical projects across the globe as surveyed by the IEA, NEA and OECD over the period 2015-2020 [29, p. 43]. Electrolyser taken from [56], hydrogen CCGT assumed to be the same as a gas-fired CCGT.

For the investment costs we rely on the work by the International Energy Agency, Nuclear Energy Agency and Organisation for Economic Co-Operation and Development. Their report on the *Projected Costs of Generating Electricity - 2020 Edition* contains data for 243 power plants and storage assets from 24 countries to be commissioned in 2025 [29]. Figure 5.4 displays the overnight costs of the individual assets. These costs include (as per [29, p. 37]):

- direct construction costs plus pre-construction costs (e.g. site licensing, environmental testing);
- indirect costs such as engineering and administrative costs;

- owner's costs, before the bushbar (i.e. excluding transmission costs);
- contingency to account for changes in overnight cost during construction.

We have made two mutations to the data. Firstly, we have converted the currency at a rate of EUR 0.92 to USD 1.00. Secondly, we have rounded to the nearest ten.

Also, we have taken two costs from a different source. We have taken the electrolyser cost from Sagdur [56], and for the Hydrogen CCGT we assume identical cost to a regular gas-fired CCGT.

5.2.5. Standard Asset Capacities

Two considerations are important to our choice of standard asset sizes. On the one hand, the size must represent a realistic investment, where the focus is on it not being too small; one can always invest in multiple. On the other hand, investment opportunities must be sufficiently granular, in that we want to prevent instances where significant market gaps are not filled because the standard size of the asset class that should be invested in is oversized. The standard asset capacities we have arrived at following these considerations are displayed in figure 5.5 and elaborated on below.

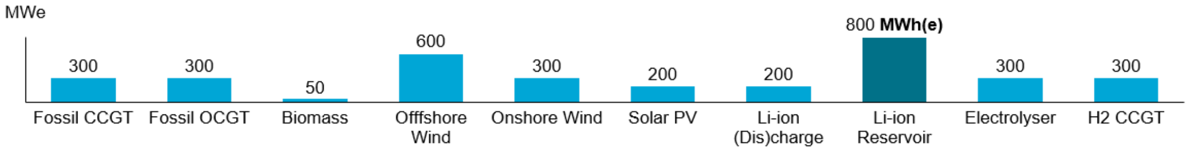


Figure 5.5: Standard asset capacity assumptions. Note the different axis unit for the li-ion reservoir.

We assume gas-fired power plants to have a standard asset size of 300MWe for both OCGT and CCGT assets, based on currently installed power plants as displayed in figures 5.6.

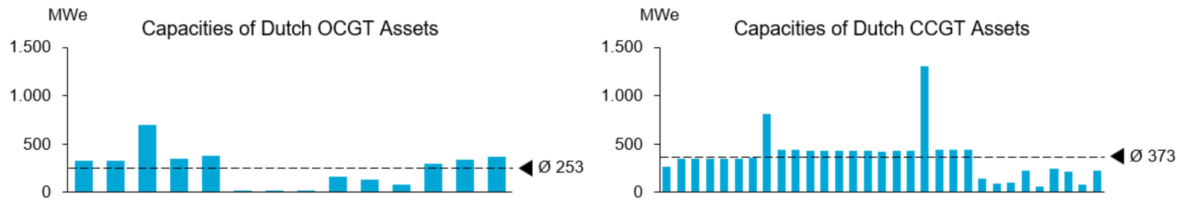


Figure 5.6: Capacities of installed gas-fired power plants in the Netherlands.

A biomass standard capacity is difficult to determine based on existing data due to the broad mix in which the resource is being employed. We will base the standard asset size on Eneco's *BGR Wervelbedketel*, sized at 50MWe [69].

Offshore wind farms that are installed range from a size of 108MWe to 752MWe, and all planned farms are set to be 700MWe or 1,000MWe. For our application, we will assume a standard asset size of 600MWe, based on the Gemini Windpark which was constructed in 2016 [51].

Onshore wind farm sizes have a large spread. For simplicity reasons, we assume standard asset sizes of 300MWe, based on some of the larger projects in the Netherlands [44]. This also captures multiple smaller onshore wind farms being developed in the same year.

Solar PV standard asset sizes are 200MWe in our case, under the same assumption that this adequately captures the aggregation of multiple projects being developed in a year, based on [71].

Lithium-ion storage assets stand to see innovation over the coming years, so we adop the prognosis by Sagdur of 200MWe standard (dis)charge size, and multiply times 4 to find an 800MWe reservoir size [9, 56].

Electrolysis and CCGT assets we assume to have the same standard size as current fossil-fired CCGTs: 300MWe.

5.2.6. Dismantlement schedules of installed capacity

Assets installed before the start of our simulation might be dismantled based on their age and expected technical lifetime. Figure 5.7 shows the dismantlement schedules in both number of assets and the amount of capacity. The headings below discuss the data in more depth.

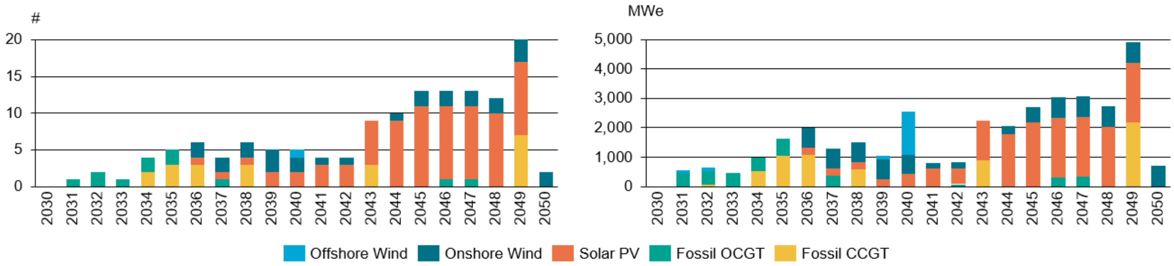


Figure 5.7: Dismantlement schedule of assets installed before 2030. Left: number of standard assets. Right: nominal electric capacity.

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We assume gas-fired generators to have a lifespan of 40 years regardless of their asset class, which is the upper bound of the 35-40 years identified by Euractiv [32]. We assume 40 years because demand for peak generators will likely increase as the system becomes more intermittent, providing an incentive to maintain generators well to keep them operational for a longer period of time.

To find their dismantlement schedules, for each plant we calculated the year in which it is scheduled to be decommissioned based on the year it was first taken into operation [69]. For the resulting initial block of capacity that should have been dismantled according to our decision rule but is still projected to be active by 2030, we spread out dismantlement equally over the period 2031-2035.

Subsequently, we divided by standard capacity and solved the resulting issue of having non-integers by mutating the data to consist of integers whilst representing the original time series as closely as possible.

For wind turbines and solar panels we assume a technical lifespan of 25 years [2, 12]. Solar panels could last longer but show significant degradation beyond this point, likely calling for their replacement.

For offshore wind, we applied the same methodology as for fossil generators since the data the wind farms went operational are known [51].

For onshore wind and solar, data on the individual assets is dispersed or behind a paywall. Thus, we took the data on available capacity development from figure 5.1, and calculated the year-over-year absolute growth numbers. Their dismantlement follows 25 years later. For the large initial block (pre-2015), we smooth the data over 4 years. We do the same for the capacity surges in 2022, which are unlikely to be dismantled all at once and would represent an unrealistically big shock to the system if treated as such. Subsequently, we implement the same data mutations as for the previously discussed asset types.

5.2.7. Thermal efficiencies

We adopt the thermal efficiencies for our thermal asset types from Sagdur, who surveyed literature on the matter [56], and display them in figure 5.8.

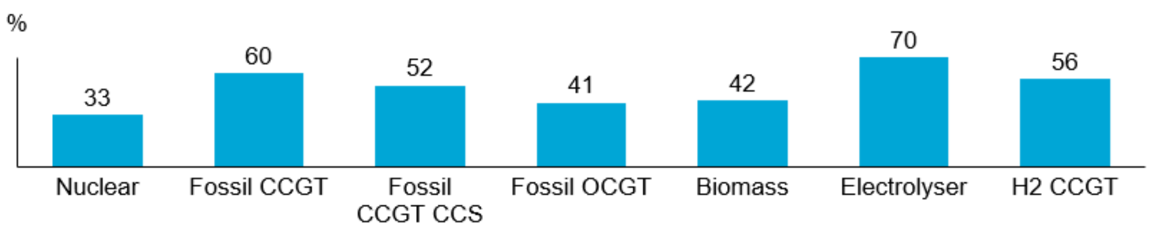


Figure 5.8: Thermal efficiencies.

5.2.8. Realisation periods

We assume a realisation period of 5 years for all asset types. In our view, there lies little value in differentiating this between assets when the realisation time is smaller than or equal to the look-ahead period, which, in our case, is also 5 years. On the other hand, having a uniform realisation period makes it easier to identify and understand model behaviour.

5.3. Post-2030: simulation scenarios

Post-2030, it is highly uncertain how the electricity system will develop. In our illustration of MODO, we therefore explore a wide scenario space to explore both the behaviour of MODO, and of the system.

Demand Development We assume the base demand growth level to be 2%, based on the historical compound annual growth rate (CAGR) of Dutch electricity demand (figure A.1 in appendix A).

The development of electricity demand is highly dependent upon the degree to which other sectors in society, such as industry and transport, electrify. As these sectors primarily consist of baseload demand, accounting for such Power-2-X demand suffices through parametrisation of the CAGR.

We are consciously using compound growth rates rather than assuming linear growth, as compound growth better reflects reality and therefore we are interested in exploring the behaviour of MODO as investors assume a certain demand level in the future, without considering the growth trend. Figure 5.9 shows the three scenarios, all starting out at 136TWh demand, a projection for 2030 in line with projections from the Energy Transitions Model and a TenneT expert session [10, 49]. Note that we display values until 2055, as we assume a 5 year look-ahead-ahead. The 6% demand growth is an extreme scenario to stress test the model, although it should be noted that a value in between the 4% and 6% growth scenario is not unrealistic: the OECD expects a global increase of electricity demand of 250% by 2050, compared to 2018 levels [19].

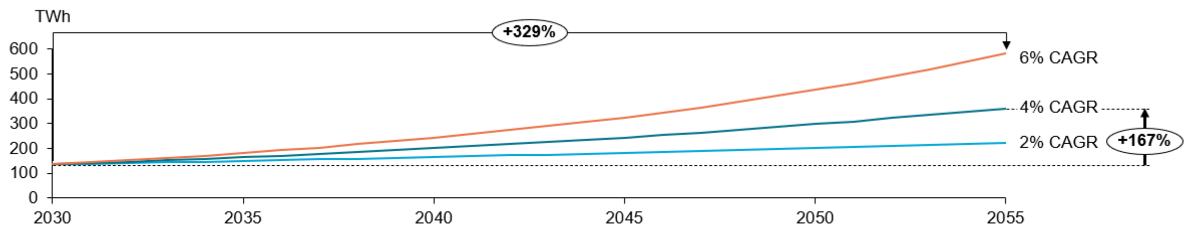


Figure 5.9: Three scenarios for total annual load.

Weather Profiles A core uncertainty from a policy perspective (and that of energy suppliers to households) is whether a system heavily reliant on vRES will be able to sustain a *Dunkelflaute*, a scenario in which wind and solar production is extremely limited or a lengthened period of time. Like Sagdur, we assume the 1997 Dutch weather year when the full month of January saw very little renewable potential, and November had an extended period without wind. Furthermore, vRES production levels were generally lower during the entire year. The data is taken from Quintel's Energy Transition Model, which relies on information from the Dutch Meteorological Institute [49]. Total monthly loads for the standard intermittent generation assets are included in appendix A, figure A.2.

Commodity Prices Commodity prices are a core uncertainty. We deduce ballpark figures from the European Heat Roadmap Project, but form the scenarios in table 5.1 based on our own intuition.

Table 5.1: Commodity price scenarios.

		Low	Mid	High
EU ETS	EUR/tonne	50	125	200
Dutch natural gas TTF spot	EUR/MWh(th)	50	175	300
Biomass	EUR/MWh(th)	30	65	100

EU ETS Targets For scenarios based on EU ETS targets, we approximate the availability of credits by 2025 based on the Dutch Emissions Authority [18] and assume a linear decrease toward 2050 (figure 5.10).

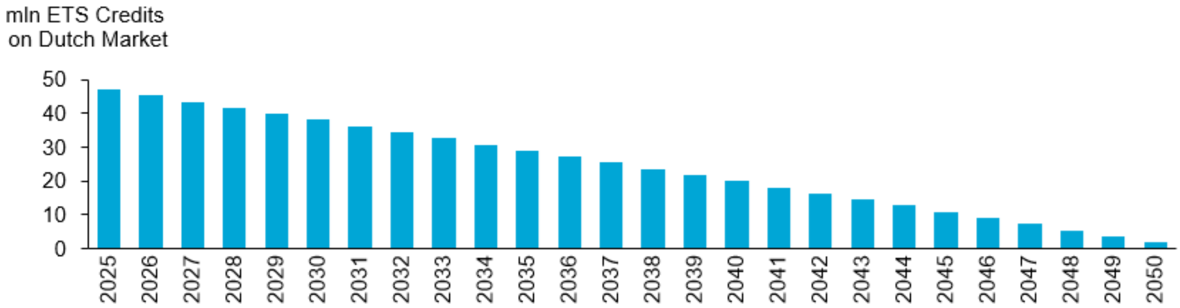


Figure 5.10: EU ETS credits for the Dutch sector.

5.3.1. Scenario Combinations

Table 5.2 presents an overview of scenarios analysed to illustrate the potential use of MODO.

Table 5.2: Scenarios - Regular Weather

		EU ETS (€/t)	TTF spot (€/MWh(th)	Biomass (€/MWh(th)	Dunkel-flaute?	Fixed Carbon Targets?	VoLL (€/MWh)	Demand CAGR (%)
1	Base Case	125	175	65	No	No	4000	2%
2	Base Case - Low VoLL	125	175	65	No	No	2000	2%
3	Base Case - High VoLL	125	175	65	No	No	6000	2%
4	Low Fuel Prices	50	50	90	No	No	4000	2%
5	High Biomass, Low Carbon, Low TTF	50	50	90	No	Yes	4000	2%

6
Results

The objective of this chapter is twofold:

1. To answer whether MODO has been successful in bringing down computational effort;
2. To answer whether MODO produces plausible results when applied to the Dutch electricity transition.

6.1. Computational Improvement

Total Runtime MODO is able to reduce runtime by approximately 85%, compared to MIDO (figure 6.1). MIDO run times were never formally tracked, but Sagdur indicates the runtime for a year-by-year simulation of a 20-year period regularly exceeded 12 hours on a personal computer with an Intel Core i7-10700K and 32GB RAM. We benchmarked MODO on a laptop with an Intel Core i7-11800H and 16GB RAM, on which the same type of run takes approximately 2 hours. In absolute terms, this is an 83.33% decrease. Since the i7-10700K used for the MIDO model is benchmarked to have a 14% higher effective speed than the i7-1100H [66] and MIDO had double the available RAM capacity, we round up to an 85% computational gain.

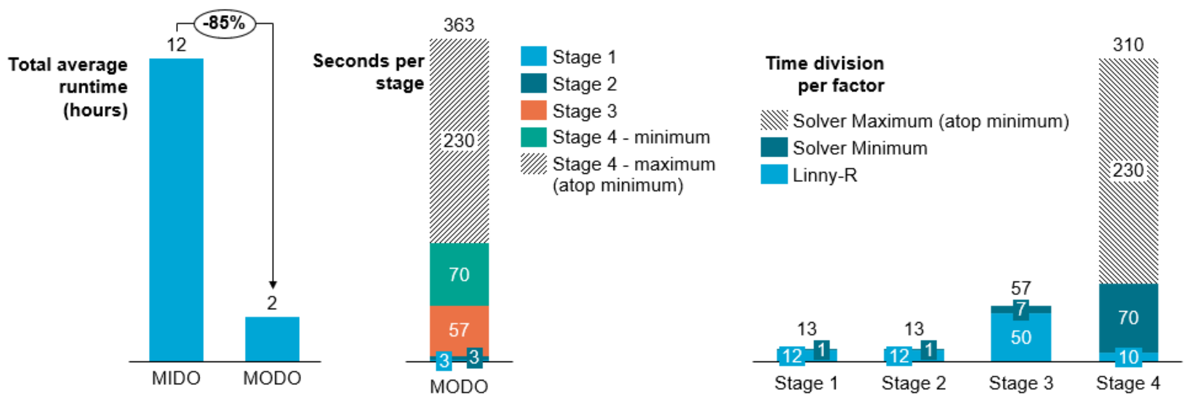


Figure 6.1: Comparison between MIDO and MODO of time required for a year-by-year simulation of a 20-year period.

Runtime per Stage The solver time is the primary constraint on total runtime, namely in stage 4 due to the need to make investment decisions, resulting in a much more complex optimisation problem than stages 1 through 3, which solely need to dispatch already available units. In terms of the complexity of the optimisation problem, this hypothesis is confirmed, as figure 6.1 shows in the rightmost chart: solver time is 1 second for stages 1 and 2, 7 seconds for stage 3, and 70 to 300 seconds for stage 4.

The non-solver related processing power required by Linny-R is the most significant factor contributing to the runtime of MODO's third stage. Interestingly, this time increases when multiple investment options are added. Most likely, the source of the computational burden is the fact that a larger amount of data needs to be processed; the number of time steps in stage 3 is aproximately 15 times that of the number of time steps in stages 1, 2 and 4.

Furthermore, we highlight the variation in the runtime required for stage 4. It appears that the larger the market gap, the more runtime is required. We have verified this by running models with a significant initial undercapacity. They indeed required more runtime than those models starting out in a balanced state. This also explains the significant variation in runtime.

On Solver Limits, Standard Asset Capacities and the Number of Investment Options Because of the size of the computational challenge involved with simulating the Dutch Case, the solver will resort to the use of heuristics rather than a pure optimisation. The amount of time the solver is allowed to take in its attempt to find a feasible solution is determined by the user. If the time is too short, the solver will declare the problem unfeasible. On the benchmark machine we have specified, a solver limit of 300 seconds (5 minutes) has proven sufficient to avoid unfeasible simulations.

6.2. The Dutch Case

6.2.1. A Deep-Dive into the Base Case

Spot Prices and Consumer Spending Figure 6.2 displays the development of total annual consumer spending and the mean electricity price. We observe and deduce the following:

- As should be the case, both factors follow the same pattern.
- The high point in 2024 is caused by dismantlement taking place in the period 2030-2034 (for dismantlement schedules see figure 5.7), whilst greenfield construction lead times are 5 years and the earliest investment opportunity is 2030, meaning greenfield projects cannot be realised until 2035. We witness a drop in spending by 2035, indicating novel investment in line with this rationale.
- After the peak in 2034, the system trends towards what could be interpreted to be an equilibrium from 2041 onward, after which dismantlement levels off.
- Despite significant dismantlement of solar PV capacity in the period 2045-2048, prices remain quite stable, indicating that the myopic investment algorithm has anticipated the dismantlement. This idea is reinforced by the main dismantlement peak in 2049, which appears to lead to a slight increase in prices but one which does not depart far from the equilibrium nonetheless.
- At the equilibrium level, the price approximates 65 EUR/MWh. As this is the price level of a thermal MWh of biomass fuel, and marginal operating cost for fossil-fired plants are much higher, we next investigate whether this makes sense given the capacity mix.

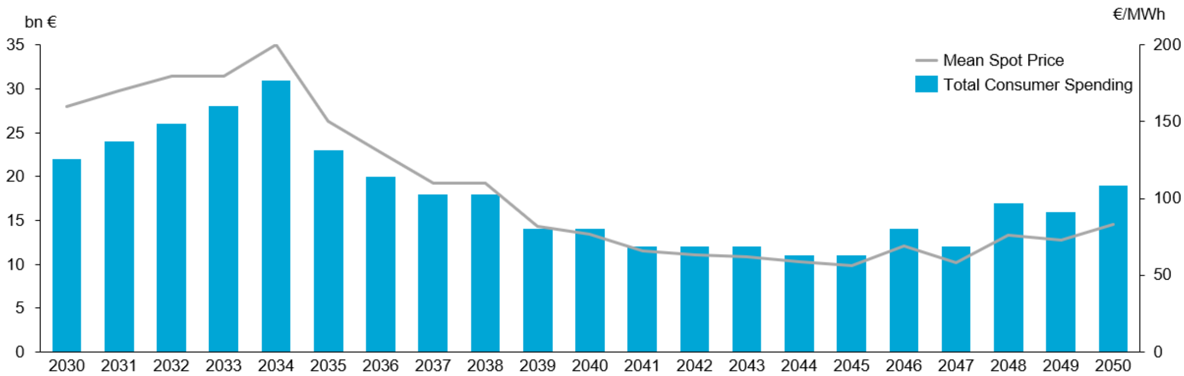


Figure 6.2: The sum of annual consumer spending (bars, left axis) and mean electricity price (line, right axis) for the base case.

Generation Mix Development Figure 6.3 shows the development of the generation mix. We observe:

- Approximately level CCGT and OCGT installed capacity, indicating that existing power plants are replaced but no capacity is installed atop it. Hence *we should witness the assets remaining profitable, else decomissioned assets would not be replaced.*

- Major investments in offshore wind, coupled with several investments in onshore wind. Hence *we would also expect to see an uptake in storage arbitrage as wind becomes available.*

- Whilst the area is small, biomass growth is inhibited by the model parameters of standard asset size and number of investment opportunities.

The two paragraphs that follow address the hypotheses addressed in italics respectively.

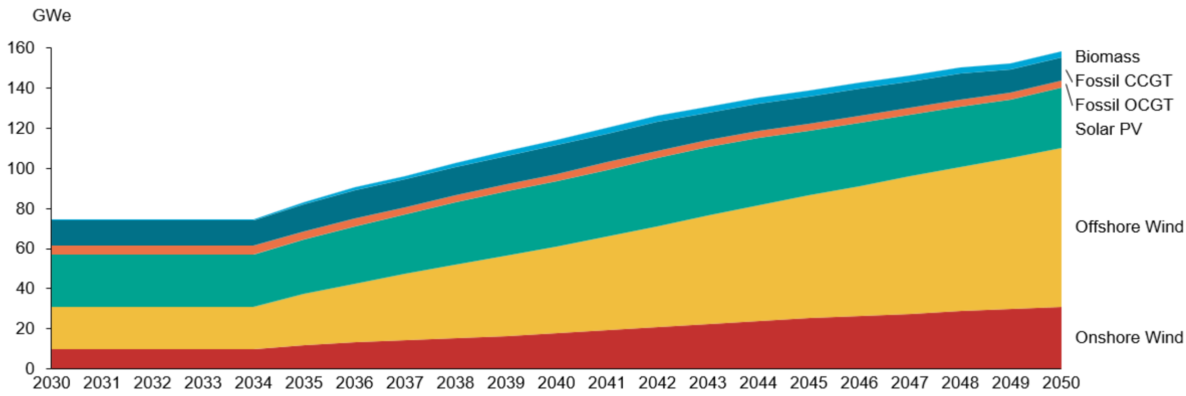


Figure 6.3: Generation mix development for the base case scenario.

Profitability of CCGT and OCGT Assets Following up on the previous paragraph, figure 6.4 investigates the profitability of fossil CCGT and OCGT assets. We observe the following:

- The profitability of the fossil peaking power plants is determined by the number of lost load hours. Incremental dismantlement of peaking assets in the initial years justifies replacement CapEx in the early years, and bulk dismantlement in 2049 brings about a scarcity environment attractive to fossil CCGT and OCGT assets.

- During the equilibrium period we identified in the previous paragraph, none of the assets are profitable. The merit order effect appears to have pushed them out of the market. Peculiarly, there are no lost load hours either. This would imply a significant role for storage, which we had already announced to be the focus of the following paragraph.

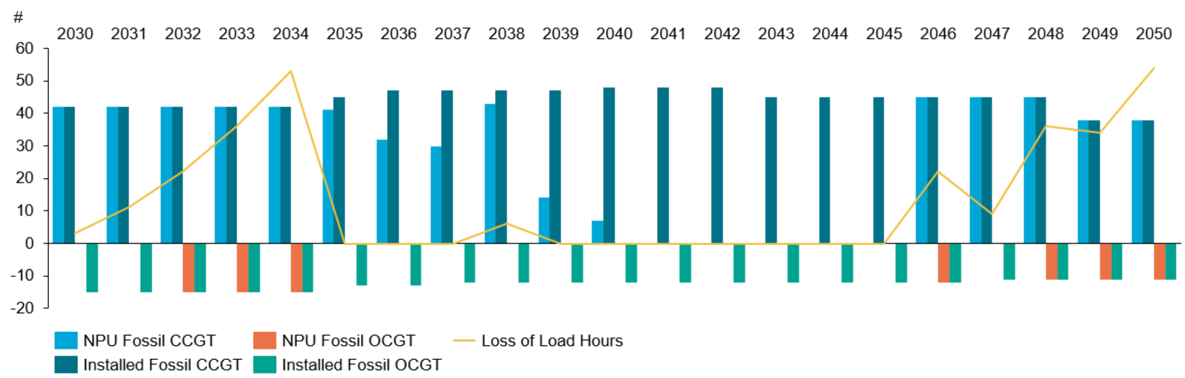


Figure 6.4: Number of Profitable Units and Installed Units of fossil CCGT and OCGT assets. Top and bottom axes purely for visual distinction, no negative values.

Hydrogen Storage In line with expectations, figure 6.5 shows elevated storage levels during the equilibrium period. Let us zoom in on the storage pattern of 2039 to investigate whether they make sense, in figure 6.6. We make the following observations:

- In stages 1 and 4 we clearly recognise the seasonal pattern, where the hydrogen storage is filled during summer due to reduced electricity demand and increased solar PV penetration. Stage 2 shows the same pattern, but utilises the initial storage level based on the end-of-year level from stage 1, thereby making the pattern less visible.

- The most interesting observation is that in stage 3, the 72 hour pegs are met (grey bars), but that apart from doing so, seasonal storage behaves as flexibly as if it were battery storage. Let us first investigate the role of battery storage in the next paragraph, before forming conclusions on this behaviour.

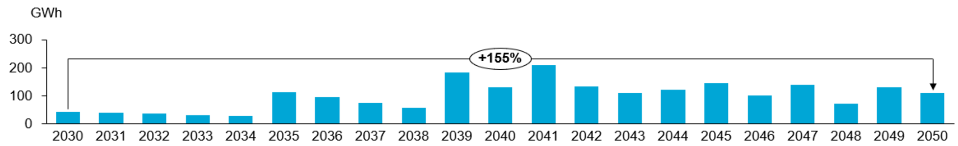


Figure 6.5: Mean hydrogen storage levels.

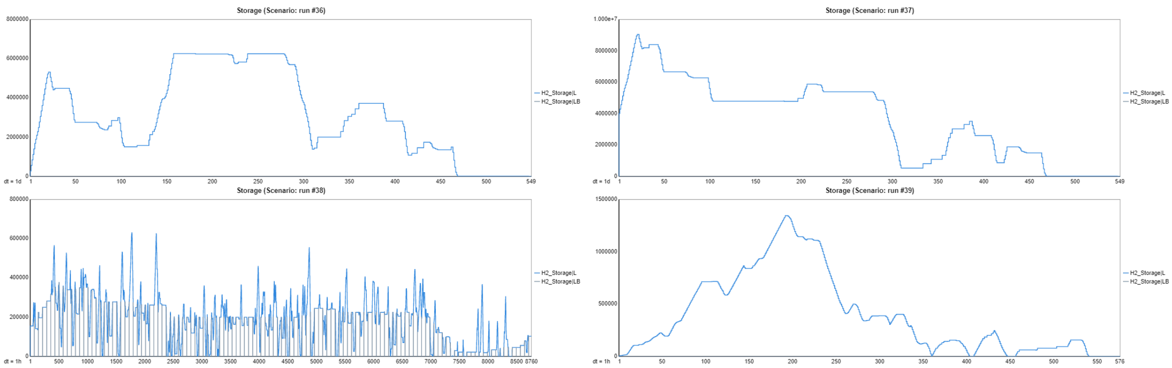


Figure 6.6: Hydrogen storage in the 2039 Dutch Base Case Simulation. Top left: stage 1. Top right: stage 2. Bottom left: stage 3. Bottom right: stage 4. Axes in MWh.

Battery Storage Figure 6.7 shows the behaviour of the lithium-ion battery by displaying its levels. We observe the following:

- The lithium-ion battery is trading heavily. As it should be, it is trading more intensively than the hydrogen storage asset.
- The battery is constrained by its maximum storage capacity. Hence the intermittent behaviour of the seasonal storage asset.
- The next logical step is to investigate whether the asset indeed makes a profit with this trading pattern, as we investigate in the next paragraph.

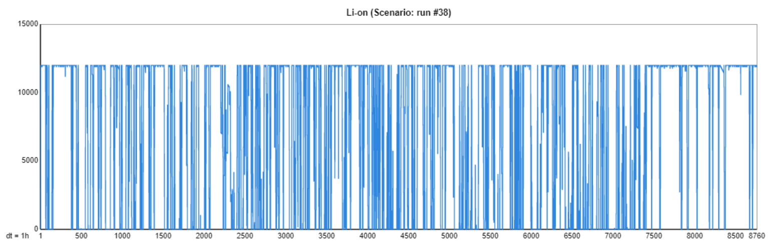


Figure 6.7: Lithium-ion levels, 2039, Dutch Base Case. Axis in MWh.

Trading Pattern The simplest way to spot that the battery's behaviour corresponds with the electricity prices is through the following observation:

- Considering figure 6.8, note how the electricity price is zero for a constant period of time between t=1-500, t=7500-7800 and t=8500-8760. There is no incentive to trade here; if the battery is filled, it should keep those contents until prices are high again at a later stage;

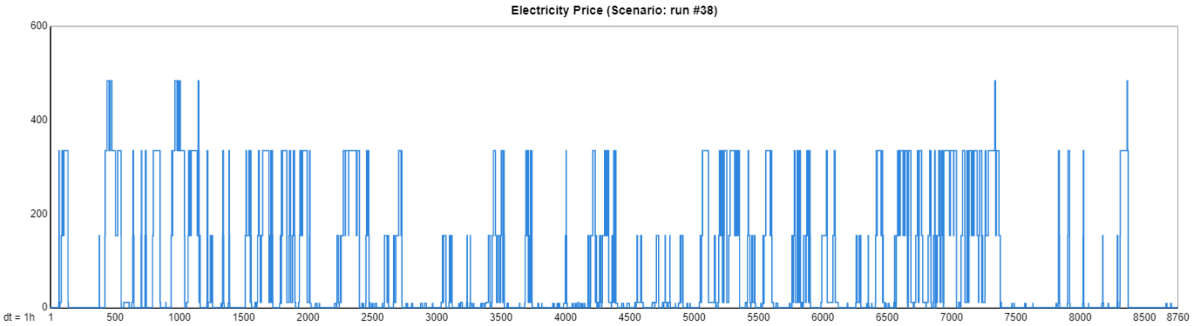


Figure 6.8: Spot price timeseries, 2039, Dutch Base Case.

- Going back to the battery storage pattern in figure 6.7, note the white boxes during which the battery remains fully charged during those same time periods.

Conclusion Based on MODO's base case output, we conclude the following:

- Results are internally consistent and logical;
- If the base case scenario were to materialise, both long and short-term storage stand to play a significant role. Annual consumer spending could find its equilibrium around EUR 15 billion annually.

6.2.2. VoLL Sensitivity

Figure 6.9 shows the sensitivity of MODO to the value of lost load. Their effect in the initial price peak is self-evident, but as the system develops their traceable effects are lost.

To start with, notice the first peak around 2035 in the right chart in figure6.9. At this point, no investments have yet been made. As a consequence, the capacity mix is still quite 'traditional', in that it does not rely on storage all that much. We are able to witness a clear effect of lost load hours on mean electricity prices: the higher the VoLL market cap, the higher the price.

As the system develops, the price differential leads to minimal differences. The left chart in figure 6.9 shows that the difference between the VoLL set at €2000/MWh and one at €4000/MWh is 6%, and that the difference between €4000/MWh and €6000/MWh is -1%. The different ceilings do lead to some emergent system behaviour as the right chart shows. However, the presence of storage seems to dampen the sensitvity to a price cap.

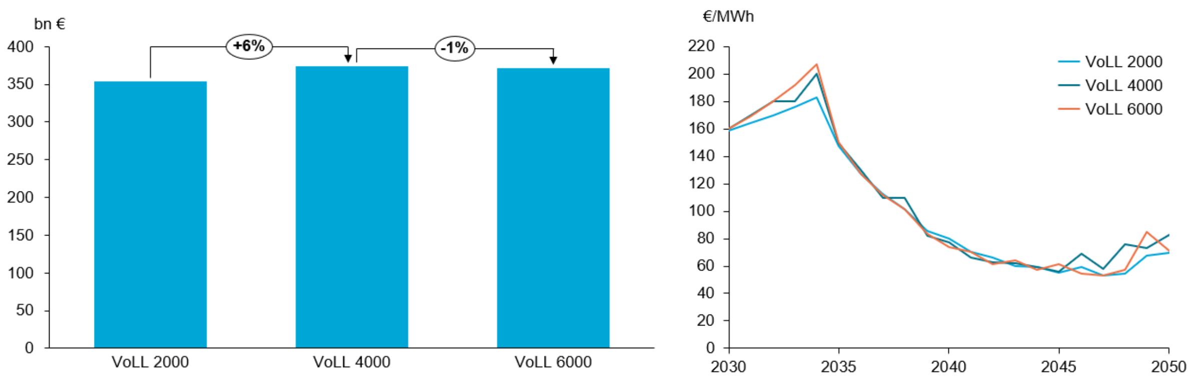
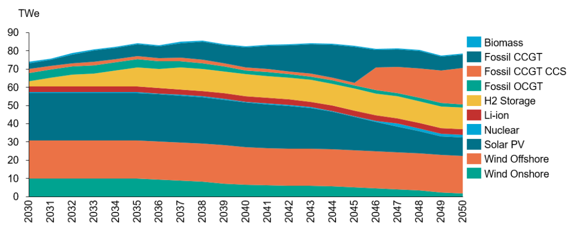


Figure 6.9: VoLL sensitivity analysis, Dutch Base Case

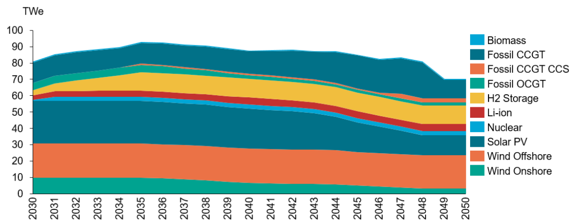
6.2.3. Impact of a Carbon Ceiling

The two runs comparing the effect of a carbon ceiling declining toward zero produce a clear difference in terms of the resulting electricity mix: regular CCGT plants are replaced with CCGT-CCS assets (figure 6.10b). The contrast with the uptake of renewables in the base case is brought about by the much lower gas prices used in this scenario.

The analysis also showcases an issue Poncelet [47] already warned for: that myopic simulation models do not account for trends observed in the rolling window of foresight. Figure 6.11 shows the sudden jump in capital expenditures when carbon targets started to constrain the production of conventional CCGT plants.



(a) VRES module top cluster.



(b) VRES module investment cluster

Figure 6.10: VRES module

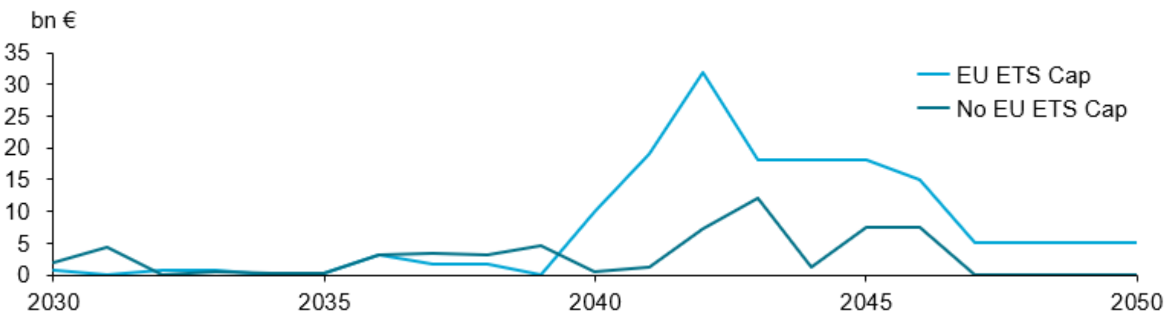


Figure 6.11: Cumulative capital expenditures.

7 Conclusion

The objective of this thesis has been to create a model that enables the long-term simulation of myopic investment in EU energy-only electricity markets with high intermittency, batteries and seasonal storage, in a way that is transparent and computationally efficient.

We conclude that the myopic optimisation detailed operational (MODO) methodology achieves that objective. We have implemented the multi-year, multi-timescale myopic simulation methodology in a modular Linny-R toolkit that anyone can use to create their own system and scenarios without needing to possess technical modeling knowledge. The runtime of a 20-year simulation period is under 2 hours on a mid-range personal computer, an 85% improvement compared to the MIDO model. Validation runs and a preliminary application to a more complex market system support MODO's applicability.

On the Myopic Investment Perspective We have conceptualised the myopic investment perspective as follows: i) the investor has perfect information about a representative year, five year in the future, and ii) the investor has no information outside this period. This is aligned with exiting research which finds that this conceptualisation approaches long-term simulation equilibria.

Subsequently, we embodied this conceptualisation into a multi-stage, multi-temporal approach: the Myopic Optimisation, Detailed Operational methodology. Harbouring the similar conceptual underpinnings as the MIDO model, MODO relies on the myopic optimisation of investments based on a set of representative days, which is subsequently analysed in detail by first calibrating seasonal storage after which a full-year, hourly run assesses system and market performance.

On Computational Efficiency By replacing MIDO's iterative investment process with MODO's optimisation, we have realised a reduction in required computational time of approximately 85%. An year-by-year simulation of a 20-year period regularly took over 12 hours with MIDO, on a PC with an Intel Core i7-10700K processor and 32GB RAM. A simulation with the same characteristics using MODO consistently finishes in approximately 2 hours, on a laptop with an Intel Core i7-11800H[1] and 16GB RAM.

On Implementation in Linny-R The stakeholder consultation revealed the importance of intuition in investment planning decision-making. For a formalised version of MODO to be used in planning arenas, be they private, public or public-private, it must be transparent and elegant. Therefore, we have implemented MODO in Linny-R, a graphical language particularly suitable for unit commitment models. A first benefit is that the graphical formalisation facilitates face validation of the system's implementation, taking away most 'black-box' objections. A second benefit is that all data entry and processing is contained within the model, which is a single downloadable file; there is no need for external datasets or scripts. Consequently, results are easily traceable and verifiable. Moreover, it makes the model 'click-and-go', in that the barrier for policy analysts or researchers to analyse system behaviour using their own assumptions is nearly non-existent.

[1] The i7-10700K is estimate to have a 14% higher effective speed than the i7-11800H [66].

On plausibility of results Results are preliminary but plausible when simulating Dutch electricity system development from 2030 to 2050. An in-depth analysis of the behaviour of assets shows sensible behaviour despite some remaining concerns about over-investment due to lumpiness of asset sizes.

Pertaining to sensitivities identified through the scenarios, at first sight, the model appears sensitive to commodity price differences, resulting in different technology choices. Due to a likely increased role of (seasonal) storage, the model appears less sensitive to the market's price cap.

8
Reflection

On the Validity of MODO In 1973, Rittel & Webber published a paper titled *Dilemmas in a General Theory of Planning*, in which they wrote:

> "With arrogant confidence, the early systems analysts pronounced themselves ready to take on anyone's perceived problem, diagnostically to discover its hidden character, and then, having exposed its true nature, skillfully to excise its root causes. Two decades of experience have worn the self-assurances thin. These analysts are coming to realize how valid their model really is, for they themselves have been caught by the very same diagnostic difficulties that troubled their clients." [55, p. 159]

At the outset of this thesis, my vision was for MODO to become the go-to tool for electricity market simulations, both in academics and the private sector. Today, I realise that modern electricity systems cannot possibly be captured in any single methodology.

Nevertheless, MODO is a highly useful tool to foster understanding of the development of electricity markets under different (policy) scenarios, provided that its results are interpreted with a good understanding of the methodology and assumptions underpinning it.

The key consideration concerning the validity of MODO revolves around the data which is used to assess an investment decision. We have employed myopic optimisation to analyse system development from 2030-2050. In hindsight, it is debatable whether the representation of myopic investment behaviour is of added value conceptually. The idea is that by providing the investor with data on a limited number of years in the future, real-world short-sightedness – brought about by matters such as political uncertainty – is better represented. However, the data we ourselves, as policy analysts, input into the model, is a scenario and completely uncertain.

Therefore, why make long-term simulation models more complex by adding a myopic component, when these models *rely fully on known unknowns and unknown unknowns*? Whether the investors assume level parameters after the window of foresight, or work with those parameters input by the analyst, has little effect on the uncertainty of the outcome.

Instead, myopic optimisation might be more suitable for the analysis of the development of systems about which several real-world developments are *known knowns*, after which a period of *known unknowns and unknowns unknown* ensues. This is where the myopic perspective becomes relevant as it can actually be argued that real-world investors have no better alternative than to continue the financial forecasts based on level parameters. To illustrate, consider the following real-world scenario for the Dutch case[1] as opposed to the fully uncertain 2030-2050 scenarios as we have analysed them in this thesis:

The year is that of the publication of this thesis: 2022. The government has just committed to double offshore wind by 2030. Geopolitical tensions will likely cause natural gas prices to remain at elevated levels for quite some time. As a result, coal-fired power plants will remain profitable and thus operational for longer, but is is certain that the government will enforce their shutdown no later than 2030. Targets for solar PV are clear, but there is no grid capacity to facilitate new projects, meaning the targets will be met at delayed rates.

[1] As we have described it in chapter 5

Based on this scenario, the most suitable application for methodologies relying on myopic foresight might be to model the investment behaviour that would be likely to ensue based on: i) quantitative scenarios in line with the relatively certain developments as we have outlined them in the above scenario, ii) assuming that the profitability levels post-2030 (the final look-ahead year) will remain level. In sum, myopic methodologies, MODO included, might be more valid – and more relevant – for the simulation of long-term system development when the point of departure is not a fully unknown scenario in itself, but based on scenarios with relatively certain directions, within which the *known unknowns* can be varied to find robust planning strategies.

On the Real-World Relevance of MODO In 1999, Shulock published a paper titled *The paradox of policy analysis: If it is not used, why do we produce so much of it?*. She wrote:

> "Policy analysis has changed, right along with the policy process, to become the provider of ideas and frames, to help sustain the discourse that shapes citizen preferences, and to provide the appearance of rationality in an increasingly complex political environment." [58, p. 240]

The interviews I conducted during the course of this thesis emphasised the importance of common sense and intuition in decision-making, which models are unlikely to ever supplant, but ever more likely to complement.

In this light, a primary application of MODO is the conceptual understanding it offers on the value of storage as shares of intermittent generation in the electricity mix increase. A novel topic, the conceptual understanding MODO fosters might be valuable in and of itself to decision-makers seeking to explore the topic, even without necessarily looking at the more technocratic details of the experiments.

Besides this conceptual understanding, I have sought to make the more technocratic component more accessible as well. Due to its full implementation in Linny-R, MODO is very intuitive and its learning curve is anything but steep. Those who would thus like to sharpen their conceptual understanding of a system by asking questions like *What would happen to [the need for li-ion storage] if [we were to commission much less offshore wind]?* can very easily do so, and intuitively understand the results due to the graphical representation.

On Linny-R Linny-R has massively progressed since I first started working with it. When I completed my BSc-thesis using Linny-R, I could only use it to solve the unit commitment dispatch. Today, the entire MODO model is contained in Linny-R.

The process of designing and building MODO also proved to be a push for innovation. All credit for the actual development goes toward Pieter Bots, the creator of Linny-R, but working on MODO led to the discovery and resolving of quite some bugs, as well as the following developments:

- The 'Number of Profitable Units' function, to facilitate profitability assessment of assets within asset stacks;
- The ignoring of investment options in non-investment runs, cutting back computational cost significantly;
- The proper functioning of shifting between timescales between runs in an experiment;
- Easier and more elegant options in expressions, to make the model more transparent and easier to work with results of large experiments.

The core benefit of Linny-R is the intuitive understanding it offers of the modeled system, because of the graphical representation and the reference to these graphical elements in the expressions used for data processing. From what I have noticed thus far, others are quickly able to catch on to the way MODO works even without any documentation, because they are visually able to trace the relations in the modeled electricity system.

9
Recommendations

The global energy system is revolutionising. MODO is a useful tool in navigating the transformation of the power sector, and whilst our recommendations include some pointers to improve MODO, the truly exciting research lies in further stocking the toolbox to create an well-aligned modeling suite for navigating the transition of the *energy system*, as its individual sectors are becoming increasingly interconnected. Additionally, qualitative research into the demand and requirements for those tools could be highly valuable.

On Technical Representation A first priority in improving MODO would be to represent technical detail of generation assets more accurately. Ramp rates and start-up cost are currently ignored, but will become increasingly significant factors in determining the viability of generation investments, especially for peaking power plants. This could be implemented quite easily in Linny-R and can be considered a quick win with high yield.

On Accuracy and Computational Efficiency A second goal could be the a more detailed sensitivity analysis. Independent variables would be i) the number of representative days, ii) standard asset capacities and iii) the number of investment options per asset type. Output variables would be i) computational time and ii) accuracy of investment decisions. For example, we have relied on 24 representative days where 7 might already be sufficient from a mathematical perspective. Because the solver optimises over the entire block, reducing the block to be optimised by a factor 3 provides opportunity to increase the granularity of standard asset sizes.

On Milestone Years In our simulations, we have opted to simulate each of the 20 years in the simulation period. A common practice in both academics and industry is to make use of milestone years. This entails that investment decisions are made only once every five years, with optional interpolation for their realisation over the years. This would reduce the computational burden by another 80%, and if one considers our proposition from the previous chapter on using myopic simulation models for scenarios where targets and parameter levels for the initial period in the future are relatively well-known, then acknowledging that the simulation will never be accurate to the year allows for the investment consideration 'in bulk' during a milestone year, especially if these investments are then (stochastically) spread out over a certain amount of years.

On Exploratory Analyses Now that the computational effort has been brought down, robustness analyses have become more feasible. However, with a runtime of 2 hours on a consumer laptop, they will likely still require some type of computational cluster.

Additionally, we re-iterate the point we made in the reflection of the scenarios that are suitable for MODO to analyse. One could consider the methodology more suitable for long-term simulations which take the year in which the research is simulated as a starting point, assuming myopic foresight up until the year for which policy targets and other exogenous trends are somewhat known. In case one opts for this line of research, we highly suggest a participatory approach to inform such choices.

On Modeling Power Markets MODO assumes perfect spot market dispatch to be a proxy for future revenues of an asset, like many existing methodologies do as well. Our stakeholder consultation revealed the importance of considering investment decisions as a function of risk allocation. Now that markets are becoming ever more unpredictable, there is a signifcant risk premium on spot market uncertainty. An exciting avenue for research would therefore be to expand the existing, but limited body of research on portfolio choices by energy trading companies when the decisions are made based on capacity allocation across different markets; short-term, long-term and bilateral.

On Modeling Investments in Battery Storage The primary markets for battery storage are the FCR, aFRR and congestion management markets. Nevertheless, spot market arbitrage may be a part of the business case. A more accurate representation of battery capacity and availability in MODO may therefore be realised by connecting MODO to a model targeted at analysing the business case for battery storage. Such a model would at minimum have i) a much more detailed technical representation of generation assets and ii) simulate the forecasting errors that bring about the need for ancillary services.

On Power-2-X Markets Research into the coupling of electricity market models market models for *X* (such as hydrogen and ammonia) could be interesting. A first question would be whether such a link is necessary, because most conversions will likely prove to materialise as additional baseload demand, which could be abstracted from by incorporating it into the growth rate for electricity demand in existing models. However, in scenarios where these developments materially impact power markets, such as the business case for electrolysers not being primarily focused on seasonal storage but facilitating it nonetheless, a linkage or data transfer may prove beneficial.

On the Invisible Hand and Government in Power Markets As we are dedicating a lot of time and effort to modeling power markets, it is important to keep perspective. The Netherlands only has seventy power plants with a nominal capacity exceeding 1MWe. Many projects are intensively coordinated with government. The 'hottest' projects: offshore wind, onshore wind and solar PV are all heavily subsidised and bound by public policy targets. The Cabinet has announced its desire for two additional nuclear power plants. Electrolyser targets have been clearly communicated. The invisible hand in today's liberalised power markets is actually quite visible, and in all the dynamic complexities that we model, it all comes down to no more than a handful of significant investment decisions annually. Extensive qualitative research into the use of simulation models in policy and corporate arenas may therefore prove very valuable in sharpening the recommendations that spring from research into energy transitions based on simulation models.

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A

Supplemental Data

A.1. Complimentary to Chapter 5

Historical Dutch Electricity Demand Growth

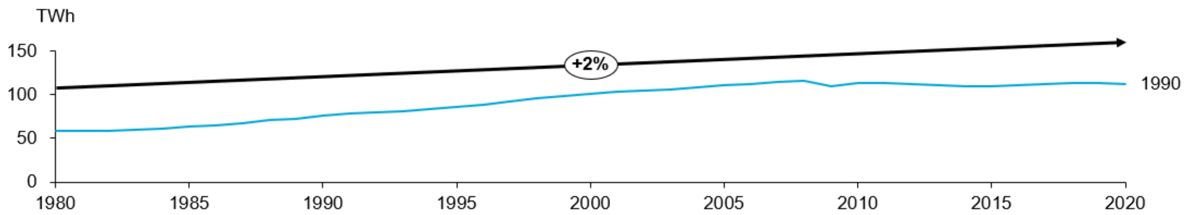

Figure A.1: Historical compound annual growth rate of Dutch electricity demand. Data from [7].

Monthly Generation by Asset Type, Dunkelflaute versus Regular Year

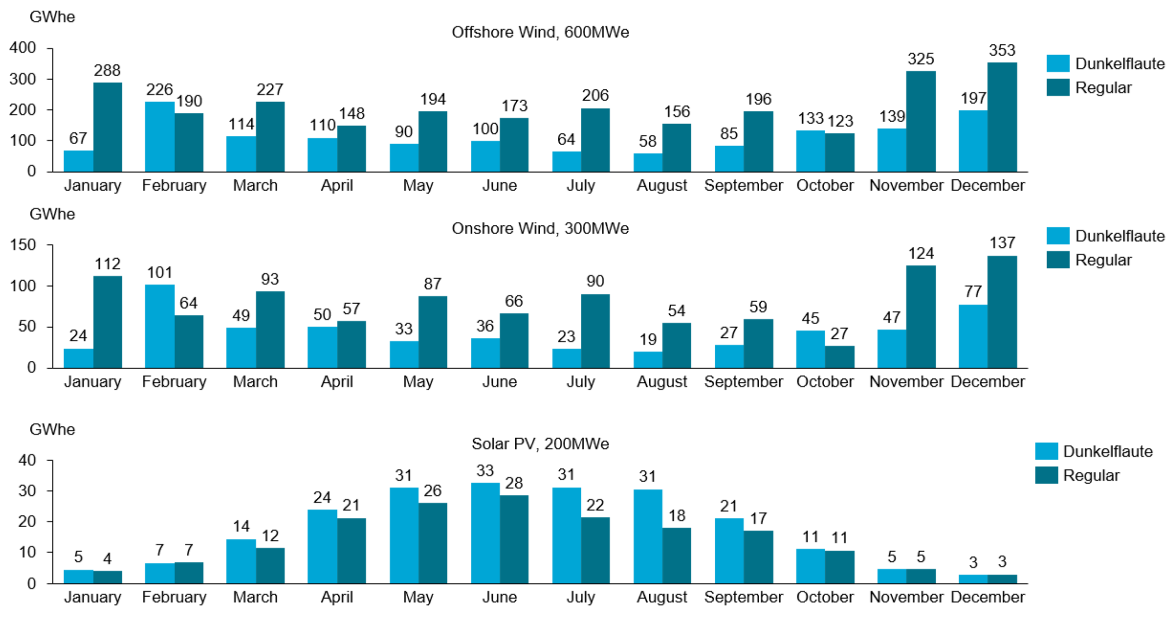

Figure A.2: Monthly Generation by Asset Type, Dunkelflaute versus Regular Year