Exploring the value of load-shifting for cost-optimal power grids

A research case for the Dutch power grid in 2035 through analysis of possible scenarios.

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Acknowledgments

Finalising this thesis marks the end of my academic journey at Delft University of Technology. I am proud to have reached this milestone, and I look back with great joy on my years as a student. During this thesis, I have enjoyed studying and delving deeper into its fundamental content and the overall process. Completing an individual project has taught me much about long-term planning and discipline.

Even though this thesis was an individual project, I would like to thank my supervisor and team members at the university. Special thanks are due to my supervisor, Simon Tindemans, who helped me shape this thesis tremendously and asked the right questions to add depth to the research. Our meetings always gave me a deeper understanding of the problem and motivated me greatly. I would also like to thank the team members of the Intelligent Electrical Power Grids group, Kutay Bölat, Ties van der Heijden, and Nanda Kishor Panda, for always welcoming my questions and showing interest in my thesis.

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Ties van de Camp
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Summary

The energy transition towards a fossil-free energy system is in progress for various countries to mitigate greenhouse gas emissions. One critical bottleneck for ensuring swift transformation is facilitating the rapid electrification of the sector, as well as managing the increasingly distributed and intermittent energy resources, such as solar-PV or wind turbine facilities in the power grid. Where traditional power grids rely on controllable power generation to ensure a reliable and secure balance of generation and demand, new solutions must be found. Currently, the Netherlands is experiencing significant amounts of power grid congestion, primarily due to this rapid introduction of DERs, without the necessary flexibility solutions to accompany, stressing the need for action and future planning.

In the Dutch context, descriptive evaluations of energy systems or simulation studies of transition pathways are mostly used to address the challenges of power grid flexibility, resulting in ambiguous results for investment planning of such flexible assets. Energy System Optimisation Models (ESOMs) can enable robust system planning by providing indicative, prescriptive pathways to aid such decisions under uncertainty. However, for all modelling frameworks, the completeness of results is contested, largely due to an interesting interplay in this flexibility domain. While power grid solutions such as energy storage are well accounted for, another type of flexibility is often neglected or oversimplified: Demand Response. Altering energy demand can offer implicit flexibility benefits by shifting the scheduled load to favourable moments or curtailing the load. However, this flexibility solution is often neglected or oversimplified in ESOMs, resulting in incomplete system outlooks for flexibility in the power sector, which slows down the energy transition.

This thesis provides a comprehensive validation of modelling frameworks used for one such Demand Response technology: load-shifting. It was found that the timely recovery of load-shifting processes for large-scale modelling is often oversimplified. This study proposes a novel approach suitable for modelling aggregated load-shifting in large-scale ESOMs. The new approach, known as the *Wasserstein* method, was found to be easily applicable and accurately account for load-shifting characteristics, including the saturation of available load-shifting and timely recovery of shifted load. Since the approach is a top-down method, it does not require extensive information and process-specific constraints to portray load-shifting effects at a top level.

Key insights were obtained from the energy system optimisation study for the selected research case. For a fossil-free power grid in the Netherlands, load-shifting can create significant value for the power grid by adding extra flexibility. This results in lower overall system costs and reduces the need for investment in other flexibility assets, particularly battery energy storage systems. However, it should be stressed that controllable flexibility assets, such as fossil-free power plants, still play a significant role in the cost-optimal network because they can accommodate peak demand and facilitate high penetration of renewable energy resources, such as offshore wind capacity in the Netherlands.

Additionally, this thesis investigated the impact of load-shifting on decision-making processes for power grid configurations. Optimal power grid configurations, both including and excluding load-shifting, were tested for different weather and demand scenarios. The results showed that network configurations incorporating Demand Response resulted in fewer additional costs due to weather and demand sensitivity. This insight is crucial for investment and energy planning, as it reveals that networks exploiting implicit flexibility are more robust and economical than those relying solely on explicit flexibility solutions. Consequently, future power grids that include implicit flexibility from load-shifting are more risk-averse and cost-effective than configurations relying solely on explicit flexibility solutions. Therefore, decision-makers for investment planning are advised to further explore the possibilities of this flexibility solution.

Contents

1 Introduction

This chapter serves as an introduction to the thesis study. In section 1.1, the current state of the Dutch energy transition is discussed, highlighting the social relevance and justification of this research. Section 1.2 elaborates further on the expected challenges for the power grid. Finally, the possibilities of energy system modelling are presented in 1.3, along with their ability to contribute to policymaking in the energy transition.

1.1. Dutch energy transition

Across the globe, the calamitous effects of global warming due to greenhouse gas emissions (GHG) are widely accepted. In recent years, many countries have formulated relevant climate policies based on their own or international needs, aiming to create a sustainable society for future generations. Research from International Energy Agency [1] has indicated that governments drive 70% of global energy investment. In Dutch context, detailed emission reduction targets were outlined per sector and published in the Ministery of Econimc affairs and Climate [2]. Following this National Climate Agreement, policy-supporting reports and outlooks provided by numerous governmental and consulting parties have been published. Informed by such reports, recent policy published by the *Ministery of Economics & Climate* outlined that a heavy focus lies on shifting towards electricity as the primary energy carrier by 2050 for the Dutch energy system [3]. Electrifying the energy system and ensuring a fossil-free power sector is, therefore, the foundation of Dutch climate success. Taking on its responsibility, the share of renewable energy resources in the Dutch power grid has risen over recent years, reaching 40% in 2022 [4].

Along with integrating more renewable energy sources, the infrastructure and functioning of the power grid will need close attention to prevent it from becoming the bottleneck of the energy transition. As a result, *integral infrastructure outlooks* have been developed to gain insights into possible configurations of the Dutch power grid. Such configurations are highly uncertain since political decisions, technological advancements, and societal support influence them. The Dutch Transmission System Operator (TSO) *TenneT*, along with regional Distribution System Operators (DSOs) and additional energy grid operators *Gasunie* developed such an exploratory configuration study [5], [6]. A range of scenarios were presented to account for the previously mentioned uncertainty. The core purposes of such policy-supporting studies can be considered as [5]:

- Sketching future energy trends in production and demand
- Exploring the use of future energy carriers and energy transport methods.
- Providing insight into necessary infrastructure to accommodate such trends
- Assessing the necessary investments and pathways to ensure a successful transition.

The study presents three scenarios with different configurations and outcomes. However, two key trends are consistent across all scenarios. Firstly, a substantial growth in electrical demand is expected. This results from the electrification of various energy sectors. Secondly, the extensive and swift expansion of intermittent RES will require increased grid flexibility solutions.

1.2. Flexibility

Due to the physical properties of electricity, the power grid must balance supply and demand. The electricity demand varies over time, and the potential electrification of sectors further increases the variation between peaks in demand. Currently, the balancing of supply and demand is ensured by fossil fuel-powered generators, adjusting their output to match demand. However, reducing carbon emissions requires transitioning to low-carbon energy sources, such as wind, solar photovoltaic (PV), and nuclear power. Each of these alternatives presents unique challenges: wind and solar PV are dependent on weather conditions, leading to variability in their electricity generation, while nuclear power is typically operated at a near-constant output for reasons of economic viability and safety. Consequently, ensuring grid flexibility in this evolving energy landscape becomes essential to accommodate these low-carbon generators' variable and often inflexible nature [7].

Power grid flexibility can be defined as the ability of the power system to adapt to changes in electricity supply and demand, maintaining balance and stability. This includes various technologies and strategies that enable the grid to accommodate the intermittent nature of renewable energy sources while ensuring reliable power delivery.

Dutch TSO *TenneT* expands on the expected trends mentioned in 1.1 in power grid flexibility, highlighting additional drivers for grid flexibility demand [8]. In addition to their intermittent generation, RES' increasingly distributed and decentralised character poses new challenges. Moreover, the ongoing electrification trend is expected to significantly increase the number of active market participants and connected devices, further amplifying the demand for flexibility solutions. This growing need for flexibility and its evolving role in the power system is illustrated in Figure 1.1.

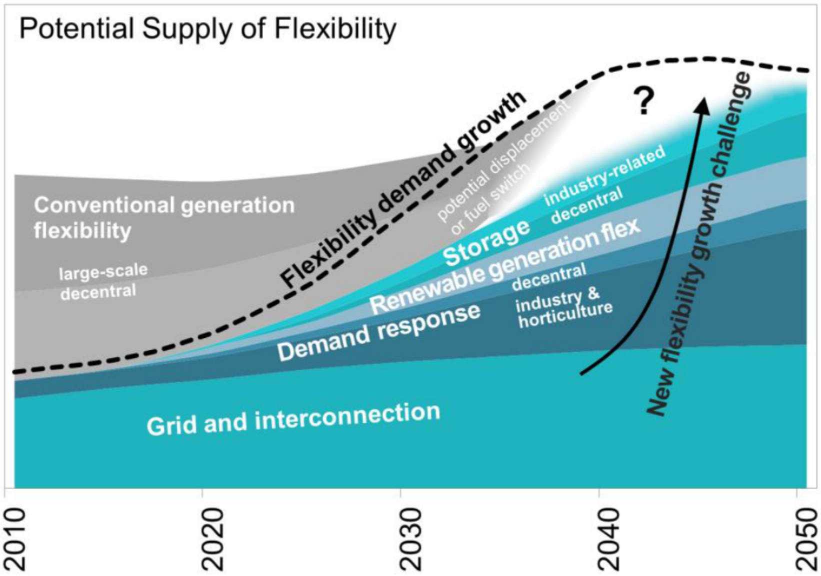


Figure 1.1: Expected trend in grid flexibility [8]

As discussed, multiple knowledge institutes and consultancy agencies involved in the energy transition agree on the growing demand for flexibility. However, the composition of the flexibility assets providing this flexibility is uncertain. Table 1.1 summarises three recent studies into the Dutch flexibility sector for target years 2030 and 2035. The table shows the most technologically mature flexibility technologies and their expected installed capacity. Although all three studies were published between 2022 and 2024, the battery capacity discrepancies highlight this domain's uncertainty. Dutch Transmission System Operator (TSO) *TenneT TSO B.V.* halved their projection from 2022 only two years later [9]. The organisation states that the economic viability is likely lower than initially expected. Almost contradictory, they also state that their economic viability will increase over time due to battery cost reduction and higher spreads in the Day-ahead electricity market.

Table 1.1: Flexibility outlooks NL

Capacity of future flexibility [GW]	TenneT TSO **2030**		Netbeheer Nederland [6] **2035**		
	MLZ'22 [10]	MLZ'24 [9]	KA[1]	ND[2]	IA[3]
P2Gas	0	3.0	4.0	13.6	5.6
P2Heat	0	3.3	5.3	8.5	3.7
Battery	**10.3**	**4.9**	**22.7**	**31.5**	**13.7**
interconnection	10.8	12.8	12.8	13.8	13.8
Demand Response	0.7	1.7	2.0	2.5	1.7
(Green) Gas powerplant	14.2	14.0	12.3	9.6	8.2
H_2 powerplant			3.5	6.0	8.5

1.3. Energy system modelling

In addition to scenario analyses shown above, creating insights and integrating infrastructure has been increasingly adopting energy system models (ESMs) [11] [12]. ESMs typically include relevant interaction of energy system components required for maintaining a stable energy grid. Through computationally combining engineering and economics fundamentals, such models can provide scientific and political insights [13].

ESMs can be subdivided into subclasses: simulation and optimisation [14]. Simulation model, are generally used for *descriptive* analysis, useful for generating insights into known system configurations. *Prescriptive* models, used for finding an optimal configuration based on a set of decision variables and constraints, are classified as optimisation models or Energy System Optimisation Models (ESOMs). A common optimisation strategy for energy planners is cost-optimisation, which provides competitive long-term energy system solutions. These have been recognised to be suitable for policy support [11].

1.3.1. Demand Response modelling

As previously discussed, while the infrastructure outlooks stated are useful for identifying key trends, there are no insights into where optimal configurations may be found, especially in the flexibility domain. Creating such an insight is critical for establishing desired futures for policy support and the energy transition.

One interesting actor in the flexibility landscape that causes trouble is demand response (DR).DR, also referred to as Demand-side Management (DSM), relate to actions conducted on behalf of the energy consumer.DR offers multiple benefits at energy system level, such as accommodating higher penetration of RES into the power grid [15], avoiding costs for line capacity expansions, providing ancillary services [16], reducing the dispatch of expensive thermal generators [17], and decreasing the curtailment of renewable energy resources [18]. In essence, DR results from incentives created in the energy market to stimulate demand-side involvement for grid-balancing purposes. Regarding flexibility solutions for a power grid, it can be considered economically more interesting to influence the load than to install new power plants or electric storage devices [19]. In order words, DR is able to provide flexibility *implictly*, as opposed to electric storage devices purposefully or *explicitly* installed to provide flexibility.

Evaluating DR impact on power grid flexibility remains difficult to predict and its characteristics make it challenging to evaluate at top-level accurately citeOconnell2014BenefitsReview. While accurate representations of specific DR processes exist, they are often too detailed and unsuitable for large-scale power system analysis [20] . DR representation at the top level is, however, often oversimplified [21]. Integration of accurate DR is therefore crucial for gaining top-level insight resulting from ESOMs since it directly influences the flexibility landscape of the future energy system.

[1]KA: Scenario 1 corresponding to climate actions
[2]ND: Scenario 2 corresponding to national growth
[3]IA: Scenario 3 corresponding to international ambition

Although insights into flexibility configuration for the Dutch power grid have been explored, there is a gap in the literature for assisting policy with cost-optimal flexibility compositions. Valuable network insights could be obtained by better understanding the interactions between different flexibility actors and leveraging prescriptive models for cost-optimal solutions. Especially interesting in this knowledge gap is the absence of top-level DR representation in ESOMs, which could yield valuable insights for decision-makers in balancing implicit and explicit flexibility for a future power grid.

1.4. Problem statement

This study aims to explore the implicit technological flexibility offered in networks including Demand Response (DR), with respect to networks only offering explicit flexibility. An energy optimisation study will be conducted to determine different configurations for the Dutch power grid in 2035.

This research was done in congruency with the engineering and consultancy enterprise *Witteveen+Bos*. Therefore, the scope of this thesis is in part aligned with research this company was conducting for the Dutch Ministry of Enterprise [22].

1.5. Research Questions

Exploring the value of load-shifting Demand Response as a flexibility solution for cost-optimal power grids

A research case for the Dutch power grid in 2035 through analysis of possible scenarios.

1. What is needed for effective climate policy, and what current challenges for Dutch policy can be identified?
2. How can Energy System Optimisation Models aid policymakers, and how is Demand Response incorporated?
3. What characterises DR, and how can this be effectively portrayed in large-scale Energy System Optimisation Models?
4. What is the effect of implicit DR load-shifting for decision-making and investment planning for NL 2035 under different scenarios?

1.6. Reader's Guide

This section provides an overview of the thesis structure and content. A graphical representation is illustrated in Figure 1.2. The thesis is organised into several chapters, progressing from foundational concepts to detailed analyses and findings.

Chapter 1 presents an introduction to the Dutch energy transition, encompassing its associated processes and policies, with particular attention to regional energy strategies and system integration studies. This chapter also establishes the research rationale and its societal significance. Building upon this foundation, Chapter 2 delves into the Dutch context, exploring various flexibility solutions whilst emphasising Demand Response. Together, these initial chapters comprehensively address the first research question.

Chapter 3 examines optimisation and energy system optimisation models, exploring their value for policymakers and the integration of Demand Response. This chapter also presents a critical review of load-shifting frameworks from existing literature, assessing their effectiveness and offering valuable insights for energy modellers seeking to implement load-shifting frameworks.

The modelling framework for energy system optimisation is introduced in Chapters 4 and 5, outlining key model choices, assumptions, and scope. Chapter 5 further details the methodological approach applied to two case studies designed to address the third and fourth research questions. This includes a thorough examination of the validation processes for load-shifting frameworks, addressing the third research question, alongside the methodological framework for tackling the fourth research question.

Chapter 6 presents a comprehensive analysis of the load-shifting frameworks' validation process. Next, chapter 7 shows the results of the impact of load-shifting in Dutch context, highlighting network effects, and insights for decision-making.

The discussion in Chapter 8 offers a detailed interpretation of the results, examining their implications and acknowledging limitations. This chapter also presents recommendations for future research directions. The thesis concludes with chapter 9, synthesising the most significant findings and their broader implications.

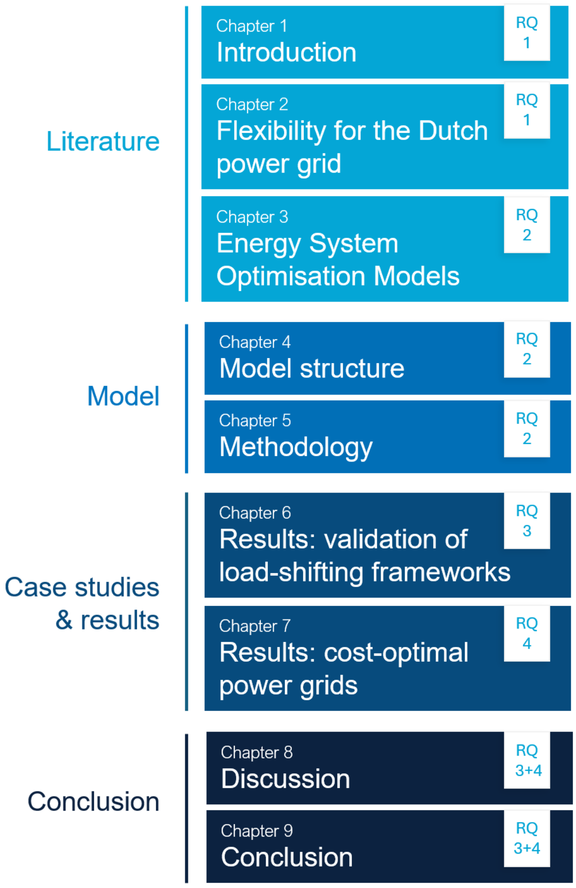


Figure 1.2: Graphical overview of this thesis

2

Flexibility for the Dutch power grid

This chapter aims to answer the sub-question, *"What is needed for effective climate policy, and what challenges for Dutch policy can be identified?"* It highlights the crucial role of policy and planning in establishing a fossil-free power grid. The chapter also provides background on key components for valuable policy and system planning and the areas where policymakers deal with complexity and uncertainty.

The chapter begins with a literature study on transition policy, focusing on the current system outlooks presented by Dutch energy grid organisations and institutions. This provides background information on the tools and aids available for policymakers in the Dutch context, aligning with the scope of this thesis. A particular emphasis is placed on flexible solutions for future power grids, elaborating on the terminology and its relevance to future power systems, policymakers, and capacity planning.

Section 2.1 discusses the importance of policymaking and good practices. In Section 2.2, the focus shifts to the scope of this thesis: policymaking in the Dutch context, discussing the current tools at hand, integration plans, and methodologies employed. Lastly, Section 2.3 expands on the trends and insights shown in Section 2.2, providing more background on flexibility and its importance for policy and decision-making.

2.1. Properties of valuable policy

The European Commission took important steps in this direction by publishing its European Commission [23] goals for 2035: 55% decrease (ref. 1990), 2040: 90%, 2050 net zero GHG, and importantly, made this legally binding through the Climate Act law with the following objectives:

1. **Long-term**
   Commitment is needed over a prolonged duration, and long-term scoping is necessary to increase achievability.
2. **Ambitious and explicit**
   Climate policy should be backed by accurate scientific numbers and state long-term goals.
3. **Legally binding**
   Ensuring reversibility and defining a framework to oppose short-term economic gain concerning long-term sustainability is essential.
4. **Monitoring**
   Additional programs for progress monitoring should be employed, as well as to provide future adaptability for further action.
5. **Uncertainty mitigation**
   Flexible policy adaptation, as well as providing predictability for investors and economic actors

The above key -points are also considered by the Climate Change Performace Index [24] as crucial points for policy effectiveness.

2.2. Dutch Policy landscape

The Netherlands has taken significant steps to address climate change through national policies and frameworks. The Dutch government passed the Climate Law and published the National Climate Agreement (NCA), which outlines specific targets and organizational structures for emission reduction [2]. The NCA sets a goal of a 49% reduction in emissions by 2030, although this target is expected to be aligned with the new European target of a 55% reduction.

The Dutch policy framework emphasises the importance of large-scale deployment and integration of renewable energy sources. This is crucial as 75% of GHG emissions in the EU come from the energy sector. The Netherlands aims to generate 35 TWh of electricity annually from large-scale onshore renewables by 2030. Policy effectiveness monitoring and evaluation are carried out through annual publications like PBL Planbureau voor Leefomgeving [25], which assess whether current policies are sufficient to meet the renewability goals.

The Dutch policy landscape also faces challenges, including the need for flexible energy solutions to accommodate the increasing share of renewables in the energy mix.
Policymakers must navigate complexities and uncertainties in the energy transition, requiring robust planning and adaptive strategies.

2.3. Flexibility solutions

As discussed in section 1.2, the future power grid will increasingly rely on flexibility solutions to maintain balance and reliability. These solutions are crucial for long-term sustainability and addressing immediate challenges like grid congestion, which will be further discussed in section 2.5.
This section will explore current flexibility solutions that help integrate renewable energy sources and support the electrification of various sectors. Specifically, the focus will be on four categories of flexibility options: flexible generation, network interconnection, electricity storage, and demand response, as illustrated in figure 2.1.

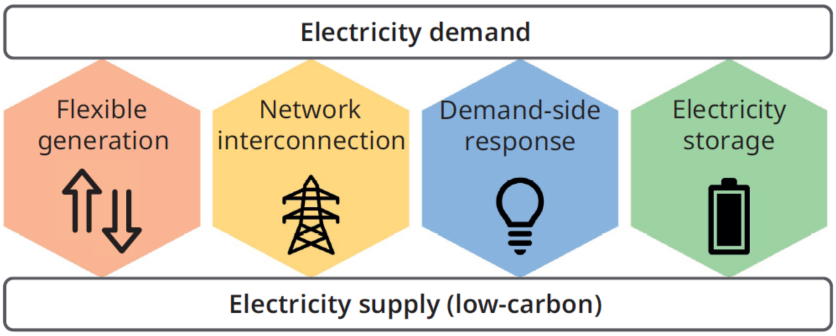


Figure 2.1: Schemataic overview of flexibility solutions. Figure obtained from [7]

In the following sections, these flexibility solutions will be elaborated further, discussing their roles, advantages, and limitations. Special attention will be given to demand response technology in section 2.4, as it is a primary focus of this study. Lastly, the current urgency of implementing these solutions will be highlighted in section 2.5.

Flexible generation

Flexible generation refers to the ability of power plants to adjust their output deliberately to meet varying energy demands. Currently, flexible generation is a critical component in maintaining a stable power grid, with approximately 3,400 GW out of the 7,300 GW of installed generation capacity worldwide being flexible[7]. This flexibility is predominantly provided by gas-fired power plants, which account for 29%, and hydropower plants, which contribute 28% of the total flexible generation capacity [26].
Flexibility in power generation can be categorized into three main types: very short-term, short-term, and longer-term flexibility. The mechanical inertia of spinning generators passively provides very short-term flexibility, which helps stabilise power system frequency. Short-term flexibility involves automated or manual adjustments to power output. Longer-term flexibility encompasses measures such as the start-up of power plants, operational improvements through advanced monitoring technologies, and flexible generation capacity availability through new constructions, retrofits, and reserves.

Variable renewable generators can contribute to power system flexibility requirements through [7]:

- Synthetic inertia:
  Configuring inverters to mimic the behaviour of traditional generators.
- Curtailment:
  Intentionally reducing output during periods of excess supply.
- Reserve operation:
  Operating below maximum capacity to allow for increased output during periods of undersupply.
- Strategic location:
  Minimizing flexibility needs by situating renewable generators in regions with varying weather patterns.
- Output forecasting:
  Enhancing the prediction of renewable energy production.

Network interconnection

The electricity network includes all infrastructure that links electricity production to areas of consumption. Primarily, it bridges the geographic gap between where electricity is generated and where it is needed. Additionally, consolidating various demand and variable generation sources helps to balance overall demand and supply patterns. This also increases the range of flexibility options available, thus decreasing the necessity for active power system flexibility. Consequently, expanding the network and enhancing connections between regions with different weather conditions is considered a cost-efficient strategy for decarbonizing power systems. However, the current global interconnection capacity between countries—acting as a stand-in for network links between regions with varying weather—is only 180 GW. Further expansion is progressing slowly due to substantial initial investment requirements, the need for coordination across regions, and potential opposition from local communities.

Electricity storage

Electricity storage encompasses various technologies that capture surplus electricity and release it during periods of deficit, thereby providing essential flexibility to energy systems. By enabling the temporal shift of energy production and consumption, these technologies can be integrated at multiple points within the electricity network, such as generation sites or consumer locations.

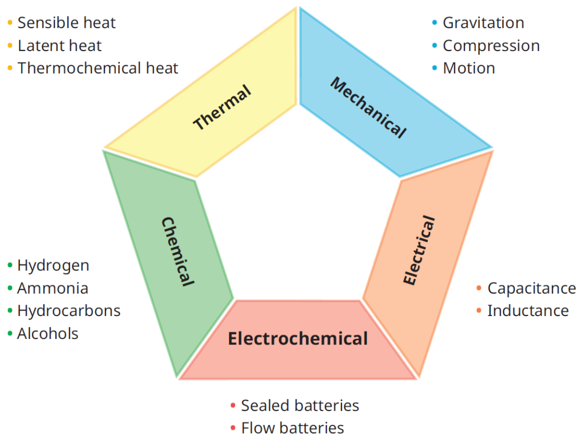


Figure 2.2: Schematic overview of electricity storage methods. Figure obtained from [7]

Electricity storage offers a variety of services, closely tied to the physical properties of the storage media and systems. A useful way to classify different storage systems and their potential applications is by their power rating and discharge time at rated power. Based on these criteria, electricity storage technologies can be broadly categorised into two main types: power-intensive and energy-intensive [27].

Power-intensive applications are crucial for providing ancillary services to the grid, such as frequency and voltage regulation or enhancing power quality [27]. These applications deliver significant power over short durations, typically on the order of seconds or minutes. They are characterised by a high power-to-energy ratio (short discharge times) and rapid response times. Examples include supercapacitors and flywheels, which are suitable for very short-term storage needs.

Energy-intensive applications focus on storing large amounts of energy to balance supply and demand, perform load levelling, or alleviate network congestion. These technologies are characterised by a lower power-to-energy ratio (long discharge times) and are used on timescales ranging from hours to seasons. Examples include pumped hydro and hydrogen storage, which are optimal for long-term storage requirements [7].

Different storage technologies within the same category are generally appropriate for similar applications. For example, chemical storage is well-suited for large energy capacities and long discharge durations, whereas thermal, mechanical, and electrochemical storage can handle medium-sized energy capacities with short to long durations. Electrical storage is best suited for small energy capacities and short durations [28].

2.4. Demand Response

Demand response (DR) and demand side management (DSM) are often used interchangeably in energy management, though DR has become the preferred term as it better emphasizes consumer agency. These terms encompass voluntary changes in electricity consumption patterns by end-users in response to market signals, typically price incentives or reliability needs. In the majority of existing literature, a distinction is made: DSM can be described as the overarching actions of the consumer consisting of two categories: Optimising energy efficiency and implementing DR. Both are measures of the same objective, using the user's energy consumption as an extra degree of freedom to decrease stresses on grid capacity. It is economically more interesting to influence the load than to install new power plants or install electric storage devices [19]. Energy efficiency in DSM is the result of permanent improvements in energy consumption through efficiency investments, such as permanent changes in equipment and upgrades in in system properties [19, 21]. Energy Efficiency measures are, however not in the scope of this study, references on this topic include [29, 30].

The variations described in Figure 2.3 as ”DR with rebound” will in this study be referred to as ”Load shifting”, and ”DR w/o rebound” will be referred to as ”Load shedding” and is further elaborated on the next section 2.4.3.

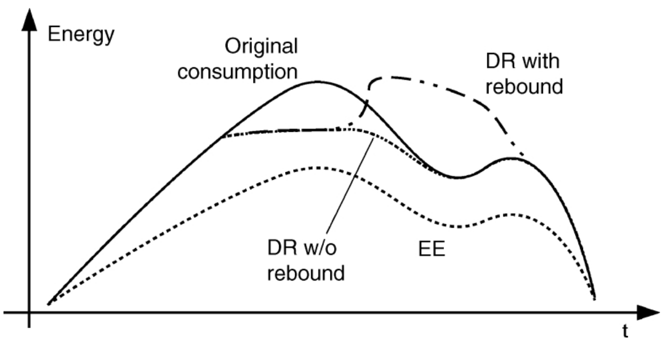


Figure 2.3: DR categories [19]

2.4.1. Benefits

DR mechanisms can provide multiple benefits to an energy system. Firstly, it can accommodate (higher) penetration of Renewable Energy Resources while also reducing the system cost of its integration [15] [31] [18].

Secondly, in power systems with high penetration of renewable energy sources (RES), DR can provide essential operational flexibility to balance the fluctuations in generation profiles and maintain grid security. A key advantage of many load types is their ability to adjust power consumption rapidly, enabling larger effective ramping rates from aggregate demand resources compared to conventional generating plants [32]. DR can also reduce dependency on imports from neighbouring countries and regions. This allows for more strategic use of interconnections based on economic opportunities rather than necessity. Additionally, it can alleviate grid congestion issues through pricing and market mechanisms or direct load control [33].

Thirdly, on a planning level, DR offers additional benefits. Acquiring and maintaining generation capacity is a costly component in total power grid expenses [34]. The ability of DR to facilitate a balancing effect between the volatility of RES generation and peak demand reduces the need for investment in expensive peak power plants such as open cycle gas turbines [17]. Importantly, this, in turn, can also contribute to reducing Greenhouse gas (GHG) emissions.

2.4.2. Activation mechanisms

DR encompasses methods or mechanisms where the price elasticity of electricity prices is leveraged to gain grid stability and or flexibility benefits. A distinction can be made in how the response was activated. **Implicit DR** corresponds to actions incentivised by time-varying prices, with the end-user determining the exact nature of the DR. Active consumers adapt their electricity consumption based on electricity price changes or other targeted incentives, thereby reducing the load in critical peak hours [35]. Implicit DR is also often referred to as **price-based DR control**[36] [37].

Explicit DR, refers to actions done as the result of an explicit signal to the end-user, triggering, for example, a contracted response in demand from the end-user in exchange for a type of remuneration program [38]. This can also be found in literature as **Incentive-based DR** [36] [37]. For industry, explicit remuneration programs are most suitable, and for residential/tertiary sectors, implicit price-based is most suitable [39].

A visualisation of DR categories is given below in figure 2.4, to illustrate the range of DR variations.

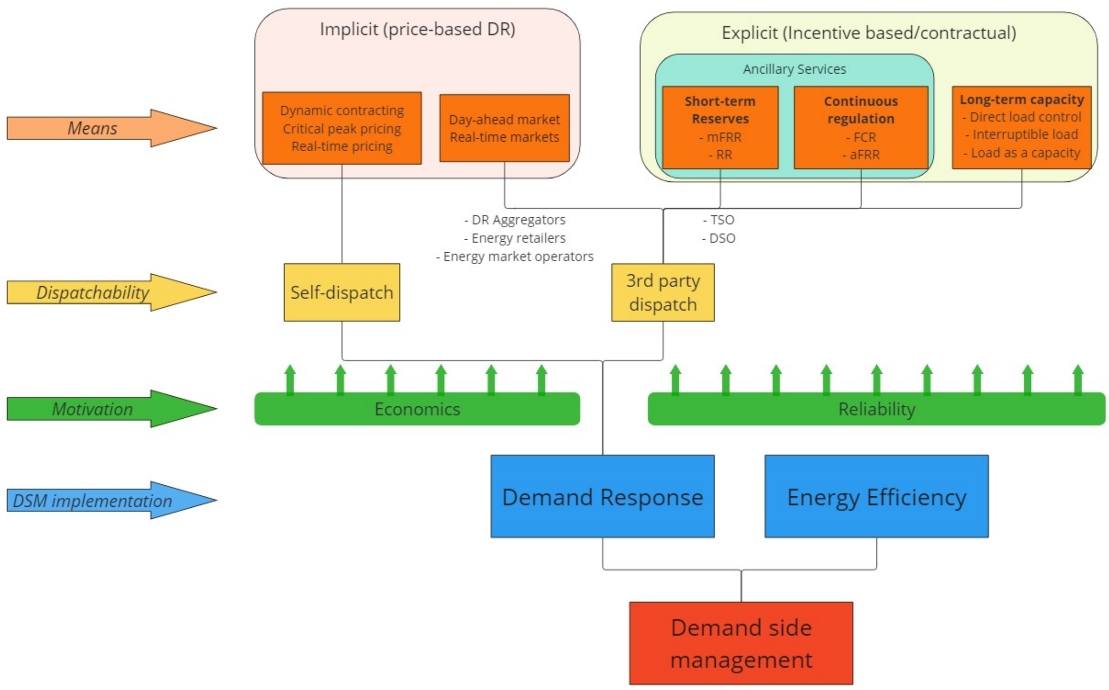


Figure 2.4: Demand response classification (Adapted from [40])

2.4.3. Modes of flexibility services

Demand Response (DR) can be categorised based on the type of flexibility it provides. By understanding these classifications, the various ways DR can contribute to grid stability and efficiency become clearer. This section introduces the primary types of DR, highlighting their distinct characteristics and applications.

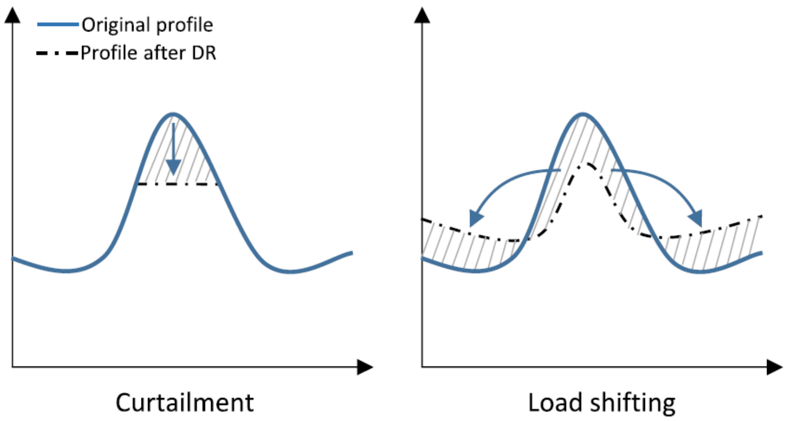


Figure 2.5: In left figure, 'Curtailment' corresponds to Load-shedding. On the right, load-shifting is shown. Figure obtained from [21]

Load shedding

This term refers to curtailing electricity consumption. This can be achieved by shutting down electricity-intensive processes or shifting to another technology to supply the needed energy [41]. As discussed in section 2.4.2, the activation for this mechanism can be either explicit or implicit. Using contractual agreements, grid operators can order load-shedding parties to reduce their energy or limit their capacity. Load-shedding may also occur through (voluntary) price response.

This type of DR is mostly available for energy-intensive processes [42]. Another option in this category is possible for industries that have access to on-site electricity generation, such as switching to CHP-provided power based on time-of-use (TOU) prices in horticulture industries.

Load shifting

Load shifting refers to changing the energy consumption from hours with high electricity prices to hours with low electricity prices, as shown in figure 2.5. Across sectors, multiple processes have been identified in the literature as suitable for load-shifting operation [43, 44], the most prevalent are summarised in table 2.1 below:

Sector	Technology	Timeshift [h]	Reference
Industry	Paper processing	3	[44, 43]
	Air separation	4	[44]
	Cement	4	[44]
Power-to-Heat (P2H)	Process heat (industry)	3	[44]
	Heat pumps (residential)	3	[44]
	District heating	12	[44]
Power-to-Gas (P2G)	Power-to-H_2	24	[44]
Residential	Wet appliances	6	[44, 43]
	Cooling/freezing	2	[44, 43]
	AC/Ventilation	1	[44, 43]
Tertiary	Cooling food retail	2	[44, 43]
	Commercial ventilation	2	[43]
	Water management	2	[43]
Mobility	E-mobility	5	[44]

Table 2.1: Overview of shifting times per sector application

Since load shifting is generally considered a more inexpensive option, this DR application is expected to have the most impactful role in future power grids [16].

2.4.4. Future outlooks

Extensive analyses have outlined the theoretical potential of DR across various European regions, emphasizing its significance in balancing energy supply and demand dynamically. Potential for DR varies significantly by sector, with the highest flexibility observed in residential heating and industrial processes. The geographical and temporal availability of DR is crucial, as it affects the overall potential across the continent. In regions with high usage of electric heating and air conditioning, DR potential exhibits substantial seasonal fluctuations, highlighting the need for strategic planning in DR implementation [43].

Sijm, Morales-Espana, and Hernandez-Serna [41] performed a DR study for the Netherlands and predicts a significant potential for DR, especially as we approach 2050. The study indicates that the annual potential of DR flexibility could reach approximately 40 TWh by 2050, more than 15 times higher than the 2.6 TWh estimated for 2030. However, several factors could influence these estimates. On the one hand, the potential might be underestimated due to higher future electricity demands and the exclusion of additional technologies or sectors that could offer DR. For instance, Power-to-Heat (P2H) in non-household residential sectors and Power-to-Mobility for non-passenger electric vehicles (EVs) could significantly increase DR potential. Additionally, including explicit heat storage technologies and addressing flexibility needs due to grid congestion or market uncertainties could enhance DR potential. Explicit DR could also offer higher flexibility by providing differentiated signals and incentives across various end-users.

Conversely, there are arguments suggesting that the DR potentials might be overestimated. For example, the dominance of gas boilers over electric boilers in 2030 could reduce the estimated DR potential for industrial Power-to-Heat technologies. Moreover, several constraints could limit DR potential, including the availability and controllability of DR technologies, investment costs, specific charging requirements of EVs, and various behavioural constraints. These barriers could significantly reduce the realisation of DR potential [38].

The uncertainty surrounding DR potential, participation rates, and willingness-to-pay hampers the ability to make accurate predictions about how this technology will evolve. This uncertainty underscores the need for further research into DR use and its potential benefits for the power grid. Addressing this research gap is crucial for developing effective strategies to integrate DR into future energy systems.

2.5. Grid congestion

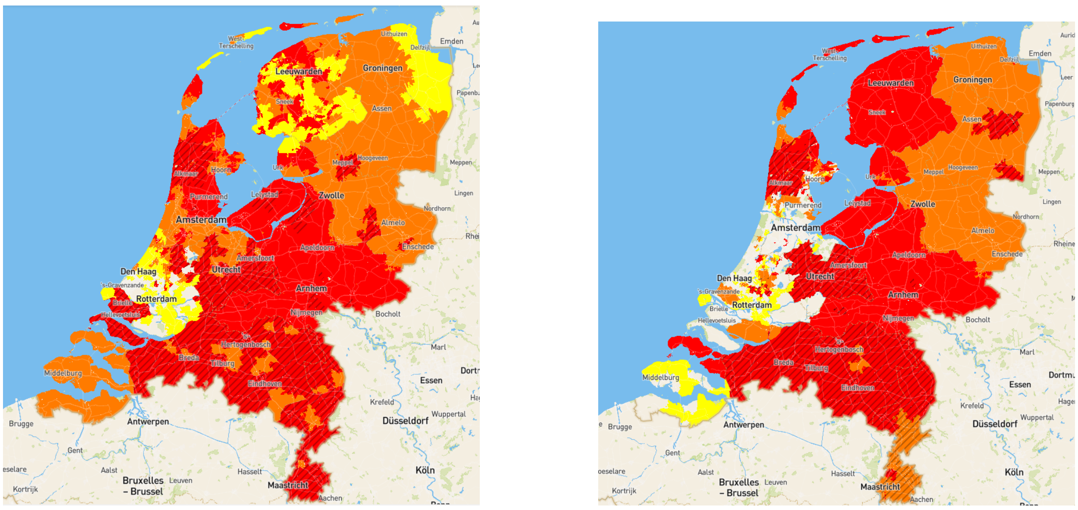
The physical properties of Distributed Energy Resources (DER) have already impacted the Dutch power grid. The power grid is configured in a way that is optimal for centralized energy production and unidirectional distribution. However, with the increasing integration of DERs, such as solar-PV, EVs, batteries, and heat pumps, the grid is now required to operate bidirectionally, which poses particular challenges, especially for rural areas [45]. Grid congestion issues manifest across different spatial scales and network levels [33]:

- At LV (Low voltage) feeders or transformer station, serving up to 100 households
- At MV (Medium Voltage) feeders or transformer stations serving hundreds to thousands of households
- At HV (High Voltage) transmission cables or transformer stations serving 10,000+ households

Grid congestion patterns show a clear relationship with network scale. At higher voltage levels and larger substations, congestion tends to follow more predictable patterns due to the averaging effect of many consumers. In contrast, local low-voltage networks are more susceptible to sudden, unpredictable congestion events, often triggered by activities like simultaneous EV charging. However, some low-voltage areas can show predictable patterns, particularly in industrial zones or neighbourhoods with substantial solar PV installations.

The main technical constraints leading to congestion are thermal limitations of grid components [46]. These issues can manifest in both directions - either through excessive power consumption or generation feed-in. While thermal constraints are typically the primary concern, voltage deviations and reactive power imbalances also present significant challenges [46] [47].

One major obstacle in addressing these issues is the limited availability of detailed congestion data. Comprehensive information about specific congestion characteristics - including their type, severity, location, and temporal patterns - remains scarce, making it difficult to develop targeted solutions. [33]



(a) Availability of grid capacity for consumption

(b) Availability feed-in grid capacity

Figure 2.6: Grid congestion in the Netherlands, 4-4-2024. Red means no availability, Orange means no availability but under investigation, and yellow means limited availability. [48]

Several solutions have been proposed to alleviate these grid congestion issues. While grid reinforcement remains necessary in certain scenarios, it's typically not the most efficient solution for managing increased grid usage. This is particularly evident when congestion usually stems from temporary capacity peaks, such as during high PV-generation periods or simultaneous EV charging, rather than continuous overloading. The strategic deployment of market-based incentives, including energy and capacity tariffs, can provide effective flexibility solutions that often preclude the need for costly grid reinforcement.

Smart utilization of Distributed Energy Resources (DER) flexibility presents a more efficient alternative to immediate grid reinforcement. Rather than defaulting to infrastructure upgrades, the inherent flexibility of DERs can be leveraged strategically. Electric vehicles, batteries, and heat pumps can adjust their operation timing, allowing them to meet energy requirements while avoiding peak loads. Additionally, photovoltaic feed-in can be either curtailed or stored in batteries, providing further flexibility in grid management.

Market-based solutions offer several promising approaches to grid management. Implementing Congestion Service Providers (CSPs) through the Grid Operators Platform for Congestion Solutions (GOPACS) has already shown effectiveness by offering financial incentives for flexibility services. This platform facilitates trading of transport capacity, complemented by smart network tariffs that encourage more intelligent network use. Additional solutions could be offered by introducing local dispatch markets or direct control of loads through demand response programs, creating a comprehensive framework for flexible grid management. However, It must be noted that introducing more energy markets could diminish the effectiveness of, for example, the grid balancing imbalance market [49]. Conversely, while suitable for grid balancing purposes, some flexibility solutions will likely enhance further grid congestion [50].

It becomes evident that more flexible solutions are needed to alleviate the power grid and prevent further grid congestion. Insufficient effort to resolve grid congestion could lead to delayed integration of more renewable energy generation and the stalling of businesses. In conclusion, flexibility will have to evolve its operation across 3 different domains: Balancing Responsible Parties (BRPs) responsible for maintaining the balance between energy production and consumption in their portfolio, grid balancing, and grid congestion. This is once again visualized in figure 2.7

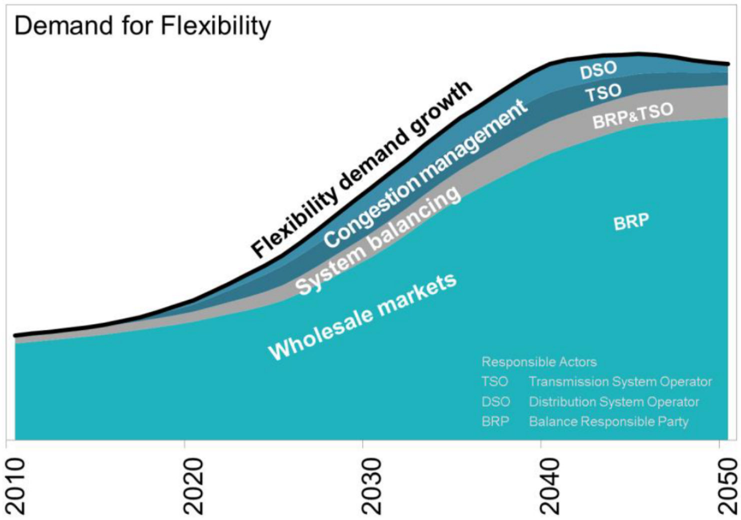


Figure 2.7: Domains in which flexibility will operate

2.6. Conclusion

This chapter examined the key elements required for effective climate policy and the challenges Dutch policy faced in the transition to a fossil-free power grid. In the realm of policy, several critical components have been identified: long-term commitment, ambitious and explicit goals, legal binding, progress monitoring, and uncertainty mitigation. These elements are essential for creating climate policies to drive significant and sustained reductions in greenhouse gas emissions.

To address the subquestion, "*What is needed for effective climate policy, and current challenges for Dutch policy can be identified?*", it is clear that effective climate policy requires a multifaceted approach. This includes setting clear, ambitious goals, establishing legally binding commitments, continuously monitoring progress, and proactively managing uncertainties. The Dutch policy framework must evolve to incorporate these elements while also addressing the specific challenges posed by the transition to renewable energy sources and the integration of Distributed Energy Resources (DERs).

Four categories of flexibility options were explored: flexible generation, network interconnection, electricity storage, and demand response. Each of these solutions plays a vital role in accommodating the variability of renewable energy sources and supporting the electrification of various sectors. The reliance on flexible generation, predominantly provided by gas-fired and hydropower plants, underscores the need for diverse flexibility solutions to ensure grid stability.

Demand Response (DR) emerged as a crucial component in the flexibility landscape. The analysis highlighted its significant benefits, including the ability to accommodate higher renewable energy source (RES) penetration, reduce system costs, and provide essential operational flexibility. DR mechanisms, such as load shedding and load-shifting, offer valuable tools for managing energy consumption patterns in response to market signals. The distinction between implicit and explicit DR, along with their respective activation mechanisms, was also elaborated, providing a comprehensive understanding of how DR can be used to enhance grid stability.

Examining current challenges, particularly grid congestion, revealed the complexities associated with the increasing integration of Distributed Energy Resources (DERs). The traditional power grid, optimised for centralized energy production, now faces significant challenges in operating bidirectionally. Thermal limitations of grid components, voltage deviations, and reactive power imbalances were identified as primary technical constraints leading to congestion. Addressing these issues requires a multifaceted approach, including smart utilization of DER flexibility, market-based solutions, and strategic deployment of energy and capacity tariffs.

The uncertainty surrounding DR potential, participation rates, and willingness-to-pay hampers the ability to make accurate predictions about how this technology will evolve. This uncertainty underscores the need for further research into DR use and its potential benefits for the power grid. This research gap, particularly in understanding the barriers and opportunities for DR, is critical for developing effective strategies to integrate DR into future energy systems.

3

Energy System Optimisation Models

As previously touched upon in section 1.3, valuable insights for policy advice can also be obtained from prescriptive sources rather than descriptive ones. By leveraging such models, policymakers and industry leaders can gain critical data-driven insights that influence energy policy on regional, national, and global scales. Energy System Optimisation Models (ESOMs) have emerged as essential tools for policymakers and industry leaders.

This chapter aims to answer the research question, ”How can energy system optimisation models aid policymakers, and how is Demand Response incorporated?” This will be done by examining the value of energy system optimisation modelling in practice, specifically by analysing their ability to provide consistent, complex, and versatile scenario analyses that are crucial for informed decision-making.

The chapter begins with an overview of optimisation principles, highlighting the core components such as objective functions, decision variables, and constraints. This sets the stage for understanding how ESOMs operate and their significance in energy planning. Then, the value of ESOMs is examined, particularly their ability to provide consistent, complex, and versatile scenario analyses that are crucial for informed decision-making. Next, uncertainties and limitations inherent in ESOMs are addressed, and various approaches to mitigate these challenges are discussed. A particular focus is given to incorporating Demand Response (DR) in ESOMs, identifying the core challenges of aggregation and realistic load-shifting dynamics.

Two prevalent bottom-up DR frameworks are discussed. They are assessed for their strengths and weaknesses, particularly in terms of computational complexity and the risk of oversimplification. This study proposes a novel approach based on the Wasserstein distance between two cumulative load distributions to address these limitations. This method aims to bridge the gap between oversimplified aggregations and detailed appliance-specific DR logic, offering a more flexible and computationally efficient framework for non-process-specific DR. A summary of the discussed frameworks and their suitability to large-scale ESOMs is given, to function as a guideline for energy modellers.

Firstly, in section 3.1, background theory on optimisation can be found, and how this is applied in an energy modelling context. Next, section 3.2 discusses the value, validity, and limitations of considering ESOMs. Section 3.3 provides further background in common concepts for load-shifting purposes. Finally, section 3.5 discusses frameworks and methods found in the literature for load-shifting purposes and a contribution to this field by proposing a novel approach.

3.1. Optimisation

To leverage the benefits from ESOMs, it is imperative to understand optimisation. Optimisation revolves around three core properties: The objective function(s), decision variables, and constraints. By maximising or minimising an objective function through a set of decision variables within the framework of system constraints, optimal solutions can be found [51]. For scenario analysis, the objective function typically aims to minimise costs or maximise social welfare, which is the sum of the consumers’ and generators’ surplus. Decision variables might include capacities and operational schedules for generators, while constraints ensure the technical and regulatory feasibility of these operations, such as ramping limits for generators. or transmission line constraints. A typical objective function for ESOMs is minimising the total annual system cost, and can be concisely exemplified below:

$$\min C^{system} = \sum_j \sum_t (C^C_{j,t} + C^O_{j,t}) \tag{3.1}$$

Here, the total system cost C^{system} is minimised by summing the annualised capital cost C^C, and annual operating costs C^O, for every system component j, per timestamp t.
Different types of optimization problems exist: Linear Programming (LP) handles linear relationships and can efficiently be selected for economic dispatch optimisation. If the situation extends to unit commitment, whether a power grid actor's capacity is activated in market clearing or not, binary variables are introduced to the formulation. This optimisation problem formulation is called mixed integer linear programming (MILP).

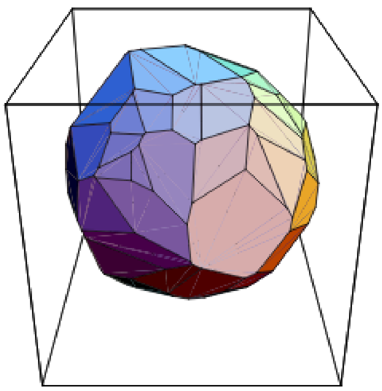
3.1.1. Linear Programming

Linear programming (LP) optimisation involves a problem with strictly linear objective function. The linear relations generally consist of decision variables for power output per grid actor, bounded by constraints for their respective limits. The main advantage of defining the problem linearly is the computational tractability, making it the most favourable method for large-scale systems. The most concise way to denote LP is as follows:

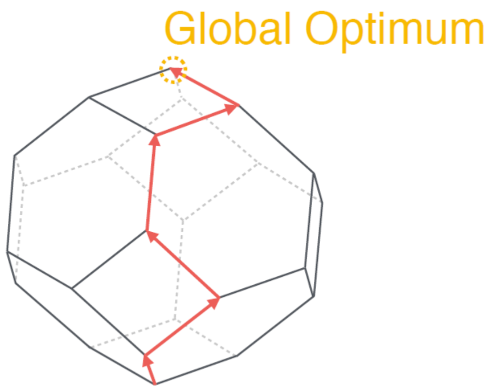
$$\text{minimise} \quad \boldsymbol{c}^T \boldsymbol{x} \tag{3.2}$$
$$\text{subject to} \quad A\boldsymbol{x} \leq \boldsymbol{b}, x \geq 0 \tag{3.3}$$

In this notation, A corresponds to the constraint coefficient matrix containing technical parameters and system requirements, x corresponds to the vector of decision variables, including generator capacities and operational decisions, and b denotes the constraints' limits or right-hand side values, such as maximum capacities or demand requirements.

The set of constraints of the optimisation problem (3.3) can be visualised by a *convex polytope*. The polytope encloses all feasible solutions to the linear problem. A 3D visualisation of such a convex polytope is given in figure 3.1a. Every edge represents the maximum/minimum of the constraints. Constraints can be considered 'active' for any combination of decision variables on this edge. It can be shown algebraically that the optimal solution can be found on one of the vertices of the polytope. Additionally, since the linear function is convex, we can ensure this solution is the global minimum.



(a) 3D visualisation of a convex polytope. [52]



(b) Visualistation of simplex method [53]

Figure 3.1: 3D visualisation of a LP problem, and the simplex method.

The simplex and interior-point methods are the two main algorithms for solving LP problems. Both methods are used widely in computational solvers. The simplex method is schematically illustrated in figure 3.1b. The suitability of each solving mechanism depends on the problem's nature and size and the solver software's strategy [54]. The fast (computational) solvability of LP problems, in combination with the guarantee of finding a global optimum, makes LP problems especially suitable for large-scale optimisation problems. [53].

3.2. Value of Energy System Optimisation Models

In the rapidly evolving landscape of global energy systems, sophisticated modelling tools are indispensable. As discussed in the previous chapter, these tools are crucial in informing both government policy and corporate strategies concerning developing new electricity generation plants and expanding transmission infrastructure. Across multiple studies [55, 56], in-depth and flexible models are essential for navigating the complexities of future energy scenarios.

The range of available energy system models is broad, each with unique capabilities and focuses. Figure 3.2 provides a visual overview and classification of energy system models. Energy system models are typically categorised into three primary types: top-down, hybrid, and bottom-up. Within the bottom-up approach, there are three distinct model types: optimisation models, simulation models, and accounting models.

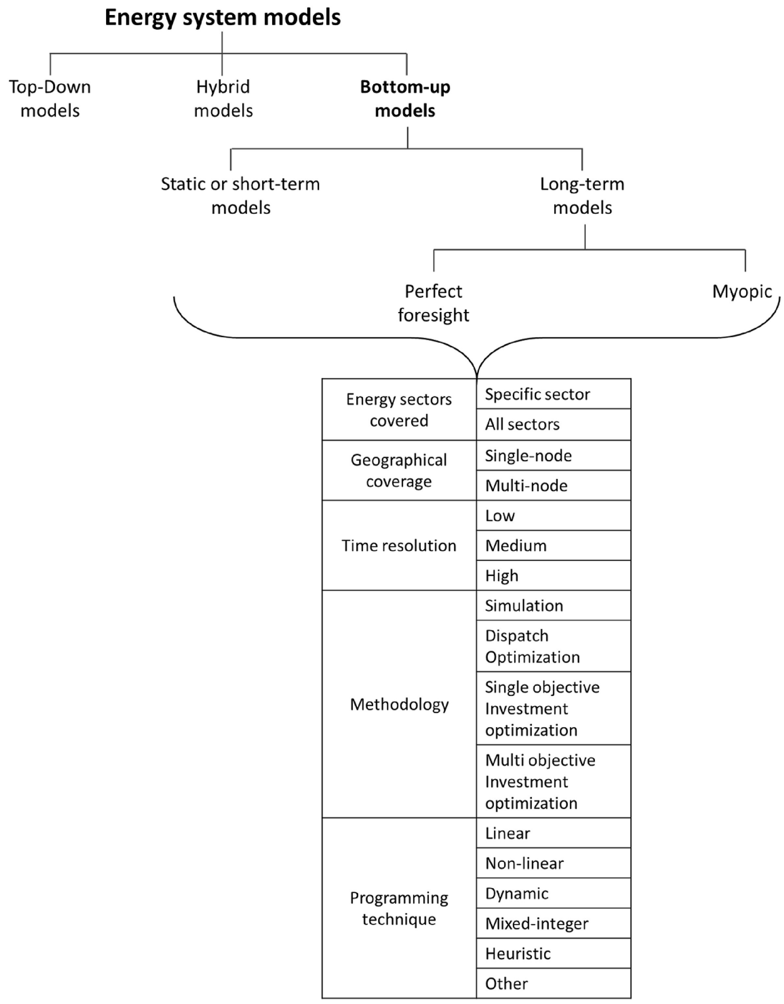


Figure 3.2: Energy system model overview [57]

ESOMs are typically divided based on their operational focus and modelling approach. There are two primary categories: dispatch optimisation models, which are geared towards short-term operational strategies, and investment optimisation models, which focus on long-term infrastructure planning. Further distinctions are made between brownfield and greenfield approaches. Brownfield models consider existing infrastructures and focus on modifications, whereas greenfield models assume no pre-existing

systems, ideal for designing entirely new infrastructures from scratch. Additionally, models can operate under assumptions of perfect foresight or myopic decision-making. Perfect foresight models assume complete knowledge of future conditions, and myopic models optimise in shorter, sequential time frames without foresight beyond each period, creating a pathway to a possible transition.
ESOMs are widely used within energy system models and are appropriate for investment planning and future-oriented studies. This comes down to three core advantageous properties in ESOMs, which can be leveraged for decision-makers [58]:

1. **Consistency**: ESOMs can specify techno-economic performance characteristics of modelled processes by providing a consistent accounting framework.
2. **Suitability for complexity**: The model formulation makes effective and swift normative goal-seeking possible for highly complex systems.
3. **Versatility in Scenario Analysis**: Corresponding to energy and environment policy objectives, they can showcase a range of energy futures.

3.2.1. Policy Value

The historical context of energy systems modelling highlights its significance in policy development. The oil crisis of the 1970s underscored the need for long-term strategic energy planning, leading to the establishment of institutions such as the International Energy Agency (IEA). These organisations developed early energy systems models that remain influential today. Initially focused on energy security and costs, these models have evolved to address contemporary challenges such as climate change, renewable energy integration, and the need for flexible demand management [59]. Energy system models have become pivotal for policy-making to identify cost-efficient system layouts that meet ambitious climate change mitigation targets [11] [60]. Flexibility can be incorporated into models by accounting for operational constraints of supply-side technologies and adding new flexibility options such as enhanced grid networks, storage units, and demand response. This comprehensive approach assists decision-makers, including portfolio planners, power plant operators, grid operators, and policymakers, in finding cost-optimal and sustainable future supply scenarios [60].

In the Dutch context, the relevance of ESOMs (Energy System Optimisation Models) for policy support is evident. *Witteveen+Bos* and *CE Delft* conducted an energy study using an ESOM in parallel with the timeline of this thesis. The Dutch Enterprise Agency commissioned the study to understand how an optimal flexibility configuration for a fossil-free power grid could be achieved by 2035. The model optimised investments in production sources, flexibility, storage, and infrastructure to meet electricity and hydrogen demand. It provided hourly energy prices and revenues for different technologies, offering a comprehensive understanding of the operation of a possible future energy system.

The purpose of these models extends beyond generating quantitative predictions; they aim to challenge our assumptions and provide a structured way of thinking about the implications of changes to parts of the system. This approach is particularly important given the large uncertainties in long-term energy planning. Models that produce narrowly focused quantitative predictions can often be misleading due to the inherent uncertainties that grow over time [58]. Moreover, focusing solely on cost optimality overlooks the social and environmental dimensions essential for real-world political feasibility, which are challenging for models to depict. Various stakeholders with differing influences and motivations are involved in energy planning, including local communities, for renewable capacity deployment decisions. While methods to consider multiple objectives exist, incorporating the numerous stakeholder objectives into a single multi-objective optimisation problem is virtually impossible.

Additionally, focusing on a single optimal solution may conceal a range of equally feasible but different system configurations. Explicitly modelling and comparing these alternatives allows energy modellers to support decision-making more effectively [61]. This uncertainty approach will be further discussed in the next section 3.2.2.

3.2.2. Uncertainty and Limitations

While ESOMs (Energy System Optimisation Models) can generate crucial data-driven insights into complex problems, it is important to acknowledge the significant amount of uncertainties involved. Virtually every model input and dimension is subject to uncertainty, so it is essential to discuss these transparently. If the uncertainties of the ESOM are not properly assessed, ESOMs provide little value for decision-makers [62].

Uncertainty can be classified into two main categories: parametric uncertainty and structural uncertainty. Parametric uncertainty refers to imperfect knowledge of ESOM input values, while structural uncertainty pertains to the imperfect mathematical relationships that govern energy system development and operation within the model. Parametric uncertainty can be further subdivided into epistemic and aleatory. Epistemic uncertainty is defined as the category where modellers can mitigate its effects by collecting more data or detail. Aleatory uncertainty occurs when such possibility is not present [63].

Several approaches can be applied to address these uncertainties. Scenario analysis can address parametric uncertainty by translating scenario assumptions into ESOM input parameters. It can also address structural uncertainty by altering the model formulation to accommodate an uncertain scenario element. Sensitivity analysis can be used to test structural uncertainties. Alternative model formulations can be employed to understand the sensitivity of model results to these variations in model formulation. Sensitivity analysis, when applied in this way, can help extract robust insights into different model formulations and help navigate the catalogue of ESOM features.

Additionally, other methods may be employed since least-cost optimisation models can easily give a false sense of exactness by presenting a single least-cost solution for a specific set of cost assumptions. Techniques such as multi-objective optimisation and modelling-to-generate alternatives (MGAs) are designed to find near-optimal solutions [61] [64].

3.2.3. Flexibility solutions

Scenario analyses of future energy systems using different models often yield varied results and conclusions due to differences in input data and the models' underlying formulations. The depiction of technologies involved for typical flexibility solutions, such as energy conversion, storage, utilisation, and transportation, is typically simplified in broad system models to manage the complexity of the mathematical problem. This simplification can lead to significant discrepancies across different models, most notably for DR, battery storage, hydropower, and power transmission [65].

Additionally, the representation of these flexibility solutions is inconsistent across studies, as highlighted by Heider et al. [60], noting the varying levels of technical flexibility representation among surveyed models. This inconsistency can lead to different interpretations of flexibility's role and effectiveness in energy systems. The study underscores the need for a dialogue with model developers to ensure that models accurately reflect the flexibility options available and are validated against real-world operations. Heider et al. [60] states sector-coupling as one of the best-represented flexibility options in ESOMs.

Kirkerud, Nagel, and Bolkesjø [16] examines the role of DR through ESOMs in Nordic countries, where the energy landscape is largely dominated by hydropower. The findings suggest that DR, particularly through electric heating appliances, can significantly reduce the reliance on conventional storage and backup generation.

3.3. Modelling approaches

Energy System Optimisation Models (ESOMs) can incorporate load-shifting through various modelling frameworks, each with distinct advantages and limitations. Two fundamental approaches emerge in the literature: bottom-up modelling, which builds system-level insights from detailed individual actor characteristics, and top-down modelling, which analyses aggregate flexibility potential from a broader system perspective. The choice between these approaches significantly influences how load-shifting behaviours and constraints are represented within the model. This section examines these modelling frameworks, particularly their implications for capturing critical load-shifting phenomena and their suitability for different analytical purposes.

3.3.1. Bottom-up modelling

Bottom-up models provide a detailed representation of an individual or a selection of similar DR actors, each characterised by unique properties. This modelling approach aggregates the flexibility of individual assets to estimate the overall system flexibility [66]. A common method for implementing DR through bottom-up modelling is the concept of *Virtual Batteries* or *Virtual Power Plants* (VPPs). These frameworks leverage the analogy between load-shifting properties and battery characteristics within power grids, making them suitable to represent load-shifting as a form of energy storage. Load-shedding, on the other hand, can be compared to a negative generator.

One significant challenge of bottom-up modelling is the computational complexity that arises with the increasing number of assets. As the number of assets grows, so does the model's size, leading to a substantial computational burden. This can make real-time utilisation difficult, even with advanced solvers [66]. Another challenge is the extensive data requirement [57]. Bottom-up models necessitate detailed information on each DR actor's characteristics, which can be difficult to obtain and manage. This includes data on load profiles, flexibility potential, and operational constraints.

Despite these challenges, bottom-up modelling offers the advantage of accurately capturing the behaviour and flexibility of individual DR actors. By considering the specific characteristics of each asset, bottom-up models can provide a more precise estimation of the available DR capacity and its impact on the energy system. This granularity is particularly beneficial when assessing the potential of specific technologies or sectors to contribute to demand-side flexibility.

3.3.2. Top-down Modelling

Top-down modelling assumptions refer to approaching demand response (DR) not from an individual actor perspective but from a broader system perspective. This approach aggregates the flexibility potential of various consumers to predict the overall impact on the energy system. The demand response can, in turn, be described by assigning price elasticities to represent load-shedding or valley-filling. Furthermore, methods exist to describe load-shifting using cross-elasticities.

Price elasticity of demand is a common metric used in top-down models to quantify how much demand varies with changes in electricity prices. This approach assumes that consumers will adjust their electricity consumption in response to price signals, with higher prices leading to reduced demand (load-shedding) and lower prices encouraging increased consumption (valley filling). Cross-elasticities represent the responsiveness of demand between different periods, capturing the effect of shifting consumption from peak to off-peak periods [32]. At the price-elasticity level, intertemporal cross-price elasticities can describe load-shifting behaviour. Positive intertemporal cross-price elasticity indicates that load is shifted from high-price to low-price hours, effectively increasing demand when preceding or subsequent prices are higher. Conversely, negative intertemporal cross-price elasticity suggests demand inertia, where demand decreases with higher preceding and subsequent prices, requiring consistently low prices over several hours to trigger a response. Recent research by Hirth, Khanna, and Ruhnau [67] demonstrates that intertemporal cross-price elasticities are predominantly positive in the German context. This is an important insight, revealing that most load-shifting occurs for hours with high prices without requiring high prices to persist for long.
However, assigning a single linear elasticity value for demand does not capture the reality and complexity of demand response. Demand response is inherently non-linear and influenced by factors such as price, temperature, time of day, and consumer behaviour. For example, the responsiveness of industrial consumers might differ significantly from that of residential consumers, and even within these categories, the response can vary based on specific circumstances and constraints. Therefore, most top-down methods fail to address challenges such as the variability in consumer behaviour and the interdependencies between different factors influencing demand.

Dynamic elasticity models have been proposed to capture the nuances of demand response better. These models allow for the elasticity values to change over time and across different conditions. For instance, Pandey et al. [68] introduced an adaptive demand response framework that uses a dynamic elasticity approach to model customer demand sensitivity. This model incorporates deterministic and stochastic approaches to capture the variability in consumer behaviour and the intertemporal constraints of load flexibility.

Importantly, Hirth, Khanna, and Ruhnau [67] highlighted the importance of considering electricity demand's very short-term price elasticity. Their study revealed that even small changes in wholesale electricity prices could lead to significant changes in aggregate demand, especially among industrial consumers. This underscores the necessity of using time-sensitive and context-specific elasticity values in top-down models to capture the impact of price fluctuations on demand accurately.
Top-down models often use aggregate data and system-level metrics to predict the impact of DR on the overall energy system. This approach allows for assessing large-scale impacts, such as the potential for peak load reduction and the integration of renewable energy sources. However, it also has limitations. For example, data aggregation can obscure individual consumers' behaviour and the specific factors driving their response to price signals. This can lead to an oversimplification of the complexity of demand response and potentially inaccurate predictions.

3.4. Demand Response modelling

Demand Response modelling for large-scale ESOMs presents several significant challenges. These challenges arise from DR's unique characteristics and the complexities involved in accurately representing these characteristics at a network scale. Oconnell et al. [32] assessed the challenges for realistic representation in detail, of which the most notable ones will be summarised. One of the primary issues is the uncertain availability of DR capacity. Unlike traditional generators or storage units, DR is not a consistently available resource. Its readiness to participate in electricity markets is variable, which introduces uncertainty in its ability to provide flexibility to the system. Another challenge lies in the economic behaviour of DR participants. ESOMs often characterize DR as acting economically rationally, similar to generators and other flexible network participants. However, this assumption may not always hold true, as consumer behaviour can be influenced by various non-economic factors, leading to inconsistent economic rationality.

Two crucial load-shifting properties often overlooked in large-scale ESOMs are saturation and load-recovery. Saturation refers to the maximum load available for postponing or preponing for an appliance or a process. Load recovery corresponds to the timely rebound of the shifted load to the default load profile. Despite their importance, these features are frequently neglected in models incorporating demand-side flexibility [15, 32].

Lastly, the diverse nature of load-shifting processes and appliances makes them unsuitable for aggregation into single network entities. Such a representation cannot accurately represent the magnitude, capacity and sensitivity of the underlying processes. As demonstrated by Evans, Tindemans, and Angeli [69], a simple summation of energy and power capacities only serves as an outer bound of the true flexibility limit for heterogeneous aggregations. Moreover, the feasibility of the capacities offered by the aggregate VPP cannot be guaranteed, potentially leading to misleading system-level insights. More advanced implementation of control and scheduling algorithms would be necessary to accurately capture the capacity of aggregated DR at any given time. However, including such realistic control and scheduling frameworks for Virtual Power Plants or batteries is often beyond the scope of many studies.

In summary, the key challenges for DR modelling in ESOMs include:

1. **Uncertain availability:** The inconsistent readiness of DR to participate in electricity markets.
2. **Inconsistent economic rationality:** The assumption of purely economically rational behaviour may not always hold for DR participants.
3. **Saturation and load-recovery:** These crucial properties of load-shifting are often neglected in large-scale models.
4. **Aggregation complexities:** The challenges in accurately representing heterogeneous DR resources as a single aggregated unit.

These challenges highlight the need for more sophisticated approaches to DR modelling in ESOMs, to ensure that the flexibility potential of demand-side resources is accurately represented and utilized in energy system planning and operation.

This study focuses on addressing two core challenges:

- **Load-recovery & saturation**
- **Aggregation**

These aspects are particularly relevant when implementing DR in models, as they introduce both structural and parametric uncertainties, concepts explored in Section 3.2.2 Since the structural uncertainties related to DR's economic irrationality and availability require detailed information at the DR actor level, structural uncertainties in the above-listed challenges primarily require information and insights into load-shifting frameworks. This study thus concentrates on the structural uncertainties associated with load-recovery and aggregation challenges. These aspects are more amenable to system-level modelling and have significant implications for the accuracy of DR representation in ESOMs.

3.4.1. Virtual battery

Energy optimisation models are often complicated frameworks, and modelling and prediction of DR can further increase it's complexity [37]. For many ESOMs, the basic principle of DR can be condensed to the following: the deviation from normal energy usage by end users induced by electricity price signals [70].

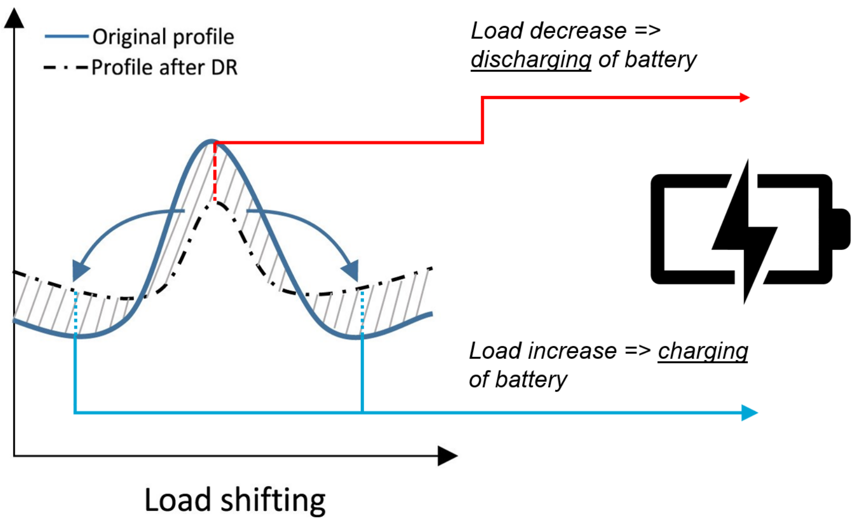


Figure 3.3: Core principle of Virtual battery representing load-shifting

The virtual battery concept extends the logic of energy storage to DR actors, as demonstrated by Gils [43]. This framework provides a powerful tool for modelling DR in ESOMs, capturing key characteristics such as saturation and load-recovery time. By representing DR capabilities as virtual energy storage, flexible resources can more effectively be integrated into complex energy optimisation models. The amount of hours the DR-actor can shift corresponds to the maximum storage level of the "virtual store", or in other words, its saturation. Additionally, the amount of time by which the intervention needs to be balanced again, also known as the load recovery time, can be seen as the maximum storage period of the virtual battery. They form key aspects of DR on a more granulated perspective of the load, i.e. sectoral or appliance-based. These key parameters will, from now on, be referred to by saturation and load-recovery.

3.4.2. Aggregation

The introduction of DR into large-scale ESOMs has implications due to the aggregation of load-shifting actors. Combining individual flexible units into a single entity is often termed a Virtual powerplant (VPP). While such concepts offer a useful framework, aggregating heterogeneous units into one such entity is not without its implications. When analysing DR at system level, the nature of the aggregation of demand can be considered very diverse. Therefore representation of DR in one single unit [32] can be misleading.

A simple summation of energy and power capacities can effectively represent the aggregate flexibility for homogeneous aggregations where the assets have similar characteristics. However, this approach is problematic for heterogeneous aggregations. As demonstrated by Evans, Tindemans, and Angeli [69], the summation of power and energy limits across diverse devices only serves as an outer boundary of the true flexibility limit. This can lead to allocating infeasible requests when such an aggregated model is used in optimisation problems. To realistically capture the capacity of aggregated DR at any given time, more advanced implementation of control and scheduling algorithms could be applied to accurately model the feasible aggregate flexibility. This study instead focuses on ensuring consistency in Demand Response aggregation and modelling: Disaggregated demand response solely represents homogenous aggregations. Different modelling requirements apply in the case of top-level, heterogeneous aggregations of demand. For example, the other key challenge to be addressed, saturation and load-recovery, is subjected to strict timeframes for disaggregated or homogeneously aggregated instances. For example. the thermal inertia of a cooling facility is subjected to a specific threshold for load-shifting. The timeframe for a heterogenous aggregation of DR actors, such as a household or an *economic entity* e.g. an industrial estate consisting of multiple processes and appliances with differing properties, is not subjected to such constraints.

Gils [42] aggregated heterogeneous DR actors for similar characteristics. This revealed an interesting methodology for combining the completeness of bottom-up modelling without introducing a great level of aggregation and computational burden.

3.5. Frameworks in literature

For many load-shifting modelling purposes, virtual batteries or variations are used. The study CE Delft and Witteveen+Bos [22] considers, also employs a virtual battery method of modelling load-shifting. This section will discuss one of the most prevalent extensions of the Virtual battery framework found in literature, referred to as the *Kleinhans* method. Also, another promising framework, from now on referred to as the *Morales* method, will be discussed, along with its suitability for bottom-up, large-scale applications.

3.5.1. Bottom-up framework 1: Kleinhans

For load-shifting frameworks in ESOMS, a popular method was introduced by Kleinhans [71]. Further used by Kirkerud, Nagel, and Bolkesjø [16] and Heitkoetter et al. [72], the structure uses a **Virtual battery** structure. The fundamental aspects of a battery component are leveraged to establish a model that includes the ability to shift load.

The framework as originally proposed is summarised below [71]. Please note that different notation is used in this study to ensure consistency of terminology and symbols.

$$d_t^{DR} = D_t^0 + d_t \tag{3.4}$$

$$e_t = d_{t-1} + e_{t-1} \tag{3.5}$$

$$\tag{3.6}$$

Here, d_t corresponds to the charging/discharging rate of the virtual battery, D_t^0 corresponds to the scheduled load, and d_t^{DR} corresponds to the realised load. These symbols and their corresponding load are also visualised in figure 3.4. Although not explicitly stated by all authors, frameworks generally include the constraint of purely load-shifting, meaning no energy was curtailed.

$$\sum_t^T d_t^{DR} = \sum_t^T D_t^0 \tag{3.7}$$

The following limits can be assigned to ensure realistic limits for upward demand shifts (charging) and downward demand shifts (discharging).

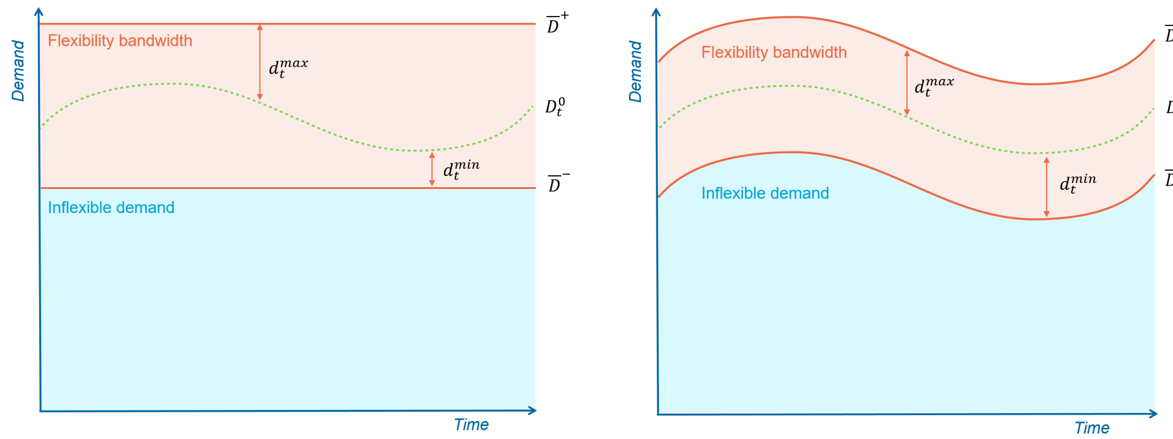
$$d_t^{max} = \overline{D}_t^{+} - D_t^0 \qquad e_t^{max} = \sum_{i=t+1}^{t+\Delta t} D_i^0 \tag{3.8}$$

$$d_t^{min} = \overline{D}_t^{-} - D_t^0 \qquad e_t^{min} =\geq - \sum_{i=t-\Delta t+1}^{t} D_i^0 \tag{3.9}$$

$$d_t^{min} \leq d_t \leq d_t^{max} \qquad e_t^{min} \leq e_t \leq e_t^{max} \tag{3.10}$$

From the above structure, the limit in equation 3.9 for e_{min} stands out, **allowing for negative energy storage**. Negative energy storage can be considered a load-shifting event, where demand is *delayed* in this context. In other words, the battery starts by discharging before charging again to equilibrium. One main improvement of this method is upon a regular battery model. Instead of assigning one maximum saturation, this method relates the maximum saturation of the virtual battery to the sum of Δt timesteps in the case of anticipation of demand. Whenever demand is postponed, the battery saturation may not be larger than Δt amount of hours of previously scheduled load.

Furthermore, from equation 3.8 and 3.9, the power limits for the virtual battery are assigned. In this study, it is chosen to formulate *dynamic* charging limits. This effectively entails that the power limits are variable over time, instead of 1 *static* limit per virtual battery. A visual representation of the difference in static versus dynamic limits is given in figure 3.4 below.



(a) Static (dis)charging limits **(b)** Dyanamic (dis)charging limits

Figure 3.4: Difference between static $\overline{D}^{+/-}$ limits, and dynamic limits $\overline{D}_t^{+/-}$

This study slightly adapts the limits for DR operation. Whereas models based on the structure presented in 3.5.1, apply bottom-up appliance/sector-specific limits to the DR actor, this study assigns a flexible bandwidth of demand, available for load-shifting, per node. The flexible bandwidth is a fraction of the demand available for DR, as described below.

$$\overline{D}_t^{+} = (1+\alpha)D_t^0 \tag{3.11}$$

$$\overline{D}_t^{-} = (1-\alpha)D_t^0 \tag{3.12}$$

3.5.2. Bottom-up method 2: Morales

This section will discuss another bottom-up logic for load shifting. This will be done by discussing literature sources that iteratively improved upon one another. It should be noted that in this overview, symbols may have been used differently than in the corresponding literature for the sake of consistency of this study. As stated by [15] and [21], the important characteristics this model aims to address are accurate saturation of DR, and also most notably, timely load recovery.

The issue of undue load recovery, as previously highlighted in 3.4, is a pressing issue for load-shifting implementation. Timely load recovery ensures that corresponding adjustments are made at another time to balance out any shifts in demand at one time. Without these balanced, time-related constraints, the full operation of load-shifting cannot be accurately assessed, leading to potential distortions in power system evaluations. This balance is essential to avoid undue load recovery, which can undermine the effectiveness of load-shifting strategies. In section 3.5.1, the *Kleinhans* method showed constraints for dynamically constraining the saturation of load-shifting. The timely recovery of a load-shifting process is connected to its physical properties or wishes. For example, for a cooling facility in retail after a time frame of $\Delta t = 2$ (see table 2.1), the delayed or anticipated load should be recovered. If a modelling framework fails to address such limits, *undue load-recovery* occurs.

Figure 3.5 illustrates a case of undue load-recovery for a load-shifting process able to shift load for $\Delta t = 1$. In this case, on the left, an instance can be seen where undue load recovery occurs, whereas timely recovery can be seen on the right.

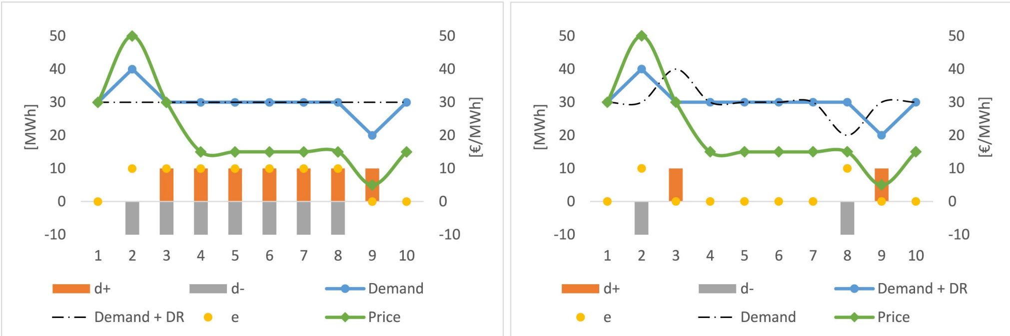


Figure 3.5: The left figure, displays a case of undue load recovery. The right figure displays timely load recovery. Figure obtained from [21]

Similarly to the *Kleinhans* framework, this bottom-up method also leverages the similarities from batteries for load-shifting purposes. The virtual battery operates based on similar fundamentals as the equations provided in section 3.5.1. Once again, the demand is split into a flexible demand and an inflexible demand; however, now, charging and discharging actions are distinguished. Also, constraints ensuring no loss demand loss

$$d_t^{DR} = D_t^0 + d_t^+ + d_t^- \qquad \forall t \tag{3.13}$$

$$\sum_{t=1}^{T} d_t^+ - \sum_{t=1}^{T} d_t^- = 0 \tag{3.14}$$

$$d_t^{+,max} = \overline{D}_t^+ - D_t^0 \qquad \forall t \tag{3.15}$$

$$d_t^{-,min} = \overline{D}_t^- - D_t^0 \qquad \forall t \tag{3.16}$$

$$d_t^{-,min} \leq d_t^- \leq 0 \tag{3.17}$$

$$0 \leq d_t^+ \leq d_t^{+,max} \tag{3.18}$$

Note how the above equations also correspond to figure 3.4b.
Next, a storage variable is introduced e_t, along with Δt, the maximum timeframe for a shifting operation. The Δt variable is used similar to the Δt variable introduced in section 3.5.1. However, additional constraints are added in this framework to ensure a recovery action.

For **delay** load-shifting events, the energy variable should be equal to or larger than the sum of past discharging over period Δt. Also, it must be larger than the (negative) sum of upward shifts over future Δt periods. Similarly, for **anticipation** load-shifting, the energy storage level must be equal or smaller than the sum of Δt previous charging events, as well as smaller or equal to the (absolute) sum of Δt future discharging events.

DR operation	Equivalent battery operation	Saturation and recovery constraints	Notation
Delay load-shift	$e_t \leq 0$	past discharging actions (-)	$e_t \geq \sum_{l=0}^{\Delta t-1} d^-_{t-l}$
		future charging for recovery (+)	$e_t \geq -\sum_{l=1}^{\Delta t} d^+_{t+l}$
Anticipation load-shift	$e_t \geq 0$	past charging actions (+)	$e_t \leq \sum_{l=0}^{\Delta t-1} d^+_{t-l}$
		future discharging actions (-)	$e_t \leq -\sum_{l=1}^{\Delta t} d^-_{t+l}$

Table 3.1: Overview of load-shifting

Next, the authors introduce binary variable δ_t, in equation 3.25, to tackle the problem of undue recovery. This problem occurs when rebound does not occur in the specified timeframe L.

$$e_t = e_{t-1} + d^+_t + d^-_t \qquad \forall t \tag{3.19}$$

$$e_t = e_{t-1} + d^+_t + d^-_t \qquad \forall t \tag{3.20}$$

$$e_t \geq \sum_{l=1}^{\Delta t} d^-_{t+l} \qquad \forall t \tag{3.21}$$

$$e_t \geq -\sum_{l=0}^{\Delta t-1} d^+_{t-l} \qquad \forall t \tag{3.22}$$

$$e_t \leq \sum_{l=1}^{\Delta t} d^+_{t+l} \qquad \forall t \tag{3.23}$$

$$e_t \leq -\sum_{l=0}^{\Delta t-1} d^-_{t-l} \qquad \forall t \tag{3.24}$$

$$d^{+,max}_t = (\overline{D}^+_t - D^0_t)\delta_t \qquad \forall t \tag{3.25}$$

$$d^-_t = (\overline{D}^-_t - D^0_t)(1-\delta_t) \qquad \forall t \tag{3.26}$$

$$d^{-,min}_t \leq d^-_t \leq 0 \tag{3.27}$$

$$0 \leq d^+_t \leq d^{+,max}_t \tag{3.28}$$

$$\delta \in \{0,1\} \qquad \forall t \tag{3.29}$$

Since the logic without δ_t allows for a simultaneous charging and discharging action within the same timestamp t, DR actions can propagate over many hours to find the optimum rebounding time for cost optimisation. The authors state that such a framework ensures a future rebound action to occur in a timely fashion, as well as respecting its maximum store reservoir capacity.

This, however, converts the Linear Programming optimisation problem into a Mixed-integer Linear programming problem. Especially for larger networks, such problems often become computationally intractable. Therefore, Morales-España, Martínez-Gordón, and Sijm [21] propose a linear relaxation of δ. They argue that depending on the tightness of the model, δ will still limit simultaneous cycling and undue load recovery and yield a solution close to the MILP solution.

3.6. Novel approach

Instead of the bottom-up approach, this study presents a new type of top-down logic. This logic attempts to bridge the gap between the oversimplified aggregations and detailed-appliance-specific DR logic. Similarly, the structure exploits the properties of the virtual store component.

The Earth mover's distance (EMD), often called the Wasserstein distance in statistical mathematics, is used to measure the dissimilarity between two functions. Assume two distributions represent piles of dirt. The Wasserstein distance is the minimum amount of effort needed to reshape one pile into the other, where effort is the product of the amount of dirt moved and the distance it is moved.

Given the characteristics of DR through load-shifting, two such distributions could be described: the cumulative inelastic load and the cumulative load including DR. Both loads should add up to the same total load.
For the continuous probability domain, the metric can be described as follows:

$$W(p_r, p_g) = \inf_{\gamma \sim \Pi(p_r, p_g)} \mathbb{E}_{(x,y)\sim\gamma}[||x - y||] \tag{3.30}$$

Here, $\Pi(p_r, p_g)$ is the set of all joint probability distributions possible between p_r and p_g. Then, $\gamma \in \Pi(p_r, p_g)$, describes one 'dirt transportation plan'. The percentage of dirt needed to be transported from point x to y, in order to make both distributions equal, is $\gamma(x, y)$.

This approach, however, does not consider probability distributions, and thus, the Wasserstein distance formula can be simplified since we are working on a 1D, discrete function. Within this context, it is also known as the *Kantorovich-Rubinstein* distance. The function is as follows:

$$W(p, q) = \sum_{i=1}^{n} |F_p(x_i) - F_q(x_i)| \tag{3.31}$$

Here, the continuous distributions p_r, p_g are replaced with discrete 1D distributions p, q. F_p, F_q, in turn, represents the cumulative load profiles (CLPs) of p and q, respectively.
Let us now implement this distance into the top-down framework. For our CLPs, we are interested in the cumulative load of **inflexible demand**, $D_t^{0,CLP}$ over timespan T, and the cumulative load of ideal **flexible demand**, $d_t^{DR,CLP}$ over timespan T. This would yield:

$$W(p, q) = \sum_{i=1}^{n} |F_p(x_i) - F_q(x_i)| \qquad \text{(general form)} \tag{3.32}$$

$$W_T(D^0, d^{DR}) = \sum_{t=1}^{T} |D_t^{0,CLP} - d_t^{DR,CLP}| \qquad \text{(specific case)} \tag{3.33}$$

If the flexible demand d_t^{DR} is created as a decision variable, the Wasserstein distance, along with a cost per distance, can be added to the objective function. This would yield the optimal timeshifting moments for a network, completing the top-down time-shifting framework:

$$\text{minimise}: \ C_{system} + C_{shift} \cdot W \tag{3.34}$$

In this explanation, the Wasserstein distance is the distance between the cumulative scheduled load over a timespan T and the cumulative flexible load over the same period. The method allows for linear implementation, which simplifies the computational complexity and makes it more efficient to solve.

3.6.1. Virtual battery application

To include the Wasserstein distance into the minimisation problem, another virtual battery framework can define a concise relation between the inelastic demand D_t^0 and flexible demand d_t^{DR}.

$$d_t^{DR} = D_t^0 + d_t \tag{3.35}$$

$$d_t^{DR,CLP} = \sum_{i=0}^{t} d_i^{DR} \tag{3.36}$$

The resulting structure is subjected to constraints and limits similar to those of the previous bottom-up models. However, instead of focusing on appliance-related dynamics for timely recovery and energy saturation, this method focuses on a selection of basic rules for load-shifting within ESOMs. The formulation of the constraints can be found below. Firstly, the equation 3.37 enforces that no load is curtailed or created. Secondly, in a similar fashion as was shown for the *Kleinhans* method in equations 3.9, 3.8, 3.10, flexible bandwidth limits charging and discharging rates of the virtual battery framework, as well as the maximum amount of demand to be displaced.

$$D_T^{0,CDF} = d_T^{DR,CDF} \tag{3.37}$$

$$d_t^{W,min} = \overline{D}_t^- - D_t^0 \tag{3.38}$$

$$d_t^{W,max} = \overline{D}_t^+ - D_t^0 \tag{3.39}$$

$$d_t^{W,min} \leq d_t^W \leq d_t^{W,max} \tag{3.40}$$

$$e_t^{W,max} \leq \sum_{i=t+1}^{t+\Delta t} D_i^0 \tag{3.41}$$

$$e_t^{W,min} \geq - \sum_{i=t-\Delta t+1}^{t} D_i^0 \tag{3.42}$$

The energy constraints limit the virtual battery to shift energy over longer periods, which is unrealistic for DR operations. The time-dependent limits correspond to past and future demand blocks, similar in fashion as described in 3.5.1. The maximum amount of energy to be anticipated, meaning for $e_t^W \geq 0$, cannot exceed Δt amount of hours of future flexible demand. Similarly, the virtual battery may not postpone more than Δt hours of past flexible demand.
Another advantage of the virtual battery logic is that any difference between $|D_t^{0,CLP} - d_t^{DR,CLP}|$ at any given t is the cumulative profile of $\sum_{t=0}^{t} d_t$. This corresponds directly to the storage level at that moment, $e_w(t)$. This results in the following definition of the Wasserstein distance trough applying a virtual battery framework:

$$W(T) = \sum_{t=0}^{T} |e_t^W| \tag{3.43}$$

3.7. Guidelines and overview

A summary table is presented below to compare the discussed methods comprehensively. This table highlights the key properties of each virtual battery model and their suitability for different sizes of Energy System Optimisation Models.

- **Model**: This column lists the name of the virtual battery framework being discussed.
- **Energy limits (Saturation of DR)**: This column describes how the framework defines the energy limits for the virtual battery. It indicates whether the limits are fixed or dynamic and how they relate to the saturation of demand response.
- **Charge discharge limit:** This column explains the charging and discharging limits imposed by the framework. It indicates whether the limits are static or dynamic and how they impact the maximum flexible bandwidth.
- **Recovery**: This column addresses whether the framework includes constraints to recover shifted load. This is crucial for realistic modelling of load-shifting, as it ensures that postponed demand is eventually met.
- **Inconvenience pricing**: This column highlights the pricing mechanism used to account for the inconvenience or cost associated with load-shifting. It specifies whether the cost is related to charge/discharge actions or the state of charge.
- **Problem formulation**: This column indicates the type of optimisation problem formulation used by the framework, such as Linear Programming (LP) or Mixed Integer Linear Programming (MIP).
- **Suitability:** This column briefly assesses the framework's suitability for different types of DR modelling. It highlights any potential limitations or strengths.

By providing this detailed comparison, the table helps to understand the key differences and similarities between the frameworks, guiding the selection of the most appropriate method for specific DR modelling needs in energy system studies. This table thus aims to provide an overview and guidance for the suitability of virtual battery use for large-scale ESOMs. However, assessing which load-shifting problem can best be described by which framework can also be interesting. Such a table can be found in Appendix C. In that table, guidance for modelling is provided based on the desired level of DR aggregation to be modelled.

Virtual battery properties				Virtual battery ESOM suitability		
				Problem formulation		Suitability
Model	**Energy limits (Saturation of DR)**	**Charge discharge limit**	**Recovery**	**Inconvenience pricing**	**Problem formulation**	
Bottom-up: PyPSA Storage-Unit	1 limit (identical for pre/postponing)	1 maximum (dis)charging rate	No recovery constraints	C1: Charge discharge action [€/MWh]	LP	**-** Oversimplification of DR characteristics
Bottom-up: Kleinhans	2 limits per hour e_t^{min}, e_t^{max}	d_t^{min}, d_t^{max}, Max. flexible bandwidth	No recovery constraints	C1: Charge discharge action [€/MWh]	LP	**-**(Prone to) oversimplification of DR characteristics
Bottom-up: Morales	4 limits per hour. 3.23 - 3.22	$d_t^{-,min}, d_t^{+,max}$	Recovery enforced by saturation constraints	C1: Charge discharge action [€/MWh]	MIP/LP	**+** Suitable for homogeneous aggregation **-** High information required
Top-down: Wasserstein	2 limits per hour$e_t^{W,min}, e_t^{W,max}$	$d_t^{W,min}, d_t^{W,max}$	Recovery enforced by costs	C2: State of charge [€/MWhh]	LP	**+** Suitable for top-down frameworks, **-** Unverified

Table 3.2: Virtual battery properties and ESOM suitability

3.8. Conclusion

This chapter addressed the research question: How can energy system optimisation models aid policymakers, and how is Demand Response incorporated? by exploring the various aspects of Energy System Optimisation Models and their application in Demand Response.

After introducing the concept and background of optimisation in section 3.1, the value of ESOMs was elaborated in section 3.2, and in the policy context in section 3.2.1. This demonstrated their role in providing consistent, complex, and versatile scenario analyses. These models effectively address the uncertainties inherent in long-term energy planning, allowing for robust decision-making in the face of evolving energy landscapes. Historical context and contemporary examples, such as the energy study by witteveen+Bos and CE Delft, underscored the practical relevance of ESOMs in policy support.

The investigation revealed important insights regarding modelling approaches for Demand Response. Bottom-up frameworks, while detailed and process-specific, often face challenges with computational complexity and data requirements. Top-down approaches, particularly when dealing with aggregate demand response, offer advantages in capturing system-level dynamics and price elasticity effects. This research found that the modeller's objectives should guide the choice between these approaches: bottom-up modelling proves more suitable for analysing specific load-shifting processes, while top-down modelling is better suited for understanding aggregate system-level flexibility potential.

However, the chapter also acknowledged the uncertainties and limitations of ESOMs. It was noted that parametric and structural uncertainties pose significant challenges, and various approaches, such as scenario and sensitivity analyses, are essential to mitigate these uncertainties. Two core challenges are identified: Consistent and valid use of DR aggregation, realistic saturation, and time recovery for load-shifting DR. It was argued that these challenges necessitate sophisticated modelling approaches to accurately represent the flexibility potential of demand-side resources.

Two bottom-up DR frameworks, the *Kleinhans* and *Morales* methods were singled out and discussed. These frameworks apply the concept of virtual batteries to model load-shifting and define additional constraints to tackle saturation and/or load-recovery challenges. The mentioned *Kleinhans* framework was identified to be prone to oversimplification due to its lack of timely recovery constraining.
A novel top-down approach based on the Wasserstein distance was proposed to address these limitations. This method bridges the gap between oversimplified aggregations and detailed appliance-specific DR logic. By leveraging the properties of virtual batteries and incorporating the Earth mover's distance, this approach offers a more flexible and computationally efficient framework for non-process specific DR.

In conclusion, ESOMs provide a powerful tool for policymakers, offering prescriptive insights that guide energy policy and investment decisions. The choice between bottom-up and top-down approaches significantly impacts the model's ability to capture DR dynamics, with each approach offering distinct advantages depending on the intended application. While virtual batteries remain a popular choice for bottom-up models, they must be implemented thoughtfully to avoid oversimplification or computational intractability. The novel Wasserstein distance method presents a promising alternative, particularly for system-level analyses, by balancing modelling detail with computational efficiency. This comprehensive exploration underscores the critical role of ESOMs in navigating the complexities of modern energy systems and supporting informed, data-driven decision-making.

4
Model structure

This chapter presents a comprehensive methodology for developing a verification network and a power grid model for the Netherlands' power sector in 2035, utilizing the PyPSA-Eur framework. The primary goal is to structure a reproducible approach.

To achieve this goal, the chapter provides context on the open-source software employed for network modelling, namely PyPSA and PyPSA-eur. Relevant dependencies, workflows, and data management practices are discussed to ensure transparency and repeatability.

The chapter is structured as follows: Section 4.1 discusses the tools used for energy system optimisation, focusing on PyPSA and PyPSA-Eur. Section 4.2 elaborates on the model choices and assumptions that underpin the scenarios. Lastly, Section 4.3 presents the design of the test case methodologies, providing a solid foundation for the subsequent analysis and discussion of results. By establishing this comprehensive methodological framework, a robust basis is created for assessing potential future developments and policy interventions in the Dutch power system, paving the way for in-depth analysis in the following chapters.
Core pillars for model and methodology based on best practices/guiding principles were assigned based on DeCarolis et al. [58].

- **Quality assurance**
  Input data for ESOM should be of high level and peer-reviewed.
- **Managed model evolution** Begin with a simple, validated model. Carefully add complexity as required by specific analysis needs while regularly assessing and managing overall model detail to avoid unnecessary complexity. Employ 'model archaeology' and version control to maintain consistency over time.
- **Consideration of endogenous & exogenous uncertainty**
  Both structural and parametric uncertainty factors are possibly impacting top-level conclusions. Effort on epistemic parametric uncertainty for cost-data is expended in section 4.2.4 and appendix A. Structural uncertainty is addressed through assessing the understanding of valid DR virtual battery frameworks.
- **Tranparency**
  ESOMs should be designed transparently since the analysis aimed at decision-makers benefits from their involvement. Clear documentation, conveying of results and acknowledgement of limitations ensures more robust findings [62].

4.1. Model framework: PyPSA-eur

This chapter provides an overview of the framework used in this optimisation study, focusing on the PyPSA and PyPSA-eur configurations. First, section 4.1.1 introduces the fundamental components and capabilities of the *PyPSA* open-source tool, illustrating how it facilitates power system analysis.

Section 4.1.2 expands on *PyPSA-eur*, detailing the workflow and data inputs that enable comprehensive modelling and optimisation of the European power grid, leveraging various open-access data and an automated workflow.

4.1.1. PyPSA

PyPSA is the acronym for Python for Power System Analysis. It is an open-source functionality designed to bridge software tools for power flow analysis and multi-period energy system modelling [73]. Unlike many traditional power system modelling tools designed for single-period network analysis, it can address complexities introduced by integrating renewable energy sources and the electrification of energy sectors such as transportation and heating. This capability can be a crucial instrument for operational planning, infrastructure investment, and integration of multiple energy systems.

Components and and Structure

The PyPSA framework consists of several core system components that interact with each other, listed in 4.1. The table was used directly from Brown, Hörsch, and Schlachtberger [73]

Network	Structure containing all network components
Bus	Fundamental nodes to which all other components attach
Carrier	Energy carrier (e.g. wind, solar, gas, etc.)
Load	A consumer of energy
Generator	Generator whose feed-in can be flexible subject to minimum loading or minimum down and up times, or variable according to a given time series of power availability
Storage Unit	A device which can shift energy from one time to another, subject to efficiency losses.
Store	A more fundamental storage object with no restrictions on charging or discharging power
Shunt Impedance	An impedance in shunt to a bus
Line	A branch which connects two buses of the same voltage
Transformer	A branch which connects two buses of different voltages
Link	A branch with a controllable power flow between two buses

Table 4.1: PyPSA components

Buses are mathematically designed to enforce energy conservation at all times through Kirchhoff's Current Law. The connected components to the bus determine the power balance. Links can connect two buses through alternative energy conversion processes.

Functionalities

PyPSA is a powerful tool since it is able to provide multiple functionalities, such as power flow analysis, least-cost optimisation for dispatch problems, and least-cost minimisation for investment planning. For AC and DC-powered networks, PyPSA solves the non-linear power flow equation through the Newton-Raphson algorithm [74].

Crucially for the scope of this study, PyPSA also can calculate leas-cost investment optimisation. Using linear network equations, the cost-optimal investment in capacities of generation, storage, transmission and infrastructure can be determined. Since this is the functionality of interest for this study, the more comprehensive objective function used for least cost investment is given below [73].

$$\min \left[\sum_{n,s} c_{n,s} \bar{g}_{n,s} + \sum_{n,s} c_{n,s} \bar{h}_{n,s} + \sum_{l} c_l F_l \right. \tag{4.1}$$

$$\left. + \sum_{t} w_t [\sum_{n,s} o_{n,s,t} g_{n,s,t} + \sum_{n,s} o_{n,s,t} h_{n,s,t}] + \sum_{t} [suc_{n,s,t} + sdc_{n,s,t}] \right] \tag{4.2}$$

The objective costs consist of the capital costs $c_{n,s}$ for 3 types of component capacities:

1. $\overline{g}_{n,s}$, Generator capacity per bus n and per type s
2. $\overline{h}_{n,s}$, Storage unit and Store capacity per bus n and per type s
3. F_l, Capacity of branch l

Secondly, the operational cost per time snapshot t is also minimised for generator and storage dispatch.

1. w_t weighting per snapshot t. If hourly resolution is used, $w_t = 1$
2. $o_{n,s,t}$ the marginal cost of dispatch per generator, store or storage unit per bus n, type s, and time t.
3. $g_{n,s,t}$, the dispatched generator capacity per bus n, and per generator type s and time t.
4. $h_{n,s,t}$ the dispatched storage unit or store capacity per bus n, and type s and time t.
5. $suc_{n,s,t}$&$sdc_{n,s,t}$ start-up and shutdown costs for generators with unit commitment.

4.1.2. PyPSA-eur

PyPSA-eur is an extended configuration of PyPSA designed to model and optimise the European power system, encompassing the entire ENTSO-E network and infrastructure at or above 220 kV. This framework leverages PyPSA's modularity and expands upon it with additional functionalities through a modular configuration file and a reproducible *Snakemake* workflow for sustainable data analysis [75]. This workflow integrates diverse and freely available data sources, enabling efficient system planning and analysis.
The Snakemake workflow orchestrates an automated pipeline, calling upon rules and dictating which scripts to run, along with their corresponding input data. Furthermore, the workflow dictates the order of this workflow and keeps track of which parts need regeneration after repeated use. The 4 most important steps in this workflow will be discussed in section 4.1.2. Key data inputs for this workflow will be discussed below.

Land availability

The availability of suitable land for power grid optimisation is critical for planning and expanding renewable energy facilities. To realistically establish the potential capacity for the specified configuration, PyPSA-eur utilizes an open tool created by the *Instute of Energy and Climate Research at Jeulich Forschungszentrum, GLAES* [76]. GLAES (Geospatial Land Availability for Energy Systems) analyses geographical constraints to identify viable areas for wind and solar installations. It utilizes several data layers:

- **Corine Land Cover**: Provides detailed information on land cover types across Europe, crucial for identifying potential sites for renewable energy projects.
- **Natura 2000**: A network of conservation areas where development is restricted, ensuring that energy projects do not encroach on protected ecosystems.
- **GEBCO**: Offers bathymetric data, important for planning offshore renewable energy structures like wind farms.

Meteorological Data

Having established the potential capacity for renewable generation, corresponding weather data is necessary. Meteorological data across spatial and temporal dimensions is therefore accessed. Two primary sources are utilized:

- **ERA-5**: Provides hourly data on various weather parameters, including wind speeds and solar irradiation, essential for projecting renewable energy outputs.
- **SARAH-2**: Supplies high-resolution solar radiation data, enhancing the accuracy of solar power generation estimates.

The data inputs are centrally organised and updated at the open science project *Zenodo*, by Hörsch et al. [77].

Workflow and Outputs

The PyPSA-eur framework employs a comprehensive workflow that converts raw data into actionable insights through a series of streamlined steps:

1. **Network Preparation**: Establishes the PyPSA network structure, aligning it with the European high voltage grid, ENTSO-E [78], along with European classification for regions: NUTS [79]. This step integrates the spatial and temporal input data. Python dependencies such as *atlite* convert weather data into energy systems data.
2. **Simplification of the PyPSA Network**: To reduce computational demands, the network is simplified by standardising transmission lines, removing non-functional components, and clustering networks to manage complexity efficiently. This effectively entails the high-resolution information per NUTS3 region into the amount of desired clusters by use of *k-means algorithms* [80].
3. **Optimisation Problem Solving**: Utilises the prepared and simplified network to formulate and solve the optimisation problem. The objective is to minimise operational and infrastructure costs while adhering to technical constraints and ensuring system reliability.
4. **Collection & summary**: Outputs are consolidated and summarised in a *.nc* file format, providing a comprehensive overview of the optimised network. This includes performance metrics, cost analysis, and system reliability indices, crucial for informed decision-making.

This structured approach enables PyPSA-eur to handle complex datasets and produce optimisation scenarios that are both robust and applicable to real-world policy and planning in the European energy sector.

4.2. Model choices

Having discussed the ESOM framework this study employs, this section will discuss the research-specific model choices applied. Since the study was performed in parallel with CE Delft and Witteveen+Bos [22], similar model choices can be observed in terms of network component selection, policy standards assumptions and resolution.

4.2.1. Foresight

when conducting an ESOM study multiple optimisation timelines can be of interest to gain specific insights:

- **Perfect Foresight**: In this approach, the optimisation model fully knows all future events. The model can thus determine an optimal strategy across the entire planning horizon. This method is often applied over a set time, e.g. 1 year. Therefore it is also referred to a snapshot optimisation.
- **Perfect Foresight with Rolling Horizon**: This variant incorporates perfect foresight but limits the decision-making to a rolling time window, which is periodically updated. Given the dynamic and uncertain nature of energy markets, this approach increases the computational burden but provides a more realistic assessment.
- **Myopic Foresight**: Myopic foresight models offer an outlook for progressive and iterative changes in a network. Multiple benchmark moments can be defined to be optimised before the desired optimisation year. The model will then run a series of optimisations, using the output of the previous benchmark as the input for the next. This method is insightful for sketching a detailed transition outlook. However, myopic optimisation also leads to the postponement and cancellation of strategic investments in key renewable technologies, and therefore, the resulting network can have increased costs up to 14% [81].

Perfect foresight was chosen for this study for several key reasons. Firstly, this choice reduces the computational burden of the optimisation problem. While the rolling horizon approach is particularly suitable for modelling uncertainty for specific temporal behaviours, it is not crucial for this study's primary objective of establishing a network configuration for the future year 2035. The main advantage of myopic foresight models is that a transition path is created in addition to an ideal configuration. Offering detailed application advice is beyond the scope of this project. Instead, the study focuses on creating a desirable baseline configuration. Additionally, using perfect foresight ensures comparability with many other optimisation studies.

4.2.2. Time-series input data

Time-series data encompasses dynamic inputs like the load profile and weather data. The selected weather year for the research cases will be set to **2013**, since this is the default in the *PyPSA-eur* setup. The temporal resolution is kept at the original corresponding data resolution, 1h interval.
Important aspect [61], [82], [83].
The demand data originates from the ENTSO-E and is further assessed by Open Power System Data [84], an open platform providing high-quality, open-access time-series data for modelling demand patterns.

4.2.3. Policy standards and assumptions

The scope of this study focuses on the power sector. The goal is to optimise freely, not limited by lobby or political decisions. It is, however, important to make two key optimisation design choices, serving as the main pillars for constructing a reference scenario that is in line with current projections. Firstly, the share of renewable power, as this is part of the research question. Secondly, the power demand in 2035, since the power demand is exogenous to the energy model, and therefore can be considered an inelastic input. To achieve at feasible and realistic decision, this section assesses the insights and scenarios provided by Dutch governmental bodies and other key future planners concerning a future Dutch power grid. The reports are summarised in Table 4.2 below.

Title	Region	Published in	Scenario year(s)	Reference
IP2024	NL	2023	2035	[6]
II3050	NL	2023	2030, 2050	[5]
Nationaal plan energiesysteem (NPE)	NL	2023	2030 - 2050	[3]
Klimaat- en Energieverkenning (KEV)	NL	2023	2030	[25]
ENTSO-E TYNDP	EU*	2024	2040 - 2050	[85]

Table 4.2: Dutch energy system reports considered for this study's reference scenario
*ENTSO-E member countries

The selected reports were carefully chosen as reference material to ensure the validity and resemblance of national and international planning, the references are exclusively from power grid operators and/or governmental bodies. The sources all provide goals and projections in 2 key areas for development in the power sector in the Dutch or European context. The findings of the above studies are summarised in table 4.3 below.

Study	Scenario	% renewable power	Electrical Energy use vs 2019
IP2024	KA (2035)	100%	+56%
	ND (2035)	100%	+79%
	IA (2035)	100%	+76%
NPE	2035	100%	x
KEV	2030	92%	+19%
ENTSO-E, TYNDP	NT+ (2040)	96%	+33%
	DE (2040)	99%	+42%
	GA (2040)	100%	+27%

Table 4.3: Electrical energy projections

Additional assumptions

Within the PyPSA-eur framework, multiple modelling decisions should be made to create a configuration of a base scenario. It is essential to select the necessary input data carefully to ensure a robust and durable base network. This will, in turn, make a solid groundwork for future implementation and optimisation of flexibility options. In addition to policy goals set on CO_2 reduction, fossil-free power sector and energy use in the Netherlands, the following policy decisions are used for model creation:

- All neighbouring countries have a fossil-free power system, and it is impossible to compensate with negative emissions (Carbon Capture Storage). This entails that the Netherlands cannot import non-green electricity.
- The optimisation is set for the power grid only. This effectively means that there is no sector coupling.
- Since there is no sector coupling, all produced hydrogen is used for electrical energy storage.
- There are no governmental subsidies to stimulate certain technologies.
- Nuclear energy is considered a fossil-free power source.

In contrast with the study performed by CE Delft and Witteveen+Bos [22], performed in parallel with this study, all components can be optimised freely through brownfield optimisation. Goals for an installed capacity of Onshore/Offshore Wind, Solar, and Nuclear energy, as stated in the [3] are not considered as fixed inputs.

Desired installed power ranges for energy sources and carriers are deliberately excluded to ensure the unbiased exploration of the optimal baseline scenario. The baseline scenario will, therefore, be able to optimise the optimal capacity of various network options freely, given in table 4.4.
Key-choices in policy assumptions

1. The Power sector is fossil-free
2. Power demand increases by 50%

4.2.4. Spatial resolution

To account for a reliable and accurate representation of the Dutch power grid, it is desirable to account for neighbouring countries in the optimisation step. Interconnection with neighbouring countries is critical to include since this impacts the required flexibility needed for energy, and it would be incomplete to consider the Netherlands as an islanded network object [22]. Therefore, the reference model will include 7 neighbouring countries: Germany, Belgium, France, Luxembourg, Norway, Denmark, and the United Kingdom. This is also in congruency with the study done by CE Delft and Witteveen+Bos [22].

Assigning the correct resolution is important since a balance needs to be struck between overcomplicating and oversimplifying. For computational tractability, assigning low spatial resolutions allows for easier power flow optimisation. However, oversimplifying the power grid's spatial structure can result in cost underestimation in cost-minimisation studies [86]. Additionally, more realistic network bottlenecks arise when higher resolution is applied, potentially shifting the optimal configuration of renewable assets to areas with lower capacity factors to mitigate such bottlenecks [86].
As discussed in section 4.1.2, the spatial resolution makes up an important dimension of the input data to be retrieved through the model workflow. The size of the spatial resolution thus heavily impacts the total amount of dimensions needed for the optimisation. Therefore, this model choice is inconsistent for the two study cases to be presented later. This will be further discussed in the corresponding methodology sections for the respective case studies.
Key-choices for spatial dimensions

1. Reference case: NL in 7 nodes, neighbouring countries in 17.
2. Verification case: NL in 6 nodes.

Network Components

It is important to include all relevant components existing in the power grid of the Netherlands and the neighbouring countries included in the power system to be optimised. Since the objective function is a system cost minimisation, the costs must be valid and realistic. Consistent data sources were used to prevent contradicting cost relations for costs, efficiency, and other technological data. All relevant cost data corresponding to these components can be found in Appendix A. All newly added components technology specifics and cost data can also be found in A. Importantly, Load-shedding was also included. The default load-shedding mechanism was utilised, which is based on research from Schröder and Kuckshinrichs [87]. The corresponding costs can be found in appendix A. Except for load-shifting flexibility, all newly added components could be implemented into the native *PyPSA-eur* framework and did not require external tools.

Category	**Component**	**Default PyPSA-eur component**
Generators	Offshore Wind (AC)	✓
	Offshore Wind (DC)	✓
	Onshore Wind	✓
	Solar - PV	✓
	Nuclear	✓
	Hydro power	✓
	Biomass	✓
	Run of River	✓
	Virtual Load-shedding generator	✓
	H_2 CCGT, retrofitted	Newly added
	H_2 CCGT	Newly added
	H_2 OCGT	Newly added
Flexibility	Li-ion battery (2h, 4h, 8h)	Newly added
	Flow - ion battery	Newly added
	CAES	Newly added
	Electrolysis	✓
	Fuel cell	✓
	Underground H_2 storage	✓
	Pumped Hydro storage	✓
	Demand Response (only Load-shifting)	Newly added
Infrastructure	HVAC (overhead)	✓
	HVDC onshore underground	✓
	HVDC offshore underground	✓
	H_2 pipeline	✓
	Converters	✓

Table 4.4: Component table reference scenario

From table 4.4, the large variety of network components can be observed, resulting in a realistic set of possible network objects to choose.

Addition of H2 network

Since this study focuses on DR frameworks within energy system optimisation frameworks, it is crucial to create a competitive and realistic flexibility actor landscape. Therefore, dispatchable CCGT is included. Since the power sector is fossil-free, these assumptions are extended to include H_2 CCGT and OCGT. Furthermore, the network is extended with the ability to retrofit existing OCGT and CCGT gas turbines. Additionally, all nodes connected by HVAC transmission have the investment option to be connected by H_2 pipeline. Furthermore, this model choice was also made in parallel with the study done by [22].

4.2.5. Model limitations

Due to the nature of the optimisation problem, results from cost optimisation should be inspected carefully. The optimisation problem cannot account for all factors influencing a true transition path, especially since a perfect foresight snapshot optimisation approach is chosen. This will result in the following core limitations:

- **Technical infeasibility**:
  While economically interesting through the set of linear cost functions assigned to the technology, the technical challenges for realising certain technologies could be challenging. Large increases in any type of technology will thus be subjected to limited feasibility due to a lack of workforce, supply chain limitations, industry maturity or logistical difficulties.
- **Societal acceptance:**
  Not all technologies experience the same level of social acceptance, and preferences exist in the capacity planning based on the general public. As discussed, an unbiased energy system optimisation study can provide data-driven nuance to such preferences, but the lack of societal acceptance diminishes the feasibility of potential outcomes. Primarily, onshore wind is a technology that is expected to be saturated in terms of capacity in the Netherlands, even though cost-optimally larger capacity might be desirable.
- **Consistent European policies:**
  The Netherlands' network capacities are linked with the energy mix of neighbouring countries. The optimal power mix assumes seamless international energy trade, especially in our reference case, which boasts high interconnection capacities.
- **H2 CCGT retrofitted location**
  The exact locations of turbines available for retrofit were outside this scope, and national retrofit limits were used. Therefore, the exact location of the H2 turbines might not correspond to the locations of existing gas turbine infrastructure. This could have implications for the feasibility of H2 capacities since the H2 turbines are placed strategically in the network to facilitate the peak demand moments.
- **Electrolyser compatibility with power grid:**
  Technical details, such as minimal compatibility with intermittent operation, are out of the scope of this study.

Key-choices for network components and costs

1. Usage of default PyPSA-eur components and expert knowledge for additional components
2. Inclusion of diverse flexibility actors, including retrofitted H_2.
3. Component costs used with a consistent data source, found in Appendix A

Since *PyPSA-eur* is designed as an energy system built from the ground up, it has to model a myriad of factors, actors and assumptions. As discussed in section 4.2.4, spatial and temporal information is aggregated for large-scale optimisation within the optimisation framework. Pointed out by the authors of the *PyPSA-eur*, using Voronoi cells to aggregate the generation and demand information has limitations [**Horsch2018PyPSA-Eur: System**]. The exact topology of the distribution grid is ignored for aggregation, potentially resulting in network components being connected to the wrong substations. Furthermore, the exogenous available local data per country is scaled in size based on GDP distribution per country but does not include the corresponding local profile. In addition to this notion, the open source data input for *PyPSA-eur*, originating from ENTSO-E, can not always be considered constant [88].
Additionally, the network components above are either technologically aggregated, meaning their technological properties result from a combination of different technologies and characteristics, or only include one technology. For example, for the *Solar PV* component native to *PyPSA-eur*, the output per irradiation results from an aggregation of different materials, technologies and materials. Whilst aggregations like these simplify reality, they can generally be considered to provide adequate representation of the energy system [89].

		Test case	Research case
Model inputs	Weather data (ERA5, SARAH)	2013	2013
	Load data (TYNDP)	2013	2013
	Component costs	Appendix A	Appendix A
Model choices	Geographical scope [countries]	NL	NL, BE, DE, FR, GB, DK, NO, LU
	Spatial resolution [nodes]	6	24
	Temporal resolution	hourly	hourly
	Power-sector	fossil-free	fossil-free
	Demand factor	1.5	1.5
	Extension to default PyPSA-eur components	Table 10	Table 10
	Foresight	perfect foresight	perfect foresight
	Field	brownfield	brownfield
Goal		verification	network insights

Table 4.5: Summary of key model choices and assumptions

4.3. Load-shifting intergration

4.3.1. Load-shifting availability

To model load-shifting, it is necessary to assign a certain fraction of the demand available for load-shifting. In reality, such availabilities are often the result of multiple external effects, such as temperature, time of year, time of day or day of the week [67, 32]. Including such dependencies introduces non-linearities into the optimisation framework, and therefore, assigning more elaborate availabilities is out of the scope of this study.

Also such availabilities can vary widely per load-shifting process, thus requiring detailed information per load-shifting actor. Since the scope of this study is not to gain insights into DR actors willingess-to-particpate, or load availabilities, a simplified approach is taken to approximate top-level aggregate load-shifting availability.

Because of the privacy sensitivity of demand of potential demand actors, little estimations exist on the overall aggregate availability for demand response. Therefore, this study leveraged expert knowledge from *Witteveen+Bos* and *CE Delft*. In their study CE Delft and Witteveen+Bos [22], three availability scenarios for industrial demand were considered between [10 - 30%]. Therefore, this study will employ a flexible percentage in this range of 10%.

As discussed in section 3.5.1, such a flexible share effectively means assigning a dynamic *flexbile bandwidth* to the total demand.

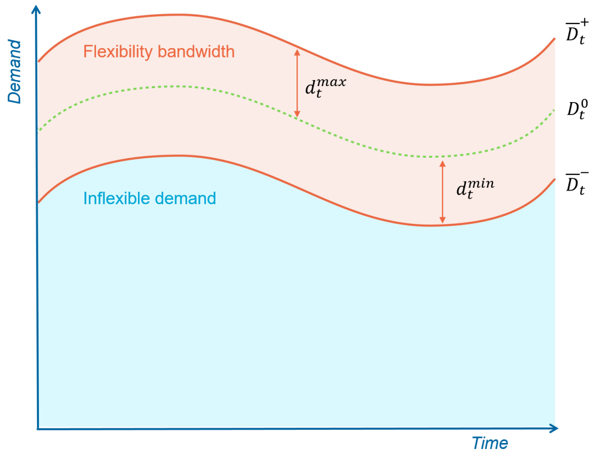


Figure 4.1: schematic overview flexible bandwidth

$$\overline{D}_t^+ = (1+\alpha)D_t^0 \tag{4.3}$$
$$\overline{D}_t^- = (1-\alpha)D_t^0 \tag{4.4}$$

4.3.2. Inconvenience costs

Assigning costs to the load-shifting is relatively straightforward because the application of virtual batteries allows for utilising native PyPSA network components and assigning operational costs accordingly. The addition of the virtual batteries in the network then automatically adds them to the total objective function, where the virtual batteries, along with the operational costs, are included through $o_{n,s,t}h_{n,s,t}$

$$\text{min}\left[\sum_{n,s} c_{n,s}\bar{g}_{n,s} + \sum_{n,s} c_{n,s}\bar{h}_{n,s} + \sum_{l} c_l F_l \right. \tag{4.5}$$
$$\left. + \sum_t w_t[\sum_{n,s} o_{n,s,t}g_{n,s,t} + \sum_{n,s} \mathbf{o_{n,s,t}h_{n,s,t}}] + \sum_t [suc_{n,s,t} + sdc_{n,s,t}]\right] \tag{4.6}$$

4.3.3. Network topology

To successfully implement the load-shifting framework, the network topology of the *PyPSA* network needs to be modified. An extra node is added to every network node to model the flexible bandwidth for load-shifting.

1. Creation of an extra *shifting* node for every network node
2. A unidirectional link between the two nodes has a capacity of difference between the upper and lower limits of the flexible bandwidth per node. This equivaltes to $\overline{D}_{n,t}^+ - \overline{D}_{n,t}^-$. In the case of 10% flexible bandwidth e.g. $\alpha = 0.1$, this equates to $0.2D_{n,t}^0$
3. To every shifting node, a virtual battery is connected. In the case of disaggregation of J load-shifting types, J multiple virtual batteries are placed on the same shifting node. This effectively entails that they 'share' the flexible bandwidth. Importantly, for this case, the total charging and discharging is limited to the same $0.2D_{n,t}^0$ to prevent cross-charging/discharging between the virtual batteries.
4. To every shifting node, a 'Flexible' load is attached. This lode corresponds to $\alpha D_{t,n}^0$. This load can thus be supplied by the larger grid, through the unidirectional link, or virtual battery operation

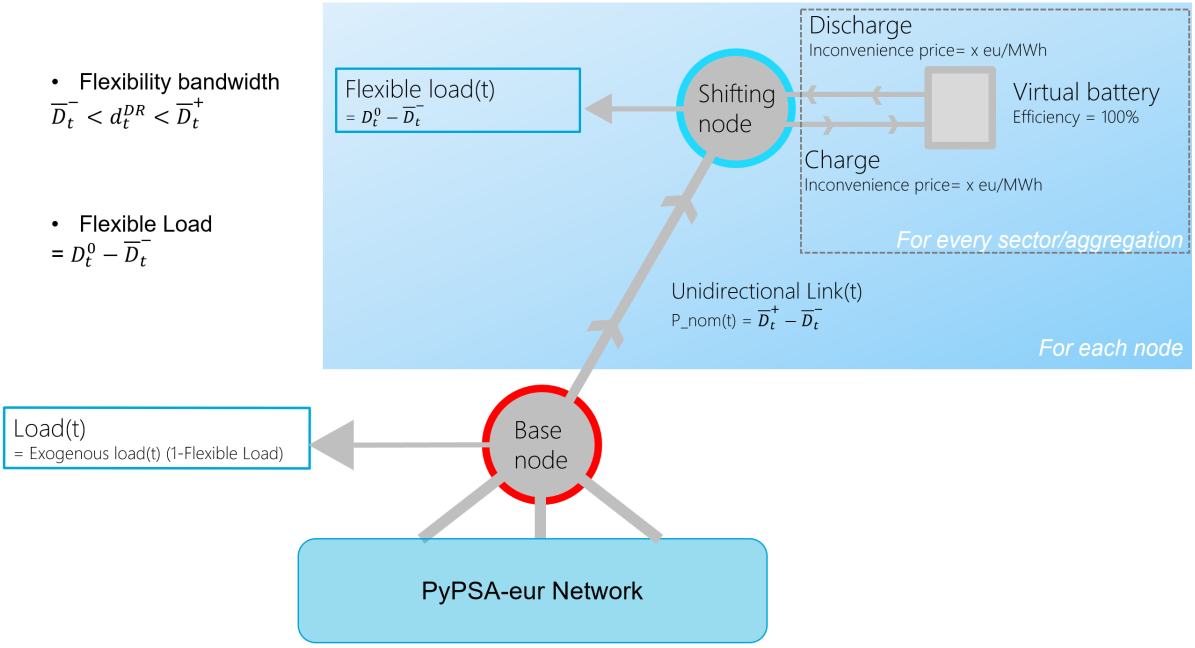


Figure 4.2: Topology of virtual battery implementation.

In summary, integrating the virtual battery concepts for the research cases requires a careful introduction to the PyPSA-our network. This is done through assigning power limits to the virtual battery in the form of a flexible bandwidth and through assigning operational costs. A generic visualisation of the topology of virtual battery integration is given below:

4.4. Conclusion

This chapter introduced the modelling framework, along with modelling decisions and considerations. The design of this framework is crucial to addressing the research questions, as the scope of the problem is further quantified and illustrated through these model decisions. After applying the framework to the subsequent sub-research questions, its effectiveness will be evaluated to determine if it successfully delivered the intended purpose.

The PyPSA framework, a powerful open-source tool for power system analysis, was presented in detail. PyPSA's capabilities, including power flow analysis, least-cost power plant dispatch, and least-cost investment optimisation, were highlighted. The extended configuration, PyPSA-eur, was also discussed, showcasing its ability to model and optimise the European power system by leveraging diverse and freely available data sources through a structured workflow.

Key model choices were made to ensure the robustness and relevance of the study. These include the geographical scope, temporal and spatial resolution, policy standards, and assumptions. The study aligns with the research conducted by *Witteveen+Bos*, particularly in terms of network component selection, policy standards, and assumptions, ensuring validation of results as well as expertise insights in the context of the Dutch power grid. The model choices reflect a balanced approach between computational tractability and a realistic representation of the power sector.

Integrating virtual battery concepts into the PyPSA-eur framework was introduced, focusing on the core concept of inconvenience cost. This cost, akin to the operational cost of a physical battery, is critical for modelling demand response (DR) mechanisms. The network topology was modified to include an extra node for each network node, facilitating the introduction of virtual batteries. This setup enables the flexible bandwidth for load-shifting and assigns operational costs to the virtual battery, ensuring effective integration into the power system model.

In conclusion, this chapter established a comprehensive methodology for developing a verification network and a power grid model for the Netherlands' power sector in 2035. Integrating PyPSA and PyPSA-eur, along with informed model choices and incorporating virtual battery concepts, provides a robust foundation for the subsequent analysis and discussion of results. This framework, once applied, will be evaluated to ascertain its success in addressing the research questions and achieving the study's objectives.

5
Methodology

In this section, the methodology employed to address the research question is detailed:
Exploring the value of Demand Response (DR)/Load-shifting as a flexibility solution for a cost-optimal power grid: A research case for the Dutch power grid in 2035 through analysis of possible scenarios.
This chapter outlines a structured approach to implementing DR load-shifting for large-scale energy planners. The methodology is divided into two main components

1. **Test case**:
   A smaller, simplified network is designed by lowering the geospatial resolution while maintaining other model choices. This allows for verifying DR modelling frameworks in a computationally feasible environment. The goal of the test case is to address Subquestion 3:
   What characterises DR, and how can it be effectively portrayed in (large-scale) Energy System Optimisation Models?
2. **Research Case:**
   The research case represents the full system of interest. One verified DR modelling framework is tested and compared with a DR framework with known shortcomings to highlight its impact on a system scale. This phase focuses on gaining insights into network behaviour from load-shifting and investment decision-making dynamics. The aim here is to answer Subquestion 4:
   What is the effect of implicit DR load-shifting on decision-making and investment planning for the Netherlands in 2035 (under different scenarios)?

Initially, the *Kleinhans* and *Morales* load-shifting frameworks undergo qualitative verification tests to replicate realistic load-shifting behaviour. Additionally, their computational traceability is quantitatively assessed to validate their applicability. A novel approach is also specified and qualitatively assessed. The two load-shifting mechanisms from the test case are introduced for the second case study to validate both models' top-level impact on decision-making. Network insights, such as differences in optimal capacities and system costs, are then evaluated to extrapolate findings to the broader context of investment planning and policy advice.
Section 5.1 elaborates on the structure and methods for the test case. Subsequently, Section 5.2 discusses the methodology used for the second case study in greater detail.

5.1. Test case: validation of frameworks

This section aims to construct a thorough validation methodology for the selected DR modelling frameworks. It contributes to the current landscape of DR optimisation frameworks by presenting data to verify these methodologies.

This approach aims to derive conclusions on the effectiveness of both frameworks for modelling DR (within a large-scale context), ensuring a balance between model simplicity and the realistic representation of DR capabilities. The insights and results will be discussed in section 6

The validation method will consist of two analyses per framework:

- **Qualitative test of DR characteristics**:
  This analysis focuses on the effectiveness of the framework in tackling the core DR challenges of saturation & load-recovery
- **Quantitative assessment of computational burden**:
  This analysis will present computation times to indicate the feasibility and applicability of the frameworks. Furthermore, inconvenience pricing ranges will be examined to determine their role in their respective framework.

The methodology is designed such that the result will yield a verified DR framework suitable for large-scale optimisation. Importantly, for the *Morales* method, two linear relaxations will be compared to test the efficacy. Additionally, another linear relation was evaluated, but it did not fit the scope of this analysis. This can be found in appendix B.

To correctly and efficiently compare the behaviour of the variations of bottom-up models, a separate network is designed, as specified in section 4.2.4. This case study focuses on the dynamics of virtual batteries within the bottom-up framework. Therefore, the bottom-up model is applied to a scaled-down network to increase computational tractability.

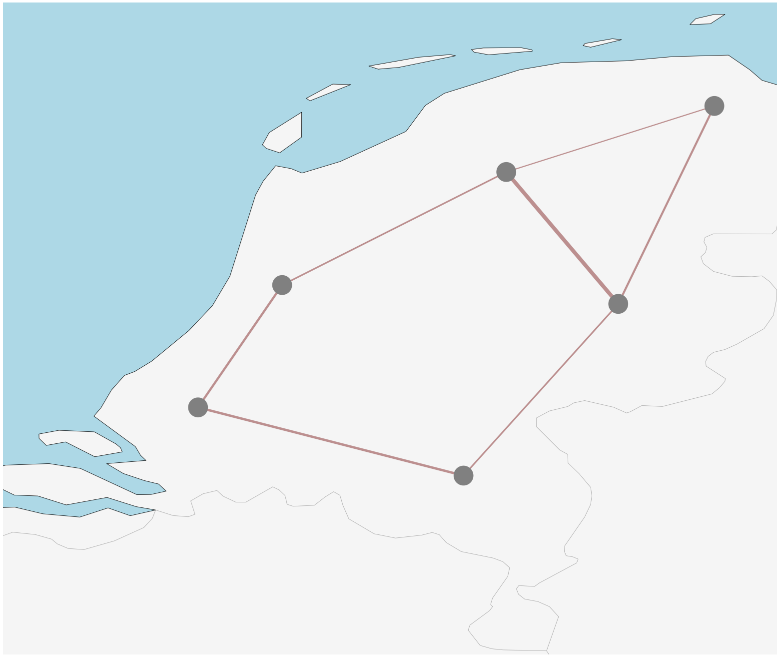


Figure 5.1: Schematic figure showing the nodes in the test case

5.1.1. Assigning Virtual battery limits

In CE Delft and Witteveen+Bos [22], a flexible share for the industry is taken 20%, without further specification of other aggregated load-shifting sectors. For the flexible bandwidth of this study, value of $\alpha = 0.1$ is assigned. The primary aim of this contribution is to gain insights into the dynamics of virtual batteries. Therefore, it must be reiterated that assigning exact flexible bandwidth for the technologies or processes of the virtual batteries in this test case is not the goal.

$$\overline{D}_t^+ = (1+\alpha)D_t^0 = 1.1D_t^0 \tag{5.1}$$

$$\overline{D}_t^- = (1-\alpha)D_t^0 = 0.9D_t^0 \tag{5.2}$$

This study explores load-shifting for different sectors. For the *Kleinhans* and *Morales* load-shifting frameworks, one virtual battery should represent a homogenous aggregation of identical appliances or processes for this sector. The exact process or appliance is not necessarily of interest for the purpose of this verification. Therefore, these three load-shifting processes will be from now on out specified as: *Industrial*, *Tertiary* & Residential process. The resulting

	Disaggregated, $J = 3$		Aggregated
	Kleinhans	Morales	Wasserstein
upper bounds charging	$\sum_j^J d_{j,t} \leq 0.1D_t^0$	$\sum_j^J d_{j,t}^+ \leq 0.1D_t^0$	$d_t \leq 0.1D_t^0$
lower bounds discharging	$\sum_j^J d_{j,t} \geq -0.1D_t^0$	$\sum_j^J d_{j,t}^- \geq -0.1D_t^0$	$d_t \geq -0.1D_t^0$
Upper bounds energy	$e_{j,t}^{max} = \sum_{i=t+1}^{t+\Delta t} D_i^0$	$e_{j,t} \leq \sum_{i=0}^{\Delta-1} d_{t-i}^+$, $e_{j,t} \leq -\sum_{i=1}^{\Delta t} d_{t+i}^-$	$e_t^{max} = \sum_{i=t+1}^{t+\Delta t} D_i^0$
Lower bounds energy	$e_{j,t}^{min} = -\sum_{k=t+1}^{t-\Delta t} D_t^0$	$e_{j,t} \geq \sum_{i=0}^{\Delta t-1} d_{t-i}^-$, $e_{j,t} \geq -\sum_{i=1}^{\Delta t} d_{t+i}^+$	$e_t^{min} = -\sum_{k=t+1}^{t-\Delta t} D_t^0$

Table 5.1: Energy and Power Constraints for Virtual Battery Framework

5.1.2. Consistent cost comparison

For the load-shifting mechanism to operate in the energy system, operation prices must be determined. These prices are often referred to as the 'willingness-to-participate' or 'inconvenience cost' for a DR actor. This concept will be referred to as the *inconvenience cost* in this study. Importantly, for Virtual Battery frameworks, this cost can be directly compared to the operational cost of the battery.
The primary objective of this section is to establish a robust framework for consistent cost comparison across different demand response (DR) modelling approaches. The bottom-up frameworks, such as *Kleinhans* and *Morales*, impose inconvenience costs for load-shifting through power costs denoted as c_1 (charging/discharging). In contrast, the top-down *Wasserstein* method assigns inconvenience costs per megawatt-hour hour (MWhh), denoted as c_2, as discussed in Section 3.6.
The goal here is to ensure that all DR modelling frameworks experience similar cost parameters, thereby allowing for valid comparative insights into their operational differences. To achieve this level playing field, the cost parameters c_1 and c_2 must be assessed and adjusted to facilitate a fair comparison. This approach ensures that the different methods can be compared, limiting the bias due to differing cost structures.
Comparing the costs for top-down, aggregated load-shifting models with disaggregated bottom-up models is a delicate matter since the composition of load-shifting costs is fundamentally different.

For bottom-up models, various technologies, each with unique costs, shifting durations, and flexible bandwidths, can be differentiated in a network. The resulting aggregate of the actions done by each of these components, or virtual batteries, then determines the total shifted load. Conversely, top-down modelling does not consider strict shifting durations, and only one cost reflects the amount of load shifting, given a certain bandwidth. Therefore, comparing these methods is cumbersome. The approach taken in this methodology revolves around using a top-down cost assumption and reliably connecting this to both time duration and costs per disaggregated virtual battery. To achieve this, the cost-per-shifting action of the top-down model needs to be approximately translated to a cost and a time duration for different bottom-up aggregated batteries with different cost structures. This strategy is further elaborated below.

Let $P(t)$ represent the charging or discharging power of the battery, and e_t is the energy level. For any load-shifting duration T, the total costs for that load-shifting action can be derived. Below, C_1 represents the costs incurred by bottom-up frameworks assigning costs per MWh and C_2 for top-down frameworks assigning costs per MWhh:

$$C_1 = c_1 \int_0^T |P(t)|dt, \qquad C_2 = c_2 \int_0^T |e(t)|dt \tag{5.3}$$

$$C_1 = c_1 P_{avg} T, \qquad C_2 = c_2 \frac{1}{2} |e_{max}| T \tag{5.4}$$

$$\tag{5.5}$$

Given such a load-shifting scenario, it becomes possible to create equivalent costs per load-shifting duration T. To ensure equivalency, we set $C_1 = C_2$ for the same duration T. Under this condition, note how $e_{max} = \Delta t P_{avg}$ and $\Delta t = \frac{1}{2}T$, as illustrated by the example below.

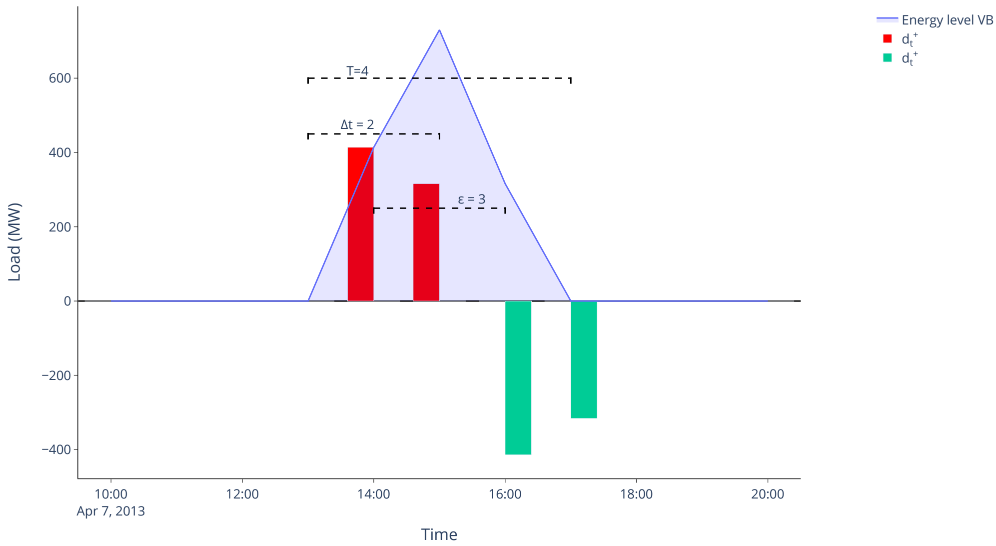


Figure 5.2: illustrative load-shifting action.

The figure also shows ϵ_j which resembles the non-zero energy level, note that this value is always $\epsilon = T - 1$. To achieve equivalency, the following steps are taken:

$$C_1 = C_2 \text{ For same } T \tag{5.6}$$

$$c_1 P_{avg} T = c_2 \frac{1}{2} |e_{max}| T \tag{5.7}$$

$$c_1 P_{avg} = c_2 \frac{1}{4} P_{avg} T \tag{5.8}$$

$$\frac{c_1}{c_2} = \frac{T}{4} \tag{5.9}$$

Given the approximation for comparison of two methods, let us now discuss the costs assigned to the test case network.

When examining costs for load-shifting at an aggregated, top-level scale, the price-elasticity level and intertemporal cross-price elasticities can describe load-shifting behaviour[68]. Positive intertemporal cross-price elasticity indicates that load is shifted from high-price to low-price hours, effectively increasing demand when preceding or subsequent prices are higher. Conversely, negative intertemporal cross-price elasticity suggests demand inertia, where demand decreases with higher preceding and subsequent prices, requiring consistently low prices over several hours to trigger a response. Recent research by Hirth, Khanna, and Ruhnau [67] demonstrates that in the German context, intertemporal cross-price elasticities are predominantly positive, supporting the notion that load-shifting is more likely to occur over shorter time frames.

This insight further validates the cost structure for c_2, assigning cost per Mwhh. Assigning costs per MWhh naturally favours short-duration shifts. This methodology, therefore, creates 5 ascending cost tiers as shown in table 5.2 below. From the disaggregated set of prices, the resulting equivalency prices can be derived approximately based on the duration of the load shift T.

	Disaggregated, J=3 c_1 [€/MWh]			Aggregated c_2 [€/MWhh]
	Industrial	Tertiary	Residential	
Δt	12	6	2	
T	24	12	4	
ϵ_j	23	11	3	
Cost Tier 1	60	30	10	10
Cost Tier 2	120	60	20	20
Cost Tier 3	180	90	30	30
Cost Tier 4	240	120	40	40
Cost Tier 5	300	150	50	50

Table 5.2: Cost structure for different DR frameworks

Although the purpose is not to specify technology-specific time duration and costs, the costs for industrial shifting can be verified based on expert knowledge from *W+B* and *CE Delft*. In CE Delft and Witteveen+Bos [22], a **total** inconvenience cost per industrial load-shift of 200 €/MWh was assigned. Whilst that study has not linked any timeshifting frame Δt to load-shifting action, the approximation shown in table 5.2 for cost tier 2 can be considered realistic

By assigning similar cost-per-time-duration ratios to the bottom-up and top-down frameworks, the two methods could effectively be compared. It is, however, important to realise that this inconvenience cost structure is therefore skewed towards more favourable pricing of DR for shorter duration time load-shifting. As discussed, this is obvious when considering *Wasserstein* modelling. However, for bottom-up modelling, this is not necessarily realistic. An obvious insight from the table is the increased costs for longer-duration shifts due to the equivalency approximation. An important notion here is that, in reality, higher inconvenience costs are not necessarily connected to longer durations of load shifts. Multiple examples of longer-duration load-shifting action can occur for fairly low prices, such as power-to-heat processes [43] [44]. At the same time, higher-cost, short-duration processes exist. However, since the purpose of this test case is not to create a realistic and complete bottom-up network and compare its aggregate with a top-down structure. Rather, this method focuses on fairly assessing and comparing the two DR modelling frameworks, and thus the prices shown for the disaggregated set do not necessarily relate to a load-shifting process.

5.2. Research case: impact of load-shifting

The main result from Section 5.1 is a well-defined, verified DR framework, suitable for large-scale ESOM.

This section discusses the methodology employed to answer the subquestion: *What is the effect of implicit DR load-shifting on decision-making and investment planning for NL 2035 under different scenarios?*

Subsequently, it examines the decision-making process for opting for a power grid utilising *implicit* flexibility through DR, or selecting a power grid configuration with *explicit* flexibility through firm flexibility assets such as Battery Energy Storage Systems (BESS).

To adequately answer the subquestion, two intermediate steps can be distinguished to gain the desired insights:

1. **Network analysis and comparison**
   Network-related insights into the cost-optimal solution are assessed for two networks: one including DR and one excluding DR. The aim is to validate the load-shifting framework on a larger

network scale and assess the effect of load-shifting on the network scale.

2. **Robust investment planning**
   Further sensitivity analyses are employed to gain insight into robust decisions. By varying multiple weather-input scenarios, a regret assessment is conducted to determine whether networks including *implicit* flexibility result in worse investment decisions.

5.2.1. Network analysis

As discussed in Section 4.2.4, the optimal network for both perturbations is put into a wider context than solely the Netherlands. Seven neighbouring countries are considered, although in smaller spatial resolution than the power grid of interest in NL.

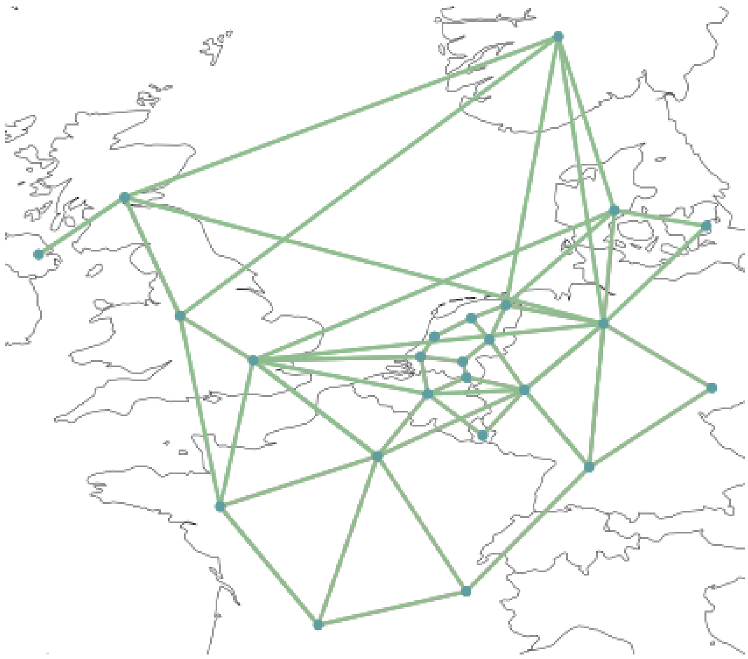


Figure 5.3: Research case geographical scope

Since the ESOM is a prescriptive energy modelling tool, the cost-optimal configuration for the energy system is the main output to be analysed. The main goal of this analysis step will therefore be to analyse and compare between networks:

- Optimal installed capacities
  Comparing differences in the flexibility sector to yield insights into possible futures in this power-grid sector.
- Optimal infrastructure expansion
  Assessing differences in infrastructure.

This analysis will be done for a power grid excluding load shifting and including load shifting to compare and analyse results. Also, to further validate the effectiveness of the results from the test case, two different load-shifting frameworks will be tested to highlight the differences.

5.2.2. Robust investment planning

To address the fourth research subquestion: *What is the effect of implicit DR load-shifting on decision-making and investment planning for NL 2035 under different scenarios?*, a comprehensive analysis is conducted to inform strategic decision-making. This analysis examines the interplay between DR and other flexibility assets, particularly emphasising their implications for investment decisions. An investment regret methodology is employed to evaluate the robustness of cost-optimal network configurations with and without DR integration, providing strategic guidance for decision-makers operating under conditions of uncertainty.

The regret approach can be described as a simplified version of the *MiniMax regret* methodology, which is particularly well-suited for energy infrastructure planning and future scenario analysis for several compelling reasons [90]:

1. The inherent uncertainty stems from future policy decisions and regulatory frameworks, making probabilistic scenario assignment inherently challenging
2. Infrastructure planning necessitates a systematic and objective decision-making framework that minimizes subjective bias
3. The methodology circumvents the need for subjective probability assignments to different scenarios, providing a more robust analytical foundation
4. The approach aligns with the risk-averse perspective typically adopted by infrastructure planners and policymakers

The simplified approach for the MiniMax regret can be described as follows.

1. First, network optimisations are performed for three additional weather years, 2011, 2012, and 2014.
2. For each weather year, two distinct network configurations are optimised:
   - Configuration A: System without DR
   - Configuration B: System with DR
3. Each optimised configuration is then tested against the weather conditions of all other years. Since the configurations are fixed, the only cost difference results from different optimal dispatches of assets, yielding a unique system OPEX per year.
4. The regret for each configuration is calculated as the difference between:
   - The OPEX when the configuration operates under different weather conditions
   - The OPEX of the optimal configuration for that specific weather year
5. The maximum regret for each configuration across all weather years is identified.
6. The configuration with the lowest maximum regret is selected as the most robust solution.

This approach can act as a suitable surrogate for an actual MiniMax approach. The most important difference is that in this approach, the optimal solution is found from the discrete set of 8 possible investment decisions: 4 weather scenarios with 2 possible configurations. An actual *MiniMax* approach would optimise for the continuous solutions space between all sets of the configurations, which might impact the results. This is an important notion since the sample size of our scenarios limits the outcome of the simplified version.

6
Results: validation of load-shifting frameworks

In this chapter, the PyPSA-eur framework is employed to optimise a network configuration specific to the Netherlands, with model assumptions and choices as outlined in Section 4. The primary objective of this chapter is to address the subquestion:

What characterises Demand Response (DR), and how can it be effectively portrayed in (large-scale) Energy System Optimisation Models (ESOMs)?

To achieve this, both quantitative and qualitative insights are gathered on how the selected DR modelling frameworks—*Kleinhans*, *Morales*, and *Wasserstein*—perform. The analysis is conducted through the following steps:

1. A qualitative analysis of timely recovery.
2. A quantitative assessment of computational tractability

Section 6.1 presents the results of the *Kleinhans* method, focusing on virtual battery operation and load-shifting effects. This is followed by Section 6.2.3, which highlights the linear approximation proposed in the *Morales* method. Finally, a comparative analysis of the *Wasserstein* method is conducted, providing a comprehensive evaluation of its performance.

As discussed in section 5.1.2, 5 cost tiers were assigned for, corresponding to the virtual battery configurations. For clarity and consistency, they are repeated here

	Disaggregated, J=3 c_1 [€/MWh]			Aggregated c_2 [€/MWhh]
	Industrial	Tertiary	Residential	
Δt	12	6	2	
T	24	12	4	
ϵ	23	11	3	
Cost Tier 1	60	30	10	10
Cost Tier 2	120	60	20	20
Cost Tier 3	180	90	30	30
Cost Tier 4	240	120	40	40
Cost Tier 5	300	150	50	50

Table 6.1: Cost structure for different DR frameworks

For consistency, whenever a specific case of virtual battery is highlighted, this will be done for virtual batteries operating in cost tier 2.

6.1. Kleinhans framework

To qualitatively validate the results of *Kleinhans* method, insights will be focused on **saturation & load recovery**.

Saturation & load recovery

The primary aim of this contribution is to gain insights into the dynamics of virtual batteries. Therefore, it must be reiterated that the exact inconvenience pricing and realistic, flexible bandwidth for the technologies or processes the virtual batteries in this test case represent are kept arbitrary since the purpose is to verify their validity rather than their top-level impact.

The first qualitative assessment should inspect the **Load-recovery & saturation**. To observe the timely recovery of load-shifting actions, the duration of non-zero energy level is observed in every virtual battery. Since every charging event corresponds to an increase in demand and a discharging event to a decrease in demand, any non-zero time interval ϵ corresponds to a load-shifting action. The non-zero time duration was counted for every zero crossing for the chosen disaggregated virtual batteries (Industrial process, Tertiary process, Residential process).

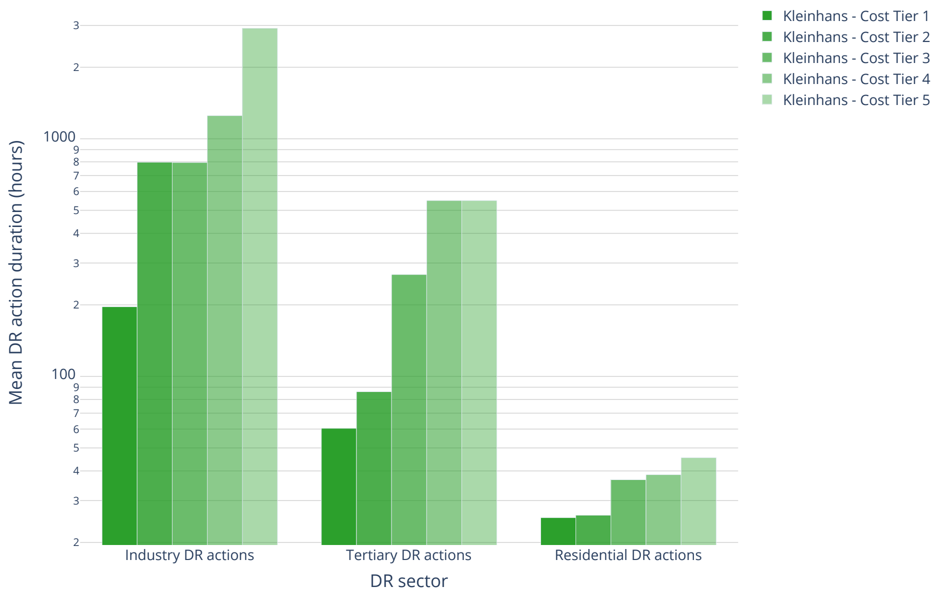


Figure 6.1: mean duration of load-shifting action by corresponding virtual batteries

From the above figure 6.1, it can be observed that the duration of the Virtual battery action, is happening at timeframes which are not in the correct range. The omission of any load-recovery constraint resulted in load-shifting durations that extended expected load-shifting durations. From the load-shifting table, given in 2.1, most shifting times are observed to be within 1 day and 24 hours. Without load-recovery constraints, the cost-optimal network position for the virtual battery is to charge and discharge selectively

From the table, this can be further visualised after inspecting the actions done by the virtual battery, which represents an aggregation of an industrial process over a full year. in figure 6.2 below.

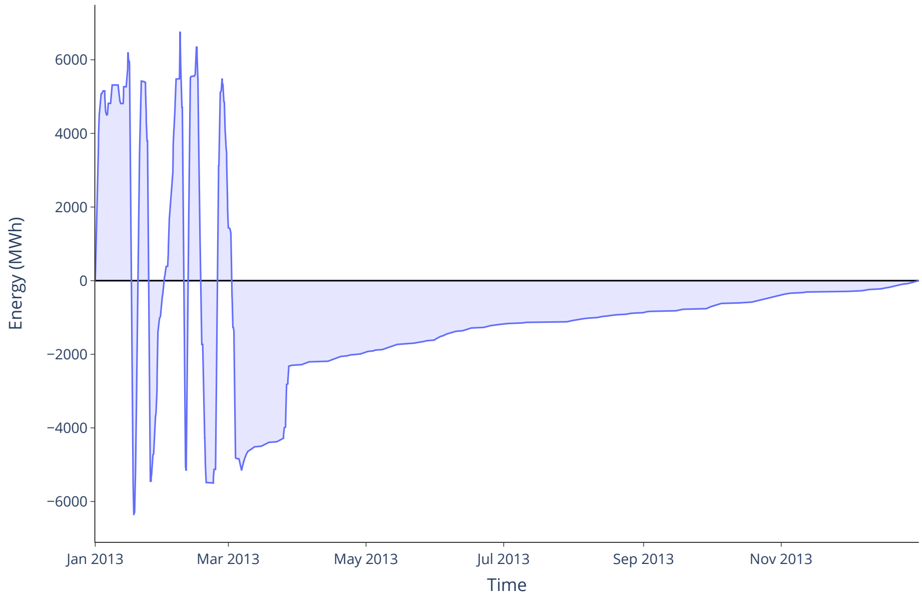


Figure 6.2: Industrial Virtual battery table test case, **cost tier 2**

From this figure, the duration and frequency of the load delay(negative energy level of virtual battery) and anticipation of load events become clear. Furthermore, it can be concluded that the DR behaviour of the virtual battery is more representative of long-term storage solutions in a power grid. Since load-shifting DR for all three sectors is not projected to operate at such time durations, this DR battery operation can be deemed unrealistic. Technology-specific **load recovery** limits are not dealt with, and demand can be postponed for time durations beyond the defined shift times.

The behaviour in charging and discharging becomes clearer after inspecting the battery behaviour for the period January to February, in figure 6.3. The virtual battery operates cost-optimally by acting on the most profitable moments. The absence of specific mechanisms ensuring recovery thus results in undue load recovery.

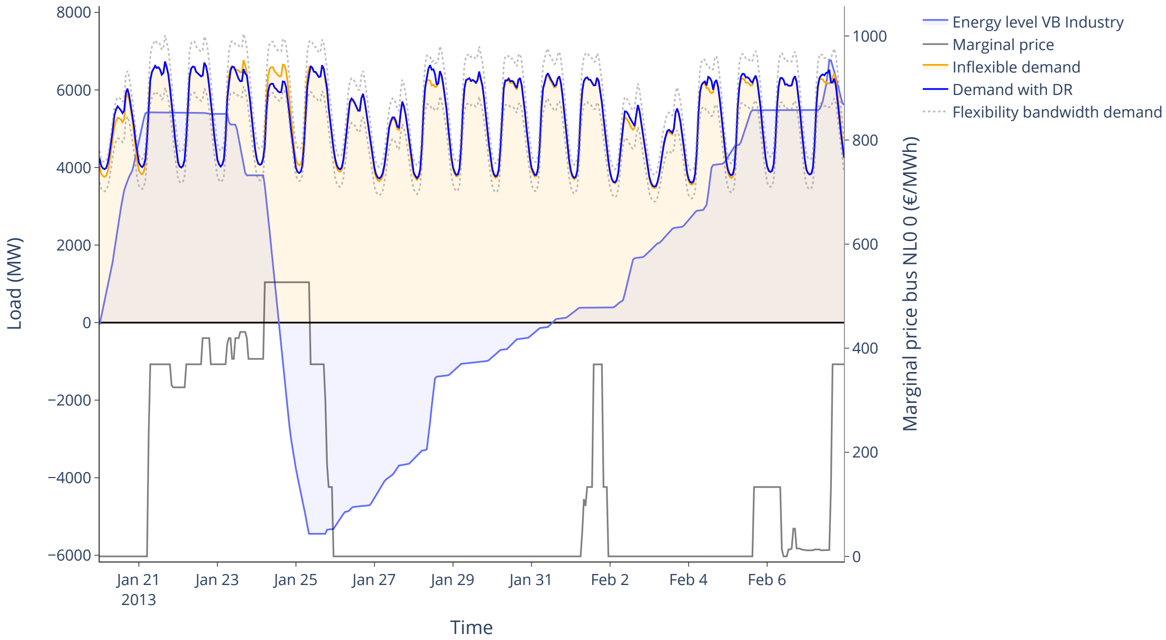


Figure 6.3: Behaviour of Industrial virtual battery, **cost tier 2**

Computation time

The computation times refer to the time needed to solve the least-cost investment problem. The objective function to be solved is described in detail in equation 4.2. The solving times for the *Kleinhans* model are listed in table 6.2. The solver settings for the used solver are listed in appendix D.

***Kleinhans* method**	**Solving time** [minutes]
Mean across cost tiers	6.88

Table 6.2: Solving times for *Kleinhans* method

Key takeaways:

1. The *Kleinhans* method does not model realistic load-shifting actions
2. The limited added complexity results in low computation times.

6.2. Morales framework

In this section, the second virtual battery method is conducted to test and verify its dynamics in the test network. Note that the goal of this chapter is not to provide accurate DR estimation for a future grid but to test the logic and operation of the virtual battery within the framework.
The goal of this section is the following:

- qualitatively assess the efficacy of the binary variable δ for ensuring load-recovery
- qualitatively assessing the efficacy of the linear relaxation of δ
- Investigating the framework's functionality without a complementarity variable.

For verifying the virtual battery mechanics in the *Morales* framework, a similar structure was applied. The topology of the virtual batteries within the *PyPSA-eur* framework can again be visualised by figure 4.2. The only exception is that the virtual battery in the figure is now replaced with a virtual battery restricted by the constraints presented in 3.5.2.

6.2.1. Mixed-integer Programming framework

The MIP network corresponds to the methodology posed in 3.5.2. Specifically, the δ operator is kept binary, as demonstrated in 3.29. Due to the scaled-down test case, MIP optimisation can be conducted. First, let us inspect the behaviour of the virtual battery and the efficacy of the binary complementarity variable δ.

Saturation & load-recovery

First, the mean times of operation are verified for the same cost range, as in section 6.1. Since this framework has explicitly constrained the load-shifting behaviour, more timely load-recovery is expected. To qualitatively asses the threshold for 'timely' recovery, every maximal non-zero energy level ϵ is shown in the graph. Recall from table 5.2, that for for Industry virtual batteries $\epsilon = 23$, for Tertiary batteries $\epsilon = 11$, for residential batteries $\epsilon = 3$.

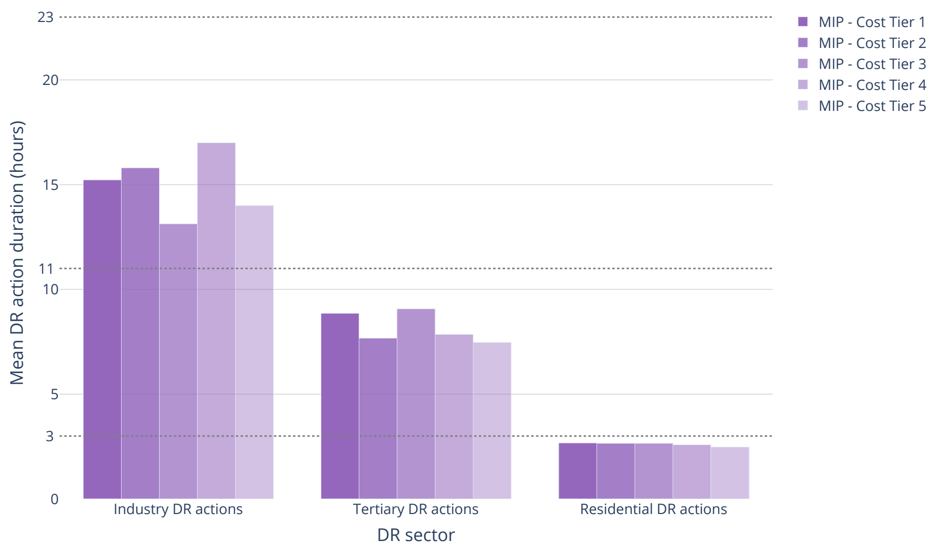


Figure 6.4: Mean load-shift duration times MIP *Morales*, with maximum non-zero energy level ϵ_j

From figure 6.4, introducing the load-recovery constraints resulted in better timely recovery. On average, all virtual stores are shown to shift load over a realistic timeframe.

To further assess this, in figure 6.5, a visualisation is given for the industrial Virtual battery in cost tier 2, to illustrate the dynamics of the virtual battery. This operation in March shows that the bottom-up model acts as intended: discharging at a high marginal bus price and recuperating at a lower price if the difference exceeds the inconvenience costs.

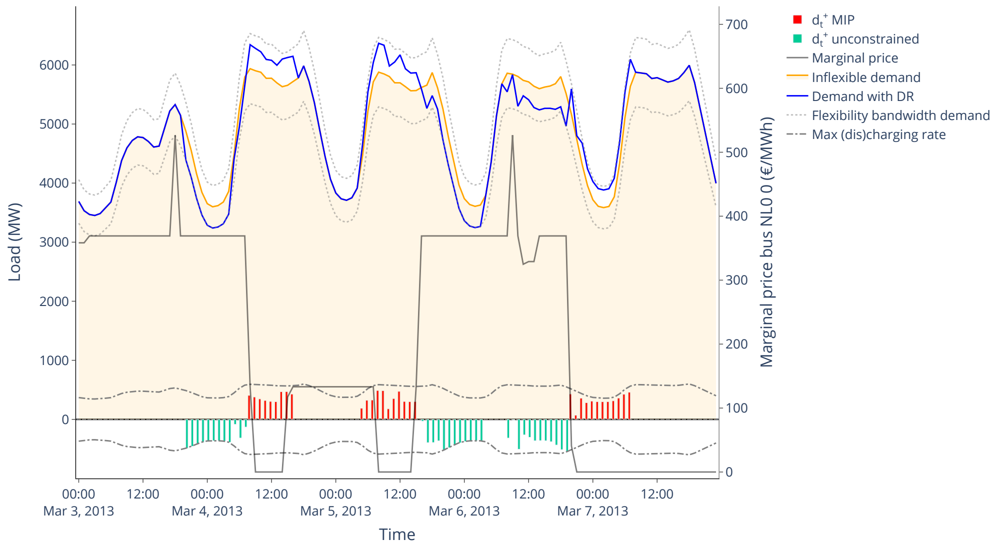


Figure 6.5: Change in Demand caused by the virtual battery

Also, from figure 6.5, the timely load-recovery can be seen. The virtual battery completes the charging and discharging action within the flexible time frame.

Another interesting insight is into the dynamics between sectors. Note how no specific bandwidth is assigned per virtual battery but rather one flexible bandwidth for all demand responses. This results in virtual batteries having to 'share' this flexibility bandwidth at times.

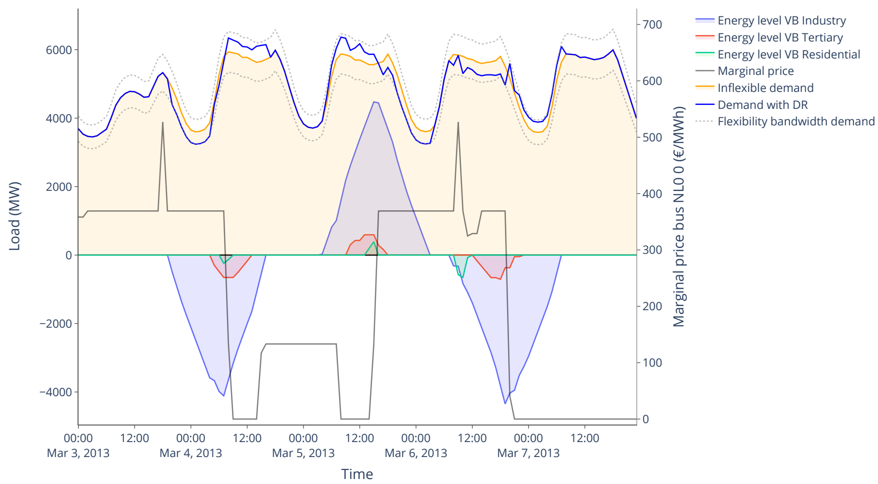


Figure 6.6: Change in demand caused by multiple virtual batteries

Note how in figure 6.6, the behaviour of discharging and charging moments is distributed over time. Since the total charging/discharging capacity is 0.1 for all virtual batteries, the cost-optimal order of charging/discharging is found per virtual battery. It should be noted, however, that these dynamics might not be desirable for illustrating real-world behaviour since DR offered by different processes generally do not influence each other.

Further inspection into the efficacy of the binary complementarity variable reveals an interesting observation in figure 6.7. The maximum duration of DR action cannot be guaranteed through the binary variable δ. From Table 5.2, we know that the maximum shifting time for the Industrial virtual battery is

$T = 24$. However, in figure 6.7, it can be seen that the virtual battery exceeds its maximum flexible time.

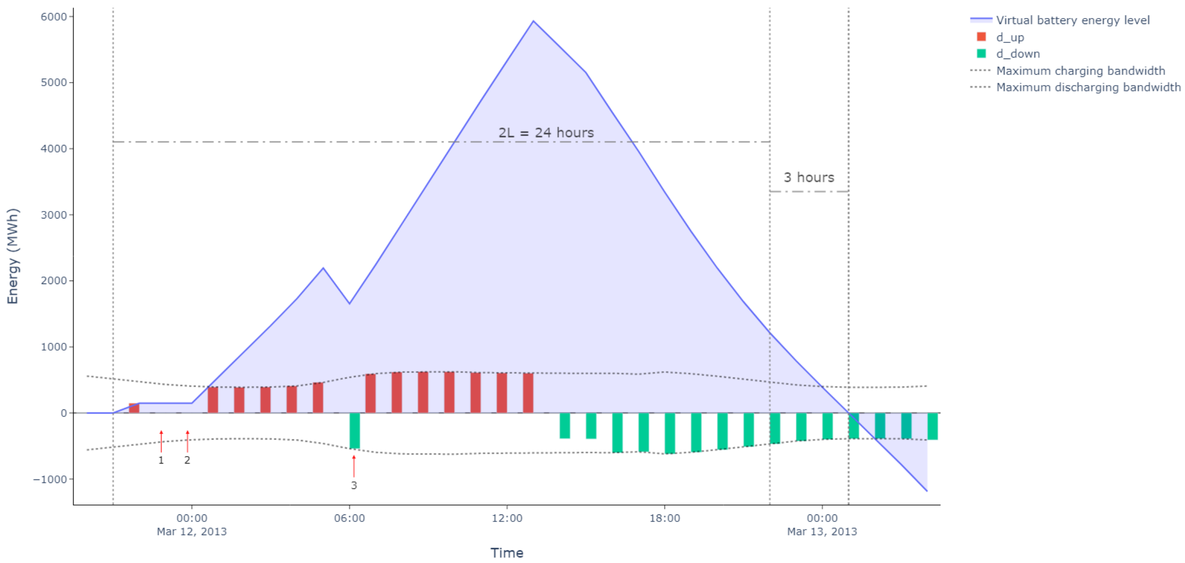


Figure 6.7: Example of untimely recovery for the MIP model

From figure 6.7, the following can be concluded by analysing the charging and discharging behaviour. **The created logic can only ensure timely recovery if there are no interruptions in the charging/discharging process.** Since there is no constraint limiting the battery to discharge or do nothing during an action, the above behaviour can occur in virtual battery dynamics.

Computation time

Method	Kleinhans method [minutes]	MIP network [minutes]
Mean across cost tiers	6.88	719.4

Table 6.3: Mean solving times for Kleinhans and MIP methods

From table 6.4, it becomes clear how the introduction of the binary variable significantly increased the computation time of the test network, as was also pointed out by the authors of this problem formulation [21]. In this example, a disaggregation of $J = 3$ was chosen. This effectively means that for every timestep t at every node, 3 binary variables exist. MIP solvers like *Gurobi* use *Branch-and-Bound* algorithms, effectively creating a multitude of subproblems (branches) which need to be explored for every binary variable. Therefore, any increase in disaggregation, temporal and spatial resolution, will further enhance the computational burden exponentially. This makes the MIP formulation especially unsuitable for large-network bottom-up disaggregated virtual batteries.

6.2.2. Loose linear relaxation

The following section will discuss the study of the bottom-up model. Before testing the efficacy of linear relaxation of the δ complementarity variable, this section will set a benchmark for assessing the other linear relaxations. Within the framework stated in 3.5.2, this effectively means this framework is the loosest relaxation:

$$d_t^+ \leq 0.1 D_t^0 \delta \rightarrow \qquad d_t^+ \leq 0.1 D_t^0$$
$$d_t^- \geq -0.1 D_t^0 (1-\delta) \rightarrow \qquad d_t^- \geq -0.1 D_t^0$$

The variable introduced for mitigating simultaneous cycling is now absent. Since this variable was added to ensure timely recovery, more untimely recovery is expected.

Saturation and Recovery

Figure 6.8 shows how the shift times are in the right domain while the mean times have increased.

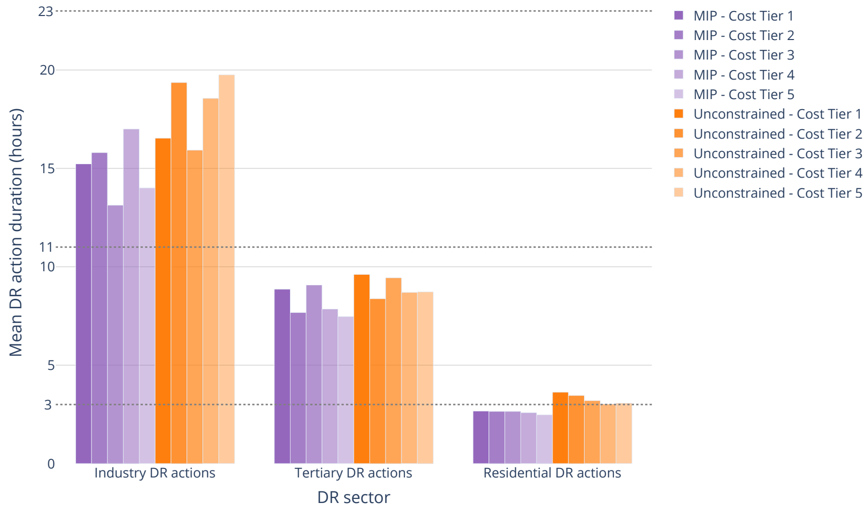


Figure 6.8: Caption

Once again, the week from the 3rd of March to the 10th is analysed for the Industrial Virtual battery.

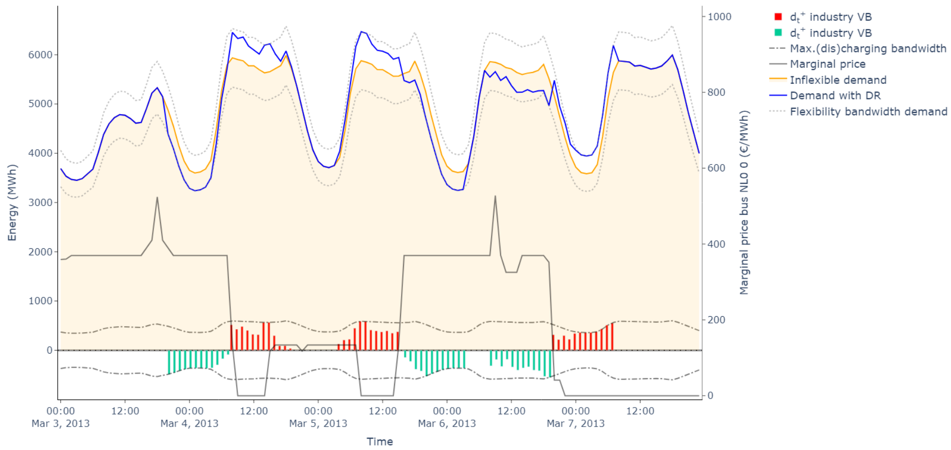


Figure 6.9: Change in demand due to industrial VB. NB: only Industry battery shown

The basic price incentive dynamics of the virtual battery work properly: Discharging the virtual battery happens at expensive prices, and charging at cheap times. Also, the charging and discharging behaviour works accordingly for this period since no simultaneous cycling is observed.

Network dynamics

In order to further analyse the effect of omitting a complementarity variable, the load-shifting properties of the virtual batteries are inspected for performance over the full optimisation timeframe of 1 year.

To test the dynamics of the unconstrained virtual battery concerning its binary counterpart, an evaluation is generated in figure 6.10. The chart shows all DR actions done per virtual battery. On the y-axis, the **number of DR actions** is shown, per **flexible time duration**. This consequently gives insight into which virtual batteries are most often activated, as well as for what timeduration, energy was shifted. Also, the amount of energy per timespan of the DR action is visualised through the 'bubble' size. In this plot, virtual batteries corresponding to the industry, tertiary and residential sectors are abbreviated by Ind, Ter and Res, respectively.

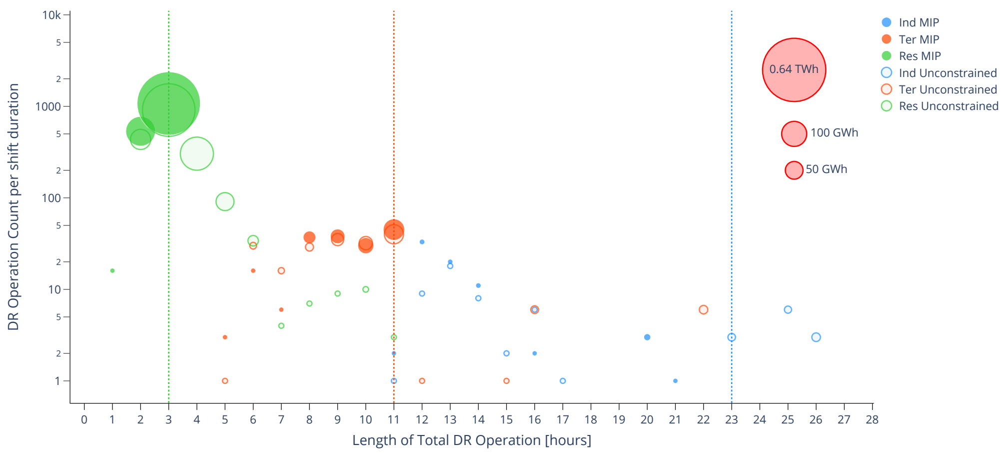


Figure 6.10: Load-shifting overview of MIP versus Unconstrained *Morales*, **Cost tier 3**

To improve the visualisation insights, **Cost tier 3** was selected. This limits the amount of load-shifting actions. From this figure, the following conclusions can be drawn:

- Most energy for both networks is displaced through short-term load-shifting. This is due to the formulation, as discussed in 5.1.2.
- Most **undue recovery** cases occur in all virtual batteries, however, primarily for the most used Residential virtual battery.
- Untimely load-shifts can still occur at a duration far beyond the maximum allocated time. For example, for tertiary with 22.

6.2.3. Tight linear relaxation

Let us now assess the quality of the δ complementarity variable within the dynamic network. Since the binary complementarity constraint was proven unable to *guarantee* timely recovery, it is unclear in what ways the linear relaxation of this variable will prove valuable.

$$\begin{aligned} d_t^+ &\leq 0.1 D_t^0 \delta \rightarrow & d_t^+ &\leq 0.1 D_t^0 \\ d_t^- &\geq -0.1 D_t^0 (1-\delta) \rightarrow & d_t^- &\geq -0.1 D_t^0 \end{aligned}$$

Saturation and load-recovery

Again, an initial check is performed to verify the range of DR actions. Figure 6.11 shows the mean DR virtual batteries to be operating in the range of duration as would be expected.

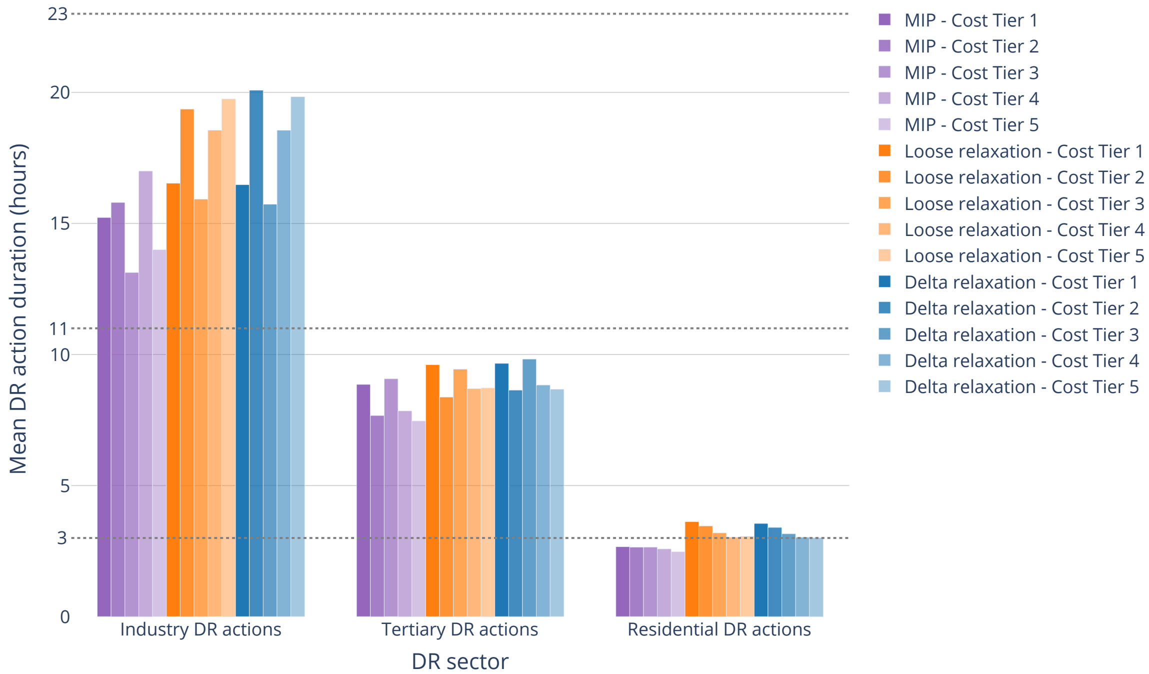


Figure 6.11: Mean load-shift duration for *Morales* methods

From, figure 6.11, little difference between the loose relaxation can be found. Also, when comparing the relaxation for the same time period in march as in figure 6.9. This is shown in figure 6.12.

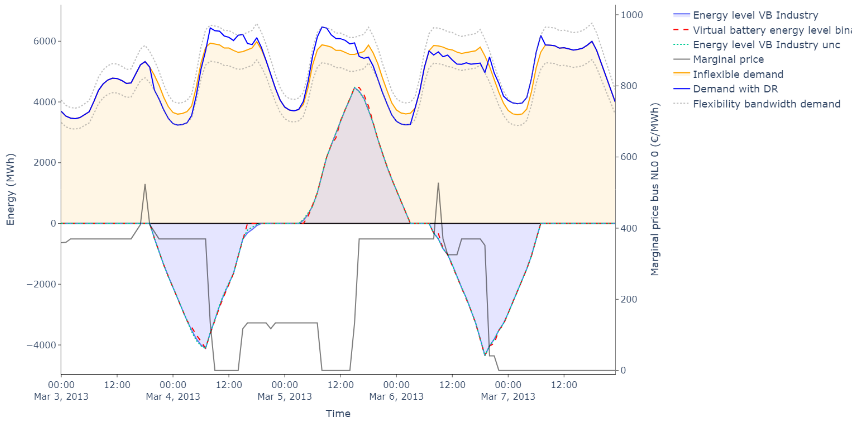
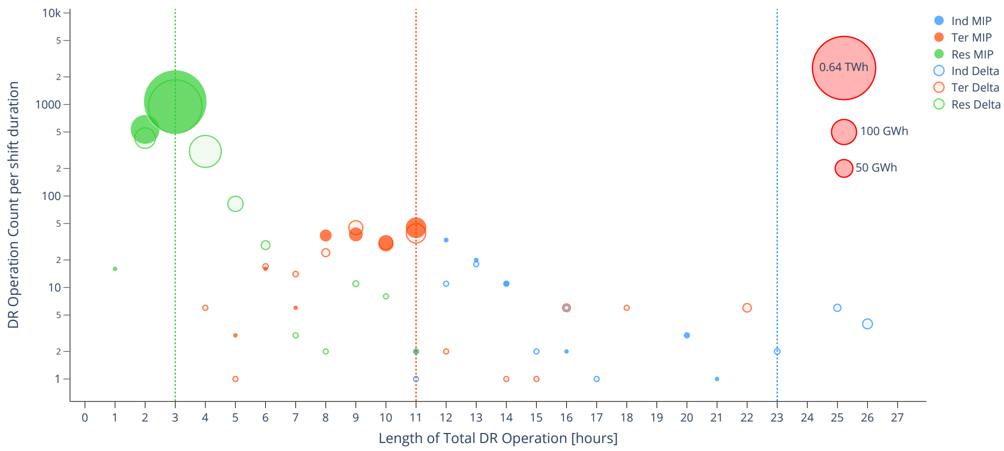


Figure 6.12: Virtual battery operation in march for δ relaxed *Morales*

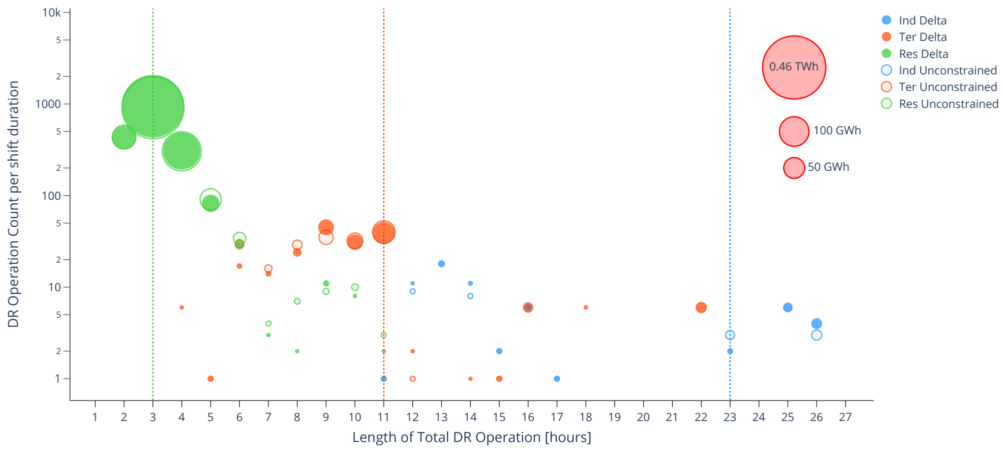
To acquire more conclusive results on the effectiveness of the tight relaxation, the virtual batteries are assessed at the network scale.

Efficacy of relaxation

The above results showed the local efficacy of the δ variable for one virtual battery at the bus level. Now, let us inspect more general metrics of the full network over a year, using the bubble plot visualisation again. The linearised δ is tested against the MIP model, as well as the unconstrained model in figure 6.13



(a) Cost tier 3 MIP DR operation, versus DR operation containing δ complementarity variable



(b) Cost tier 3 Unconstrained DR operation, versus DR operation containing δ complementarity variable

Figure 6.13: Combined bubble plots of unconstrained virtual batteries vs delta

From figure 6.13a, interesting observations can be made at the top level. Firstly, similar results are observed for the loosely relaxed, unconstrained version: most undue occurrences happen for the residential virtual battery. Fit can be observed that **residential virtual battery** is **less utilised** in the linear delta model. Secondly, the number of 'illegal' DR operations increased significantly for the tertiary virtual battery. Also, the industrial virtual battery seemed prone to more DR actions that exceeded the maximum flexible time of the virtual battery.

From figure 6.13b, the most important observation is the prevalence of similar DR actions between both models. For DR actions done by the industrial virtual battery, the unconstrained model can be seen to operate slightly more. For example, the unconstrained model operated in time duration buckets [45 - 46], and [49-50]. These illegal actions were mitigated by the introduction of the linear delta model, however also actions occur in the [43-44] bin.

6.2.4. Summary of Morales variations

This section will summarise the findings on Morales's load-shifting mechanisms on load-recovery, saturation and computational burden. It will present the parameter axes on which the level of load recovery was tested. From figures 6.10 6.13a, both the energy displaced per sector and the number of hours of untimely load-recovery could be obtained. In order to now concisely display the number of untimely actions done per sector, per morales variation, another visualisation is presented below in figure 6.14. Here, the amount of **untimely load-recovery actions, as a percentage of all DR actions** for the corresponding virtual battery is presented.

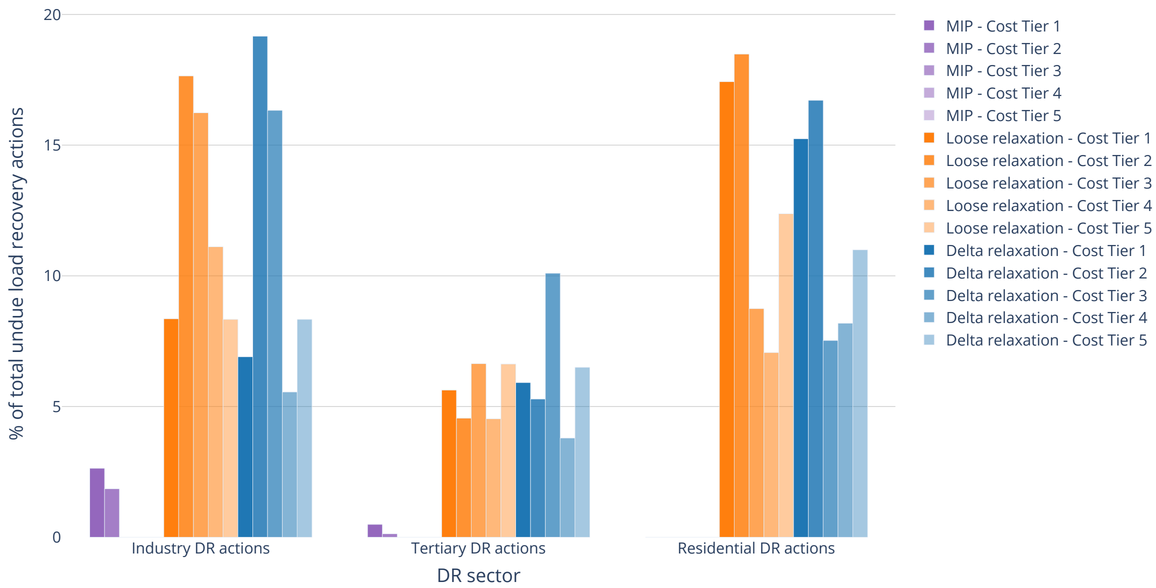


Figure 6.14: Percentage of undue load-recovery actions, of all load-shifting actions

From figure 6.14, interesting insights can be obtained. Firstly, a trend can be observed that for most instances, the δ relaxation resulted in less undue load recovery.

However, irregularities for all virtual batteries remain between cost tiers. The irregularities in the industry of virtual batteries can largely be attributed to the small sample size. As shown for cost tier 3 in figures 6.13a, and 6.10, the total amount of industrial virtual battery actions is fairly low. Due to the low sample size, one additional undue recovery case impacts the percentage more heavily. For other sectors, these irregularities also occur due to decreased sample size, however, at later cost tiers. It can therefore be concluded that increasing costs has limited positive impact on limiting undue recovery.

Importantly, from figure 6.14, the efficacy of both linear relaxations can be assessed. Although impacted by the irregularities from the small sample size, slightly fewer undue recovery actions can be observed. The initial reason of the authors of the *Morales methods*, as discussed in section 3.5.2, highlighted the problem of simultaneous cycling as the reason. This does not seem to be a significant issue for this test case because of the similarity in results of both relations. To gain insight into how simultaneous cycling is prevented, another comparison chart is given below:

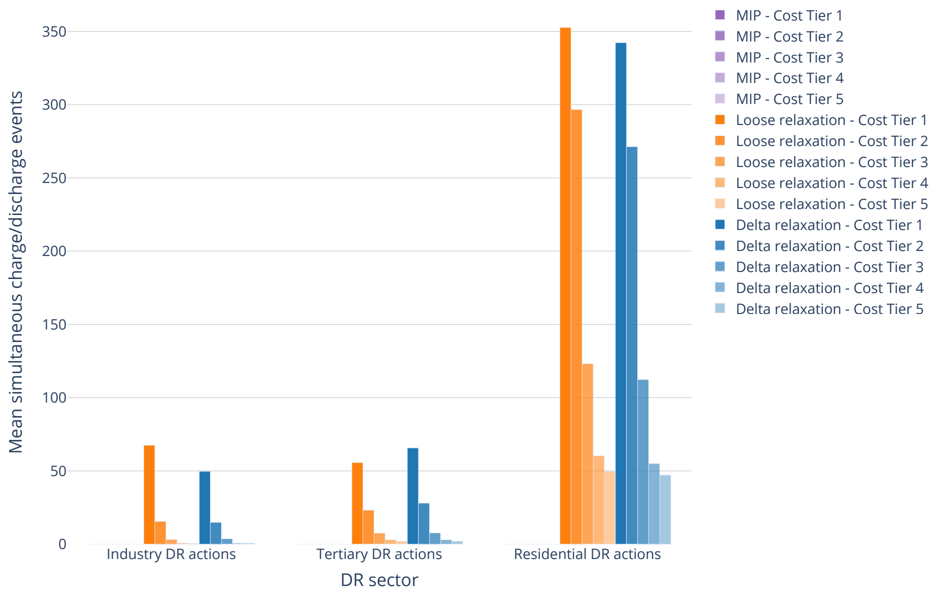


Figure 6.15: Simultaneous cycling present in *Morales* variations

From this chart, the high number of simultaneous cycling events in the residential virtual batteries can be explained by their high overall share in load-shifting events. This figure once again shows the limited but positive effect of the higher relaxation.

From a computational perspective, the MIP framework is not computationally tractable for large-scale ESOM. This is once again shown in table 6.4.

Method	Kleinhans	MIP	Loose relaxation	Tight relaxation (δ)
Mean across cost tiers	6.88	12.0	13.9	13.0

Table 6.4: Mean solving times for different methods [minutes]

Key takeaways:

1. all *Morales* bottom-up frameworks enable realistic load-recovery timeframes for virtual batteries within large-scale ESOMs.
2. No framework can guarantee load-recovery
3. The tighter relaxation offers limited added performance but is also an identical computational burden to the loose relaxation. Therefore tight relaxation can best be used.
4. The computational time of the MIP formulation inhibits implementation for large-scale ESOMs.

6.3. Wasserstein framework

The newly generated Wasserstein metric can be linearly implemented in the new objective function, along with a penalty, C_{shift}, which is essentially a cost per MWhh.

$$\text{minimise}: \; C_{system} + C_{shift} \cdot W(t) \tag{6.1}$$

This method was tested in these test cases again, and the results for the same March period are shown in figure 6.16 below.

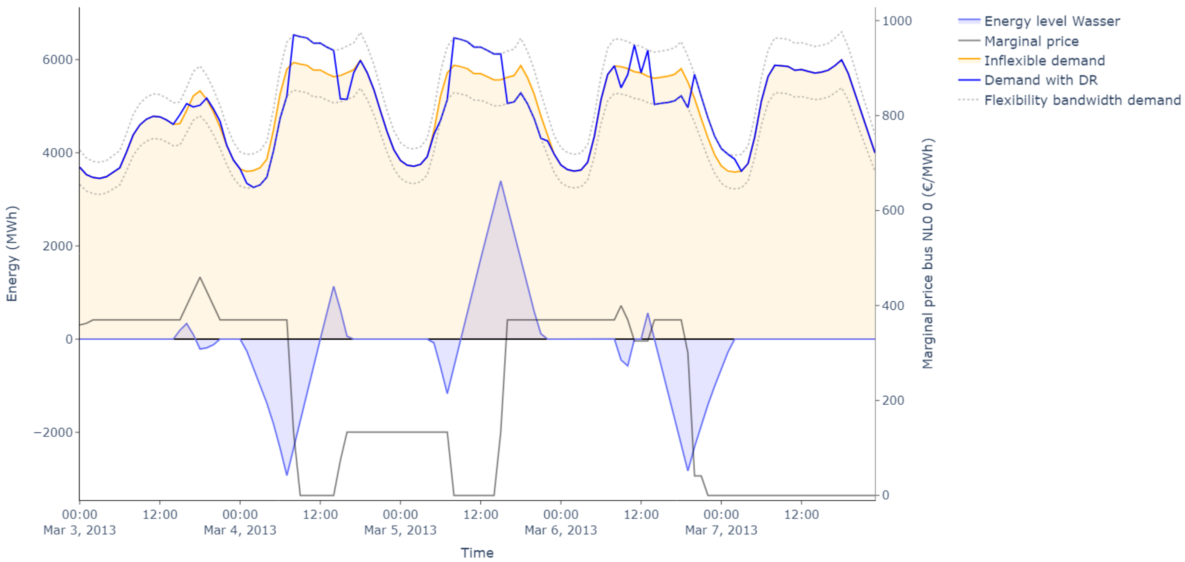


Figure 6.16: Demand versus Demand incl DR, bus NL0 0 1st week of March. **Cost tier 3: 30 MWhh**

From figure 6.16, the effects of the alternative virtual battery approach are neatly shown. Although no recovery limits are assigned, as for the bottom-up model, the virtual battery recovers its load in realistic time durations. This is due to the inconvenience costs allocated to the virtual battery's state of charge/energy level. Deviations from the original load occur for reasonable timeframes corresponding to real-life DR actions.

To analyse the Wasserstein VB method on the full timescale of the optimisation, a similar structure is employed as in the bottom-up verification. The results from the *Wasserstein* method are visualised in the same manner as for the bottom-up frameworks, sorting the DR actions per count, duration, and energy displaced. In figure 6.17, cost tiers 1, 3, and 5 are shown.

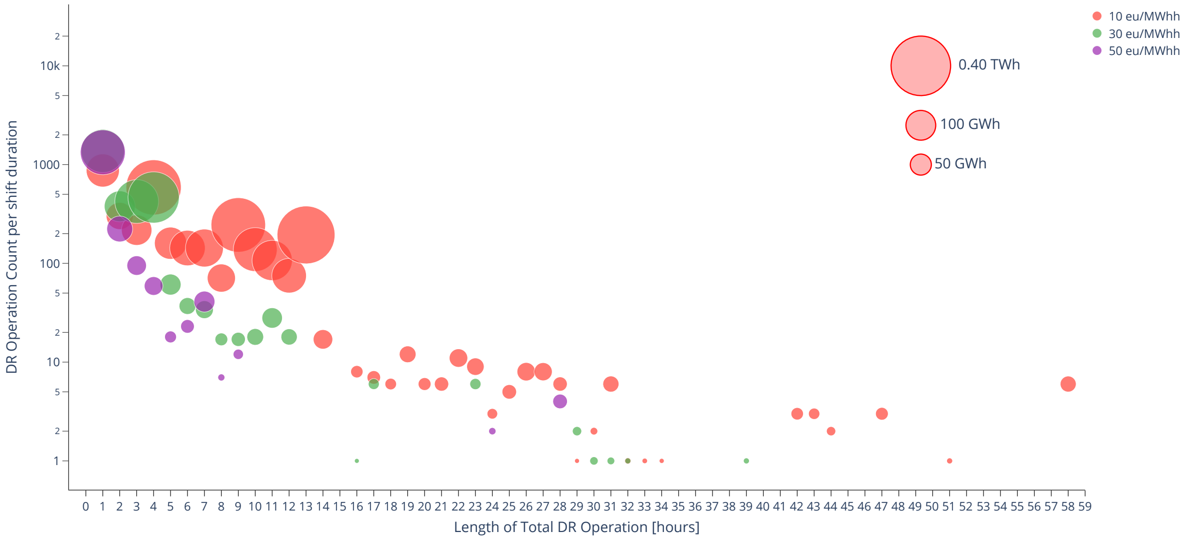


Figure 6.17: Load-shifting actions by the *Wasserstein* modelling framework, for cost tiers 1, 3 & 5

From figure 6.17, it can be observed that most load-shifting actions occur for short shifting timeframes. This is as expected since the formulation of this method effectively penalises load-shifting with increasing duration.

From the lowest cost tier (10 €/MWhh), a substantial load is shifted for 9 to 13 hours. This trend decreases with increasing load since the return on investment diminishes.
Note how similar conclusions can be drawn from a top-down perspective. That is, the categorisation of DR activity from the bottom-up modelling can also be done post-optimisation using top-down methods by observing the shifts happening for longer intervals. The virtual battery actions done by the industry sector are categorised by acting in larger than 18-hour bins.
In the previous section on bottom-up modelling, the observation was that for realistic top-level DR action, it could prove useful to include sector-specific flexible shares for a more realistic representation. From the Wasserstein method, however, an alternative approach can be employed. Instead of categorising per sector, it could be interesting to categorise by estimated MWhh cost. That is, a small section of demand available for DR could, for example, be categorised as very inelastic and have low MWhh costs. A larger section of demand operates at more elastic MWhh prices.

Comparison between frameworks

The visualisation for DR operation over the full timescale revealed similar curves for both methods, validating the effectiveness of both approaches for analysing top-level load-shifting behaviour.

Due to the careful cost standardization approach, both methods produce comparable results, which validates the effectiveness of the Wasserstein method as an alternative to bottom-up frameworks for analysing aggregate DR behaviour.

From the cost standardisation in section 5.1.2, a benchmark was set to approximate equivalency based on a fixed shifting duration T. From the equation below, it can be observed that for decreasing T and consistent c_2, for equal pricing, c_1 should also decrease to maintain equivalency.

$$\frac{c_1}{c_2} = \frac{T}{4} \qquad\qquad c_1 = \frac{Tc_2}{4} \tag{6.2}$$

Since, in this framework, the costs are fixed, and thus such equivalency cannot be maintained for a different time duration, the Wasserstein method is more economical for shifts shorter than the benchmark T. This can also be seen in figure 6.18.

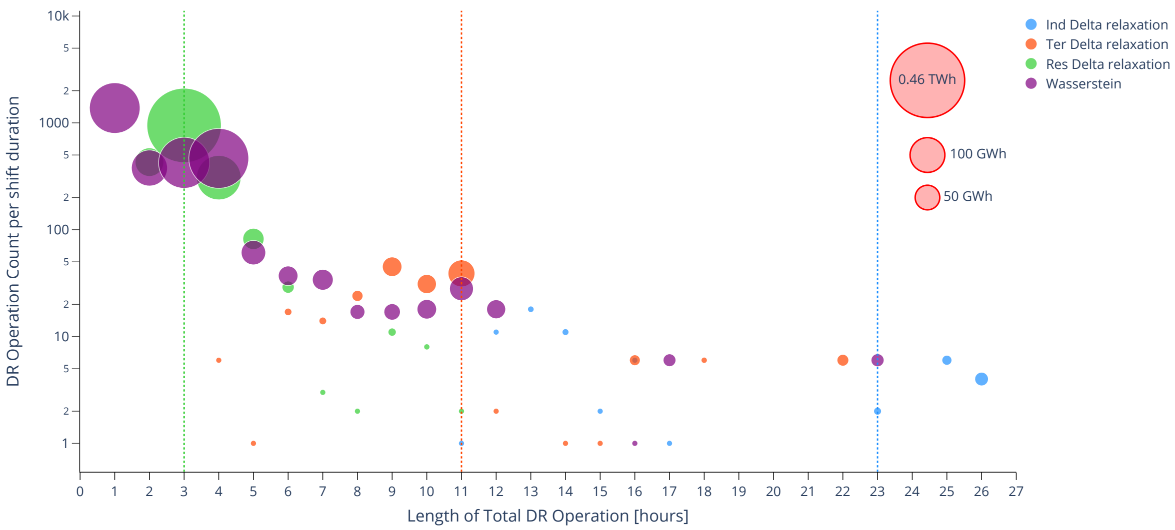


Figure 6.18: Comparison of DR methods, **Cost Tier 3**

This step has validated the effectiveness of the *Wasserstein* methods since it can be shown to shift loads over primarily short-term time duration and recover its shifted load in due time. This makes it a suitable virtual battery framework for top-level, aggregate load-shifting models.

For energy modellers more interested in DR process specifics, the tight relaxation *Morales* method remains a valid option. However, timely recovery cannot be guaranteed for each DR process modelled. If the goal is to model specific DR processes rather than aggregate top-level load-shifting, the costs and shifting time parameters can be adjusted to create different time-scale load-shifting behaviours. However, since the scope of this study focuses on aggregate load-shifting behaviour, the Wasserstein method's ability to effectively capture short-term DR activities makes it the preferred choice. Additional examples of specific DR process modelling scenarios are provided in appendix F.

Key takeaways:

1. The *Wasserstein* method effectively models load-recovery within realistic timeframes.
2. The preference for higher counts and energy shift in load-shifting is a realistic characteristic of top-level DR.
3. The method is easily linearly applicable, making it computationally efficient.
4. No information on large sets of load-shifting processes needs to be assessed, as the load represents aggregated DR.
5. The method captures short-term load shifting, which aligns with expected DR behaviour patterns.

6.4. Solving time summary

This section concludes with a chart of the previously mentioned solving times. The solving time for the test case without load-shifting frameworks was included for completeness. All times are summarised in figure 6.19.

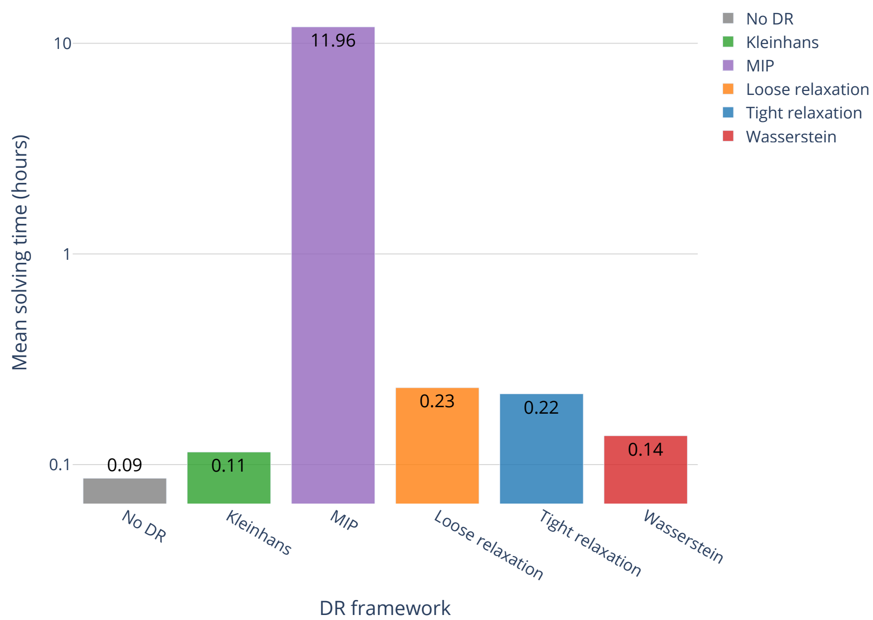


Figure 6.19: Summary of solving times per load-shifting method

The solving times for the linear frameworks can be considered comparable. One consideration is, however, that if the amount of disaggregation J would increase, and thus the number of virtual batteries per node, the solving times for the *Kleinhans* & *Morales* methods are expected to increase.

6.5. Conclusion

This chapter aimed to verify the efficacy of bottom-up methods for modelling Demand Response (DR) within large-scale Energy System Optimisation Models (ESOMs). The analysis revealed several key insights into the operation and feasibility of these frameworks. Firstly, the *Kleinhans* method was found inadequate in ensuring timely recovery, rendering it unsuitable for accurate load-shifting behaviour. This method's inability to account for load recovery within realistic timeframes undermines its validity for DR modelling.

In contrast, the *Morales* method demonstrated a more robust approach to DR modelling, although it could not guarantee load recovery. The Mixed-Integer Programming (MIP) formulation provided the most reliable results, ensuring timely recovery. However, the associated computational burden proved a significant drawback, making this method unsuitable for large-scale ESOMs. The linear relaxations of the *Morales* method, including both loose and tight relaxations, showed an increase in undue recovery cases compared to the MIP formulation. Despite this compromise on accuracy, the tight relaxation, in particular, offered a substantial improvement in computational tractability, making it a viable option for bottom-up DR modelling in large-scale ESOMs.

The *Wasserstein* method emerged as a promising alternative for top-down DR insights. It effectively ensured load recovery within realistic timeframes, making it suitable for aggregate DR modelling. The method's ability to incorporate all DR without requiring extensive additional information further enhances its appeal for large-scale ESOMs. The load-shifting profile of the *Wasserstein* virtual battery aligns with insights from literature: most load-shifting occurs in the very short term. Additionally, the computational tractability of the *Wasserstein* method is favourable, making it a practical choice for comprehensive DR analysis.

In summary, while the *Kleinhans* method falls short in ensuring accurate DR modelling, the *Morales* method offers a balanced approach between accuracy and computational feasibility, particularly in its tight linear relaxation form. However, for large-scale aggregate DR modelling, the *Wasserstein* method proves most advantageous due to its ability to capture short-term load-shifting behaviour while maintaining computational efficiency effectively. Therefore, the *Wasserstein* method will be employed to achieve a comprehensive and realistic portrayal of DR in large-scale ESOMs.

7
Results: cost-optimal power grids

This chapter extends the model scope to the larger network, as discussed in section 4. The primary objective is to address the sub-question:

What is the effect of implicit DR load-shifting for decision-making and investment planning for the Netherlands in 2035 under different scenarios?

A comprehensive network analysis is conducted in section 7.1 to adequately answer this research question. The analysis begins by examining the cost-optimal configuration within the full geographical scope, excluding DR. This is followed by a focused and detailed analysis of the cost-optimal power grid for 2035 in the Dutch context. These properties are then compared with introducing DR into the full network scale to assess the overall effect on power system capacity and, more specifically, on flexibility assets.

Subsequently, in section 7.2, results from the sensitivity analysis will present the robustness of the power grid for different optimisation weather and demand years. Here, valuable insights for decision-makers are provided, which can further assist in decision-making in light of the energy transition in the Dutch context.

7.1. Network analysis

The scope of this study is focused on providing an in-depth analysis of a future power grid for the Netherlands. This will be done by providing a comprehensive overview of the total network, as well as the specific Dutch context. Next, the implications and intricacies of introducing load-shifting in the network are discussed.

7.1.1. Total system overview

This subsection discusses the full system scope, focusing on the optimal distribution of installed capacities for various power sources. The aim is to illustrate the interconnections and the diverse regional power sources contributing to a cost-optimal, fossil-free power grid. Figure 7.1 presents a visual representation of the optimal capacities at each power grid node, highlighting the distribution of different energy sources and the role of hydrogen assets within the network.

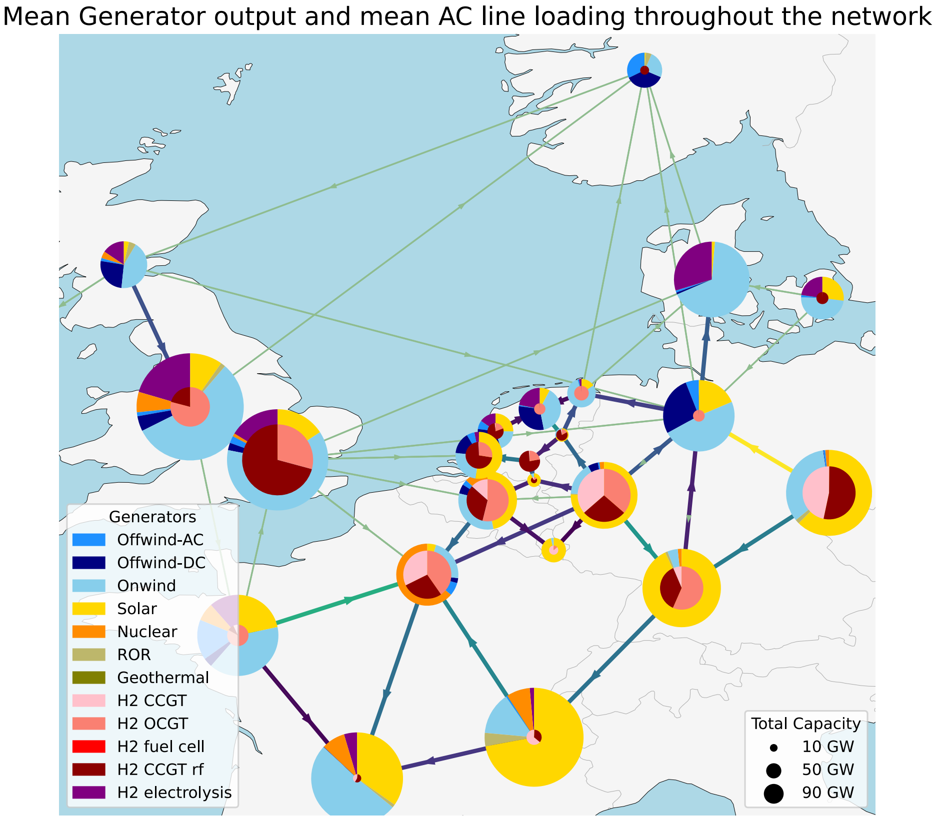


Figure 7.1: Optimal capacity per node

The first overview (Figure 7.1) provides insight into the network beyond the Netherlands, illustrating the interconnection and diverse regional power sources. This figure visualises the optimal installed capacity for various power sources. Each node's pie chart shows the distribution of different energy sources, and the smaller pie charts inside represent the optimal capacities of hydrogen assets.

From figure 7.1 it becomes clear that cost-optimisation favours significant investment in two core RES: solar-PV generation and onshore wind turbines. solar-PV is especially prevalent in the southern areas of France and Germany. Onshore wind locations are distributed throughout Northwestern Europe, with especially large quantities in Great Britain.

Due to the fossil-free nature of the power grid, there is a high demand for renewable solutions with controllable power. Without controllable power, the intermittency of renewable sources would result in volatility of local marginal prices that drive system costs.

This controllable power dispatch is partly covered by the utilisation of H_2 CCGT retrofitted plants, which are fully maximised across the network. This is expected since the CCGT retrofitted turbine is the most inexpensive option for converting the stored hydrogen to electricity. The countries bordering the North Sea host a large share of electrolysers necessary to facilitate the system's hydrogen network. These electrolyser hotspots can be attributed to the correlation of cheap wind energy surpluses resulting in cheap electricity prices.

A summary of the optimal capacities aggregated per category, present in the network for Northwestern Europe, is given in figure 7.2

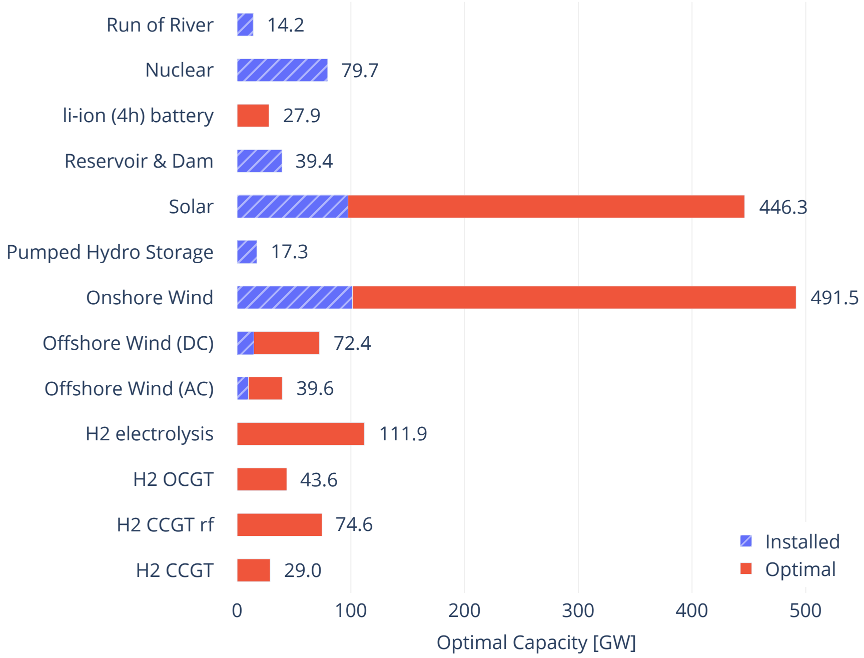


Figure 7.2: Total Optimal Energy Mix

In addition to the controllable power output provided by the hydrogen OCGT and CCGT, energy storage is necessary in a cost-optimal power grid. The storage options are summarised in the figure below:

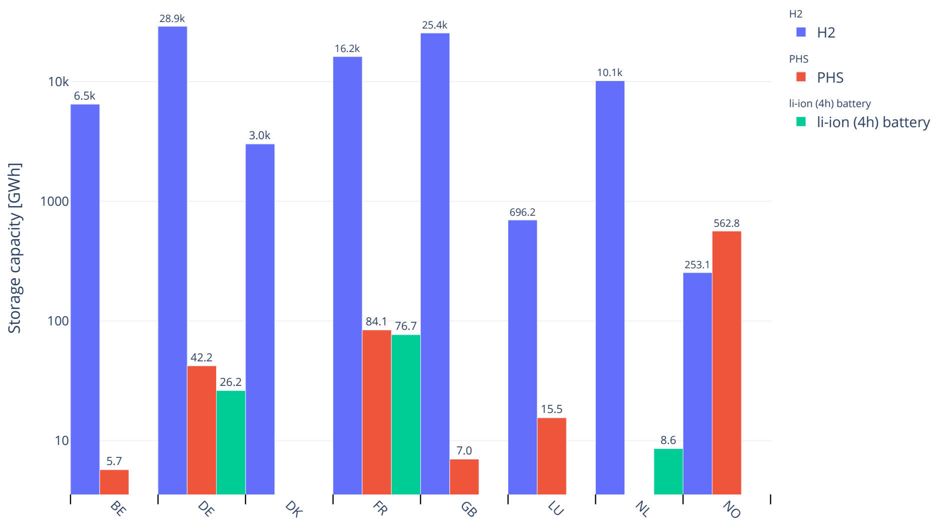


Figure 7.3: Caption

From figure 7.3, the importance of utilisation of salt caverns for H_2 storage becomes clear. Due to the large volumes present, and the low costs, extensive hydrogen storage is key for enabling controllable electricity output from H2 OCGT & CCGT.

Figure 7.3 highlights the system's reliance on various storage and conversion technologies to maintain grid stability and meet demand. These solutions only include batteries, Pumped hydro storage, and hydrogen storage, each playing a distinct role in balancing supply and demand. It becomes clear that H_2 caverns are used extensively by the model. A total underground hydrogen storage of 91 TWh is amassed. This is within the range of current estimation of technical potential [91]. Hydrogen storage is critical to facilitate the flexibility offered by the CCGT and OCGT hydrogen plants. These power plants are critical for power generation in demand situations with little renewable power production.

Other network insights are listed below:

- Li-ion 2h Battery: Not utilised in the optimised scenario. The capability of flexible hydrogen turbines to handle smaller peaks in demand appears more economical, rendering high power, low storage, and Li-ion batteries unnecessary.
- Li-ion 4h Batteries: Significantly installed across most countries, these batteries address longer-duration peaks and the absence of renewable energy sources. Their widespread deployment indicates their crucial role in providing mid-term energy storage solutions.
- Li-ion 8h/Mechanical Batteries: Hardly utilised in the cost-optimal network. The flexibility offered by interconnectivity, hydrogen assets and Li-ion 4h batteries prove to be sufficient.
- Existing pumped hydro storage infrastructure in counties contributes to grid flexibility.
- Compressed Air Energy Storage (CAES) and Flow-ion batteries were not utilised in the cost-optimal power grid.

7.1.2. Power grid NL 2035

Having assessed the optimal outlook of the larger system, this section now focuses on the power grid in Dutch context. First, figure 7.4 displays the cost-optimal capacities resulting from the optimisation.

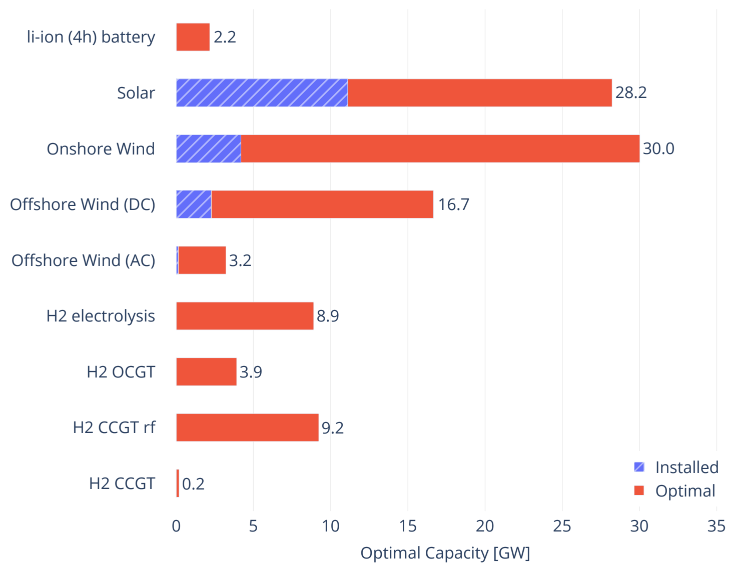


Figure 7.4: Optimal Energy Mix in NL

From figure 7.4, the importance, and value of onshore wind capacity becomes clear. Since the Netherlands is dominated by wind resources, a range of flexible and controllable units can be found. The flexibility is mainly provided by interconnection through neighbouring countries, hydrogen assets, and Li-ion 4h batteries. The investment in OCGT turbines instead of CCGT turbines can be explained by their lower investment costs, making up for their lower efficiency and higher variable costs. Since the OCGT units will also be used for select peak hours, it is the more economical path in this configuration.

7.1.3. Impact of load-shifting

This section shows the results after introducing the different virtual battery models. Inconvenience costs must be assigned to assess the impact of load-shifting at the system level. Since extensive research and data collection into the load-shifting and demand response inconvenience pricing, or willingness-to-pay is out of scope for this thesis, the prices result from the expertise of *Witteveen+Bos*. CE Delft and Witteveen+Bos [22] study estimates the willingness-to-pay for a load-shifting action in industry at **200 eu/MWh**. From the standardisation method derived in section 5.2, this yields the following comparison for a comparative analysis between Wasserstein and Kleinhans frameworks. Note how these costs correspond to **cost tier 2** from 5.2. Since the costs in the table refer to the costs per charging/discharging action, the total costs for the industry are approximately the same.

	Kleinhans, disaggregated J=3 Price per (dis)charging action [eu/MWh]			Wasserstein, aggregated Price per battery energy level [eu/MWhh]
	Industrial	Tertiary	Residential	
Δt	12	6	2	
T	24	12	4	
	120	60	20	20

Table 7.1: Inconvenience costs for load-shifting reference case.

The introduction of the load-shifting frameworks in the cost-optimal power grid yielded the following differences in installed capacity for the 3 distinctive solutions.

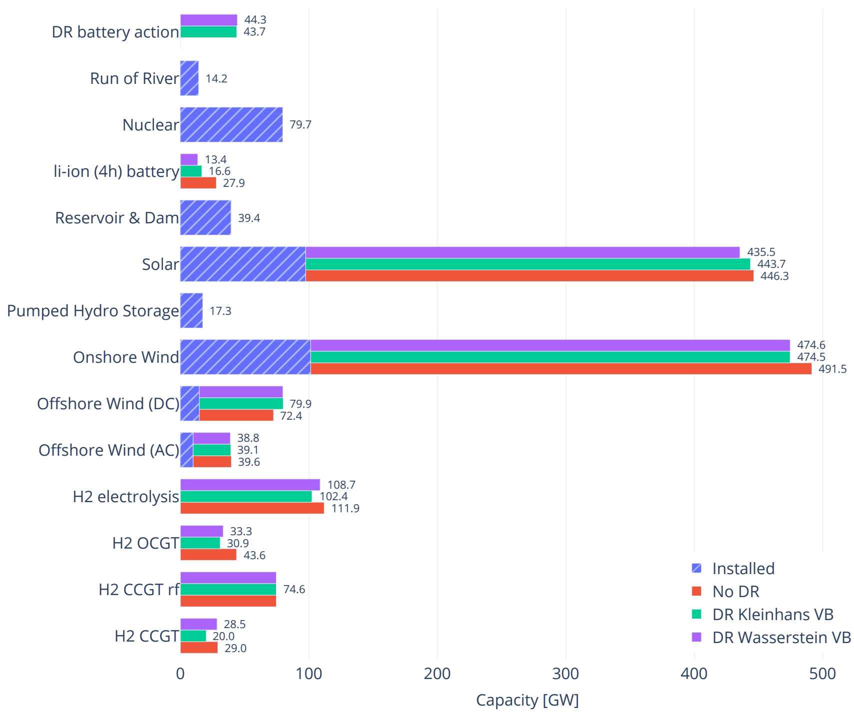


Figure 7.5: Impact of *Kleinhans* & *Wasserstein* load-shifting frameworks on the cost-optimal power grid

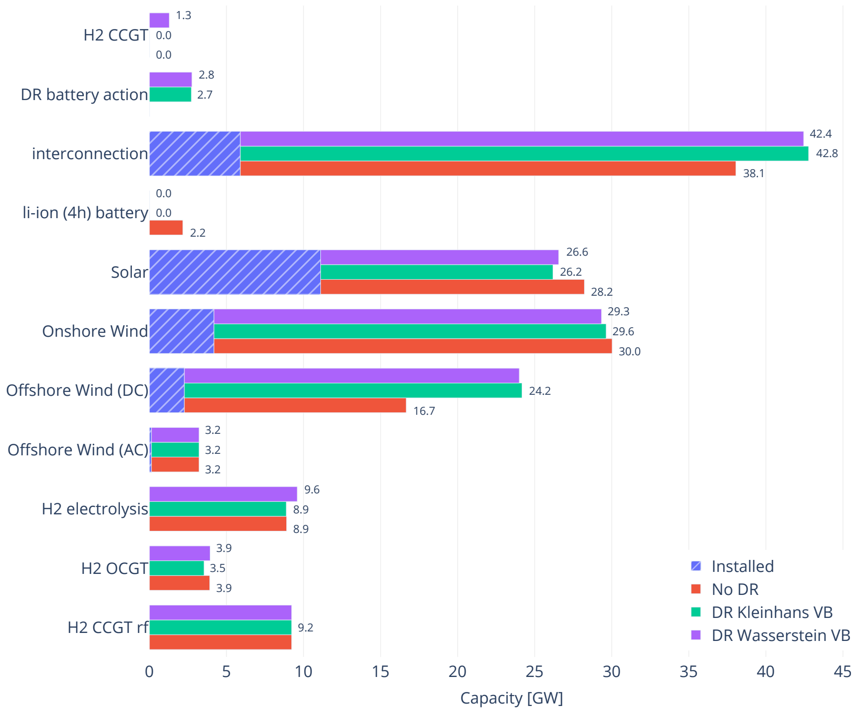


Figure 7.6: Impact of *Kleinhans* & *Wasserstein* load-shifting frameworks on the cost-optimal power grid in Dutch context

Scenario	Total system costs (10^9 EUR)	NL system costs (10^9 EUR)
NO DR	119.04	10.70
Kleinhans	114.58	12.36
Wasserstein	115.41	12.33

Table 7.2: Overview of total system costs and Dutch system costs per scenario

An important notion is the capacity for the load-shifting Virtual battery in figure 7.6. The resulting capacity in this figure is the result of aggregating the maximum capacities for the virtual batteries in the system for one point in time, and does not represent the available capacity at any given time. Since the charging/discharging capacities of the virtual batteries are directly linked to the corresponding load at bus level, the stated capacity for DR can only be available at high-demand moments in time.

From the above figures 7.5, 7.6, and table 7.2, four key trends will be identified.

1. **Load-shifting competes with Li-ion batteries**
   In figure 7.6, both frameworks show a significant decrease in installed Li-ion storage. Notably, on the larger network scale, the Kleinhans method, however, overestimates the capacity of Li-ion due to the problems highlighted in section 6.1: the virtual battery operates at longer-duration timescales.
2. **Load-shifting unlocks increased Offshore Wind investment in NL**
   The introduction of load-shifting properties allowed for more RES penetration. For the Netherlands, this expanded the potential of offshore wind, from 16.7 GW to 24 GW. Increasing the penetration of RES is desirable since this makes the network more robust and provides the possibility for more exports.
3. **Load-shifting does not significantly mitigate the necessity for hydrogen network**
   While both load-shifting frameworks illustrate the ability of load-shifting to decrease the reliance on OCGT in peak demand situations, both figures 7.6 and 7.5 indicate that load-shifting modelled

through Wasserstein frameworks do not mitigate capacity for controllable power output. Due to the absence of timely recovery constraints, the Kleinhans framework's virtual battery can function similarly to the CCGT. This results in a misleading underestimation of flexibility assets necessary for the non-peak demand moments.

4. **Load-shifting results in lower total system cost, but increases investment in NL**
   The introduction of load-shifting allowed for lower system costs. This can be expected since there are no capital investments to include load-shifting, the objective function essentially gained a decision variable, meaning the network is the same cost as the case without DR at worst. Interestingly, however, the introduction of load-shifting led to an increase in system cost for the context of the Netherlands. This can be attributed to the increased amount of offshore wind.

To ensure the validity of the optimisation result, the network is compared against the predictions from Netbeheer Nederland [6] scenarios and TenneT TSO B.V. [9] to further verify the cost-optimal configuration, and put results in perspective. Furthermore, this study aims to provide an unbiased future network regarding current policy, opinion, or societal preference. Therefore, interesting insights can be obtained in the table since any large discrepancy between the cost-optimal configuration and the scenarios could highlight a missed opportunity from a purely economic standpoint.

		[9] 2030	[6] 2035			**This study 2035**	
		MLZ'2024	KA	ND	IA	no DR	DR Wasserstein
Demand [TWh]	Total	151	234	314	209	204	208
	for H2 storage		48.3	101.1	47.8	33.5	37.4
Production [GW]	Wind onshore	9.1	10.6	12.7	8.1	30	29.3
	Wind offshore AC	16.7	27.5	29.5	25.5	3.2	3.2
	Wind offshore DC					**16.7**	**24.1**
	Solar	59.3	75.9	98.2	52.6	**28.2**	**26.6**
	Nuclear	0.5	0.5	0.5	0.5	0	0
	Gas powerplant	14.0	12.3	9.6	8.2		
	H_2 powerplant		3.5	6.0	8.5	**13.1**	**14.4**
	Total	99.6	130.3	156.5	103.4	91.2	97.6
Flexibility [GW]	P2Gas	3.0	4.0	13.6	5.6	8.9	9.6
	P2Heat	3.3	5.3	8.5	3.7		
	BESS	4.9	22.7	31.5	13.7	**2.2**	
	interconnection	12.8	12.8	13.8	13.8	**38.1**	**42.4**
	DR	1.7	2.0	2.5	1.7	0	2.8

Table 7.3: Comparison of cost-optimal configuration with descriptive scenario studies for NL

The most notable observation in comparing the scenarios for the Netherlands is that the cost-optimal configuration from this study leans heavily towards onshore wind capacity investment for the Netherlands. In contrast, the reference studies rely on solar capacity. Moreover, the inclusion of load-shifting into the network increased Offshore wind capacity.

Interestingly, the cost-optimal solution invests substantially in high interconnectivity, as opposed to BESS. This is because the optimisation does not differentiate between countries and interests and preferences for energy independence.

The cost-optimal capacities for H_2 power plants exceed the expectations set by the other scenarios. However, gas powerplants are still present in the scenarios from *Netbeheer Nederland* and *TenneT*.

7.2. Sensitivity analysis and decision-making

From the above results, the effect of load-shifting purposes on the network has been illustrated. To more adequately answer the subquestion and research question:

Sub-question 4: What is the effect of implicit DR load-shifting for decision-making and investment planning for NL in 2035 under different scenarios?

As described in section 1.3, Energy System Optimisation Studies like this thesis typically aim to present indicative data in optimal network configurations for a fossil-free future in the most economical way. Therefore, on an investment planning level, the economic impact of introducing a load-shifting mechanism into the model is important to decision-makers. The introduction of load-shifting predictably results in a more economical configuration, which follows directly from our research design. With load-shifting requiring no capital expenditure (CAPEX), the system determines a new cost-optimal equilibrium between reduced flexibility capacity and the dispatch costs of available load-shifting batteries.

To demonstrate this, the model choices for the reference case are extended for additional years beyond the initial input year of 2013. Table 7.4 shows the magnitude of the system cost decrease.

For clarity, the steps involved with the simplified MiniMax from 5.2.2 are once again summarised here.

1. First, network optimisations are performed for three additional weather years, 2011, 2012, and 2014.
2. For each weather year, two distinct network configurations are optimised:
    - Configuration A: System without DR
    - Configuration B: System with DR
3. Each optimised configuration is then tested against the weather conditions of all other years. Since the configurations are fixed, the only cost difference results from different optimal dispatches of assets, yielding a unique system OPEX per year.
4. The regret for each configuration is calculated as the difference between:
    - The OPEX when the configuration operates under different weather conditions
    - The OPEX of the optimal configuration for that specific weather year
5. The maximum regret for each configuration across all weather years is identified.
6. The configuration with the lowest maximum regret is selected as the most robust solution.

This approach ensures that the selected network configuration performs adequately across various weather conditions rather than being optimised for a single weather year. The strategy helps decision-makers identify solutions that minimise the risk of poor performance under different scenarios.

		System details		NL details	
		Annualised cost (CAPEX+OPEX) [€10^9]	Total demand [TWh]	Annualised cost (CAPEX+OPEX) [€10^9]	NL demand [TWh]
NO DR	2011	101.61	2556	8.68	166.02
	2012	96.96	2556	7.47	152.87
	2013	115.66	2556	10.70	170.92
	2014	102.05	2556	9.33	161.98
DR	2011	98.16	2556	10.10	166.02
	2012	94.37	2556	7.83	152.87
	2013	112.42	2556	12.42	170.92
	2014	98.86	2556	10.77	161.98

Table 7.4: Combined system and NL details

Interestingly, however, the system cost for the Netherlands increases with the introduction of DR in the total system. This can be attributed to the network effect as described in section 7.1.3, such as the increased capacity of Offshore wind. Figure 7.6 showed the increase in Offshore Wind production in the Netherlands. This trend can be observed across multiple weather and demand scenarios, indicating that a more flexible network results in the Netherlands becoming a larger host for renewable energy sources (RES).

For investment planning decision-making, however, insights into risk-averse, robust investment decisions cannot adequately be addressed by differences in investment per year. Therefore, the focus is shifted to the robustness of the two types of optimal network configurations for different scenarios. Weather and demand input data sensitivities are extended to include cross-testing of different network configurations, as discussed in 5.2.2. The resulting costs are then compared with the optimal solution for that year, and the difference in cost is defined as the 'regret' cost, as it displays how much worse the chosen network performed compared to its optimal counterpart. Table 7.5 below shows the resulting regret costs.

Interestingly, the system, including DR, results in lower regret costs in almost all cases. This is not trivial, as the decreased amount of explicit flexibility installed might result in a less robust network when tested over multiple years.

For example, in the case of 2013, the configuration, including load-shifting, enabled more investment in the Netherlands, as well as the total system, in Offshore DC wind production. If the wind conditions in another year are then less favourable, this investment cost is likely to result in regret costs when compared with the optimal configuration for that year. Thus the observed trend that the inclusion of demand response generally results in less regret costs than

		Regret **System level**				
		2011	2012	2013	2014	Max.
NO DR	2011	0.00	7.35	32.62	3.56	32.62
	2012	42.87	0.00	81.60	53.79	81.60
	2013	9.59	14.90	0.00	10.15	14.90
	2014	3.40	5.88	35.27	0.00	35.27
DR	2011	0.00	6.77	31.90	3.93	31.90
	2012	26.70	0.00	68.20	35.62	68.20
	2013	10.28	14.09	0.00	10.36	**14.09**
	2014	3.30	5.26	33.62	0.00	33.62

Table 7.5: System regret: total system demand fixed for every year

When the method is scoped to just the Netherlands, the regret data also poses interesting results. Note how negative regret costs are possible here when the system costs for a chosen year are cheaper than the optimal configuration cost for the year in question. This is only possible because the scope is narrowed to a subset of the optimisation problem and could not occur if the optimisation network included only the Netherlands. Furthermore, as seen from Table 7.4, the scaling factor applied to the electricity demand does not yield the same electricity demand for the Netherlands for all years. In Appendix E, the same sensitivity analysis is applied to a standardised NL electricity demand. Generally, the trend that DR networks result in smaller regret costs from Table 7.5 is less consistent.

		Regret **NL system level**				
		2011	2012	2013	2014	Max.
NO DR	2011	0.00	1.85	-0.22	-0.64	1.85
	2012	2.10	0.00	-0.77	0.51	2.10
	2013	1.93	3.48	0.00	1.29	3.48
	2014	1.22	2.62	0.61	0.00	2.62
DR	2011	0.00	3.10	-0.37	-0.41	3.10
	2012	0.57	0.00	-0.39	0.09	**0.57**
	2013	2.13	4.47	0.00	1.47	4.47
	2014	0.89	3.56	0.41	0.00	3.56

Table 7.6: NL system regret

As described in Section 5.2.2, this approach is similar to a minimax approach but is not as comprehensive since the available configurations are limited to four existing ones.

7.3. Conclusions

Firstly, the extended network configuration analysis reveals significant insights into the future of the Netherlands' power grid. The cost-optimal, fossil-free power grid configuration for the Netherlands in 2035 demonstrates significantly higher levels of interconnectivity and onshore wind capacity than current planning projections. Additionally, the inclusion of offshore wind capacity increases with the introduction of load-shifting.

Secondly, with selecting a suitable modelling framework, key insights were obtained from the energy system optimisation study. Load-shifting can create significant value for a fossil-free power grid in the Netherlands by adding extra flexibility. This results in lower overall system costs and requires less investment in other flexibility assets, especially battery energy storage systems. However, in the Dutch context, it should be noted that for this energy system optimisation, the system costs increased with the introduction of load-shifting. Controllable flexibility assets such as fossil-free power plants still play a significant role in the cost-optimal network due to their ability to accommodate peaks in demand.

Thirdly, the impact of load-shifting on decision-making was assessed through sensitivity analyses. Optimal power grid configurations were tested for different weather and demand scenarios, including and excluding load-shifting. Network configurations, including demand response, reduced additional costs due to weather and demand sensitivity. This insight is valuable for decision-making in investment and energy planning, as it reveals that investment in explicit flexibility services is neither more economical nor more risk-averse.

8
Discussion

This chapter interprets the findings presented in the previous chapter, placing them within the broader context of our research objectives. The primary goal is to discuss effective Demand Response (DR) methodologies and their characterisation within large-scale Energy System Optimisation Models (ESOMs). Specifically, the aim is to answer the research question:

Exploring the value of Load-shifting Demand Response as a flexibility solution for a cost-optimal power grid: A research case for the Dutch power grid in 2035 through analysis of possible scenarios.

By examining the results of the test case, this chapter assesses the selected models for their suitability for energy system modellers. It provides insights and guidance on choosing appropriate DR frameworks, highlighting the strengths and limitations of each approach.

The discussion includes key takeaways from the introduction of DR into a fossil-free power grid, focusing on its impact on system flexibility, investment decisions, and operational costs.

Furthermore, the chapter explores the implications of DR on network configurations under multiple scenarios, such as varying weather conditions and demand patterns. These insights are crucial for energy planners and decision-makers, as they offer valuable information on how DR can enhance system robustness and reduce uncertainties in planning.

Section 8.1 provides a detailed discussion of the DR framework results, addressing research question 2 and evaluating the performance of each methodology. Section 8.2 explores the broader context implications of the findings, focusing on the 2035 fossil-free power grid in the Netherlands and offering key takeaways for investment planners and policymakers. Section 8.3 discusses the model application, examining its effectiveness and potential improvements. The chapter concludes with Section 8.4, presenting promising directions for future research in virtual battery use, DR, and the application of ESOMs in energy policy.

8.1. Validity of DR frameworks

In section 6, results on the validity of three DR applications for ESOMs were presented. Given these results, this section aims to answer research question 3:
What characterises DR, and how can DR be correctly modelled for large-scale ESOMs?

Given the core challenges inherent to DR, the key to employing valid load-shifting mechanisms can be summarised in 3 main practices:

- Valid simplification of inherently complex framework:
  When employing a virtual battery structure, realistic dynamic **Saturation**, as well as **load recovery** needs to be accounted for.
- Applicability to large-scale ESOMs:
  Reformulating a battery framework for DR load shifting keeps the objective function linear, without oversimplifying core load-shifting properties.

- Information accessibility:
  Top-level decisions require information. If the goal is to estimate system/network load-shifting potential, modellers should choose top-down or bottom-up approaches based on the level of available information.

This study focused on three DR modelling frameworks, utilising *Virtual battery* properties to model load-shifting.The *Kleinhans* method, *Morales* method, and the newly proposed *Wasserstein* method. The results indicated that the *Kleinhans* method did not adequately ensure timely recovery, making it unsuitable for accurate DR modelling in large-scale ESOMs. Its inability to account for load recovery for realistic timeframes resulted in long-duration load shifts.

On the other hand, the *Morales* method, specifically the linear programming (LP) variant, offered a robust approach to DR modelling with a good balance between accuracy and computational feasibility. Although it could not guarantee load recovery in all instances, it was found to be viable for large-scale ESOMs due to its enhanced computational efficiency compared to the MIP formulation.

The *Wasserstein* method emerged as a promising top-down approach, effectively ensuring load recovery within realistic timeframes and demonstrating favourable computational tractability. This method's ability to incorporate all DR without requiring extensive additional information makes it suitable for aggregate DR modelling in large-scale ESOMs.

Given these insights, the selection of the top-down Wasserstein framework was considered valid and most suitable for providing top-level insights without delving into the remuneration and willingness-to-pay likelihood of possible Dutch actors. For energy system modellers looking into the impact of specific processes on a network scale, the Morales LP framework would be valid and suitable based on the same three practices listed above.
In order to create more insights into the validity and use cases of DR modelling frameworks, this thesis provides guidance to energy system modellers through prosing a suitability table given in 3.2. Here, multiple virtual battery frameworks are compared based on their properties, applicability and suitability, thus offering a valuable overview.

Importantly, the method of verifying the DR frameworks employed in this research leaned heavily on testing the methods on the criteria of saturation, load recovery, and aggregation, in the context of virtual batteries. These were highlighted as dimensions in which structural uncertainty could be explored without intensive research in DR-specific technologies. It should, however, be considered that other bottom-up and top-down frameworks exist to test these criteria. One interesting approach for a top-down method was proposed by Schledorn et al. [92]. This research assesses a soft-linking framework named Frigg, which uses a demand response function to model end-consumer behaviour and then soft-links this with an energy system model, using the post-response demand as input to the model. This approach is fundamentally different from our approach.

8.2. Value of load-shifting

This research was designed to provide insights into the future of the Netherlands' flexibility landscape. In order to arrive at a valid insight for this matter, the main research question was phrased as follows: *Exploring the value of Demand Response (DR)/Load-shifting as a flexibility solution for a cost-optimal power grid: A research case for the Dutch power grid in 2035 through analysis of possible scenarios.*

Assigning value to load-shifting was done in two distinct ways: Firstly, at a detailed network level, the value of load-shifting was found to mitigate the need for large capital investments, especially in Li-ion 4h batteries. In addition to this insight, the introduction of DR facilitated more capacity of RES in the Netherlands. Furthermore, the introduction of load-shifting into the network-enabled a lower system cost.

In reality, the economic value of flexibility options is more complex than is taken into account by a cost-minimisation. A cost minimisation considers simply the sum of investment costs and operational expenses. Comparing their economic value outside the created model space requires more insights

into the current flexibility landscape and how flexibility offers value in electricity markets. Without perfect foresight present in the optimisation formulation, availability, quick reaction, and dispatch ability play a crucial role in valuable flexibility assets, which is not taken into account for this study. The inclusion of a separate financial network is an ongoing field of study and will be further discussed in the future research section 8.4.
Secondly, this thesis aims to aid decision-makers by not only showing the network effects of DR but also how it impacts the robustness of an investment choice. That is, the value of load-shifting is tested in a decision-making context for investment planning. Through cross-testing multiple cost-optimal network configurations, this study found that on a system level, deciding on the implicitly flexible system diminishes the regret with respect to the system which opted for investing in explicit flexibility assets
While this sensitivity showed interesting results that further give insight into decision-making, an important consequence of decision-making based on MiniMax regret principles is the high sensitivity to the chosen set of scenarios. For this analysis, it was purposefully chosen to exclude an extreme weather scenario. The inclusion of an extreme year could, therefore, drastically change results, as will be discussed in 8.4.

The value of load-shifting was primarily assessed based on its economic benefits, mainly due to the nature of the optimisation problem: cost minimisation. However, a more comprehensive valuation of demand response and other flexibility assets might yield a different outcome. If the analysis was extended to account for reduced material use, CO_2 footprint, or other social welfare properties, it can be argued that DR can offer additional value for a future energy system.

8.3. Model approach & Methodology

This section will further evaluate the model approach and its consequences for top-level conclusions. In chapter 4, core model pillars were devised, and the implications of the model choices for important factors will be further discussed in this section

8.3.1. Uncertainty

Uncertainty was considered at structural and parametric level in this study. As discussed in section 3.2.2, the parametric uncertainty of the applied model relates to the uncertainty of the input data for the ESOM. To account for parametric uncertainty, additional verification was conducted into the economic input parameters. While out of the scope of this study, the results from the model presented would have benefited significantly from adding more sensitivity analyses for the input data used. Through analysing a larger set of inputs, the eventual outcome of the cost-minimisation can prove more valuable for decision makers because of the increased level of uncertainty accounted for. Additional cost projections and discount rates for used network components or different projections of technical parameters would contribute to a more robust conclusion. Furthermore, the regret is the result of the parametric uncertainty considered in the model. That is, important risks might be missed since parametric uncertainty for future cost evolutions, demand and weather patterns are not included. Conversely, if very wide sets of parametric uncertainty were to be included, more conservative regret decisions could be expected, potentially changing the results. This is further elaborated in section 8.4.

Structural uncertainty for the load-shifting mechanism was identified as a research gap in the current field of ESOM and has a central role in this study. Through a thorough verification, best practices for energy system modellers were established by presenting a table 3.2, and C.1. Additionally, 3 alternative weather scenarios were presented to increase the robustness and validity of the results.

Additional structural uncertainties, however, remain in the model. The most crucial structural uncertainty that is unaddressed is an exploration of the near-optimal space through *Modeling-to-Generate-Alternatives* (MGA). The presented model would have benefited in validity had this method been explored, as discussed in section 8.4.

8.3.2. Transparency

Transparency and traceability are essential pillars in conducting energy system optimisation studies. In this research, transparency and reproducibility are communicated through listing data sources, frameworks, and publishing code. Importantly, open-source ESOM infrastructure of *PyPSA* and *PyPSA-eur* was employed, both of which extensive documentation exists.

It should be noted however, that most computational processes were performed on the TU Delft IEPG server, thus computation times might be lower when a local computational set-up is employed. Additionally, all problems were solved using the Gurobi solver. Gurobi is a commercial solver that provides free access to academics. While open-source solvers are available, their performance is not on the same level. All (mean) computational times are given in appendix D.

8.4. Future research

Exploration of Near-optimal space

More in-depth research should be done on how DR affects the system's 'must-haves' and 'nice-to-haves' to debate the impact of DR on the configuration accurately. For this, MGA is a widely used, valuable tool to diminish structural uncertainty and strengthen the actual indicative results of the ESOM [58] [61]. To achieve the most complete uncertainty analysis, exploration of the near-optimal space should be combined with global sensitivity sweeps to account for parametric uncertainty, as demonstrated in studies by Neumann and Brown [64].

Focusing on DR frameworks, including DR parameters such as the willingness-to-pay, flexibility share, or bandwidth in such sensitivity analyses is essential for more in-depth insights into top-level DR impact.

Increasing detail in LP DR framework

DR appliance-specific dynamics such as seasonality, dynamic pricing, and dynamic flexible bandwidth could be accounted for. Linear approximations of non-linear properties, like temperature dependence, could also be explored. Furthermore, research into the symmetry of demand response is important. As Oconnell et al. [32] pointed out, different DR actors tend to respond differently to price changes. Price decreases might not incentivize certain actors and only respond to increases, or vice versa.

Separate market optimisation

In the model presented in this study, the underlying economics result from meeting nodal bus balances, operational costs, and capital investment costs per technology. However, a more detailed representation of actual markets and remuneration programs could improve the overall quality of the ESOM, as well as insightful comparisons such as implicit versus explicit flexibility benefits, as presented in this study.

An interesting future research direction could, therefore, be a separate market optimisation. Instead of using the optimal dispatch as a result of the cost-optimal solution, a market-clearing optimisation could be performed. This is much like the actual Day-ahead markets, such as the *EPEX* spot market. All demand and production are collected per bidding zone per hour. Next, through the merit order marginal costs per producer, the market clearing is determined. It should be noted that market optimisations like these do not include Power Purchase Agreements (PPAs) or other long-term contracts. *W+B* recently showed a useful approach to such an additional financial market optimisation.

The proposed strategy by *W+B*, as well as the current financial 'market' in the model, including representation of the flexibility market, remains a future challenge. Mainly because the timescale of these markets is smaller than 1 hour, and they are the direct result of non-perfect foresight. This leads to an underestimation of the potential revenue streams and functionality of flexibility assets.

Information gap in DR participation

One of the main inhibitors for modellers is the lack of transparency in the willingness-to-pay of potential DR actors. Consequently, most DR explorations in ESOM now only model how DR *could* contribute to a future energy system, rather than how it will. Additionally, the rollout and cost of DR-related hardware remain unclear. Different sectors would need to be involved at various levels of hardware and IT services implementation, further complicating the assessment of DR potential and its associated costs.

Expanding sensitivity analysis to MiniMax regret

More research into the choice of weather scenarios, since these ultimately decide the outcome. For example, to be most robust would be to test and compare both configurations for extreme weather scenarios, low-demand/high-demand and high renewable years.
This method is also limited to a sensitivity analysis of regret, rather than a true minimisation of maximum regret, as highlighted in section 5.2.2. That is, the current approach does not consider the entire model space of decision variables and optimises for the cost-optimal configuration, resulting in the least amount of regret for the given weather scenarios. This could be a future step in providing robust investment planning decisions. Therefore, for future research, a more extensive exploration of the regret between the two system choices is desirable to validate the results shown here.

9 Conclusion

This thesis presents an assessment of load-shifting frameworks suitable for large-scale energy system optimisation and proposes a novel load-shifting framework. Additionally, an energy system optimisation study is presented, optimising the Dutch power grid in 2035 and providing insights into the effect of load-shifting on power grid dynamics. Furthermore, the effect of load-shifting properties on power grid configuration was examined in decision-making analysis to ensure valuable insight for investment planning. This contributes to filling the gap in the current understanding of suitable frameworks for load-shifting, as well as providing insights into possible power grid flexibility outlooks.

Considering the research question: *Exploring the value of Load-shifting Demand Response as a flexibility solution for a cost-optimal power grid*, three main conclusions can be drawn.

Firstly, when implementing load-shifting actions into large-scale Energy System Optimisation Models, energy modellers are tasked with selecting a valid methodology to gain accurate network insights. Virtual battery frameworks are often used to model load-shifting effects. This thesis found that such virtual battery frameworks are susceptible to modelling assumptions and simplifications, thereby failing to account for core load-shifting effects accurately. The novel Wasserstein approach was proven to be a valid and easily applicable modelling framework for energy modellers aiming for top-level insights into load-shifting network effects. The model proved to be accurate in representing the saturation of available load-shifting, as well as the timely recovery of shifted load. Also, since the approach is a top-down method, it does not require extensive information and process-specific constraints to portray the load-shifting effects at a top level.

Secondly, with selecting a suitable modelling framework, key insights were obtained from the energy system optimisation study for the selected research case. For a fossil-free power grid in the Netherlands, load-shifting can create significant value for the power grid by adding extra flexibility. This results in lower overall system costs for the total geographical scope, and requires less investment in other flexibility assets suitable for providing such flexibility, especially battery energy storage systems. It should be stressed, however, that controllable flexibility assets such as fossil-free power plants still play a significant role in the cost-optimal network because of their ability to accommodate peaks in demand. Furthermore, the cost-optimal configuration enabled more penetration of renewable energy resources, resulting in increased capacity of offshore wind in the Netherlands.

Thirdly, another key research area was to gain insight into load-shifting and its impact on decision-making. For this, optimal power grid configurations were tested for different weather and demand scenarios, including and excluding load-shifting. It was found that network configurations including demand response, resulted in fewer additional costs due to weather and demand sensitivity. This insight is valuable for decision-making in investment and energy planning since it reveals that investment in explicit flexibility services is neither more economical nor more risk-averse. Therefore, this research contributes to the highlighted research gap, aiming to provide clearer pathways into how the flexibility landscape of the Netherlands should be organised to ensure an economical and reliable future power system.

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A

Network Component costs

Generators	FOM [%/year]	VOM [eu/MWh]	investment [EUR/kWel]	lifetime [years]	efficiency	Reference
Biomass	45.3		2338	30	0.468	[93]
Onshore wind	12.0	1.37	1100	30		[94]
Offshore wind	2.25	0.02	1622	40		[94]
Nuclear	1.27	3.55	8600	60	0.33	[95]
Solar	1.99	0.01	450	25		[94]
Run of River	2		3412	80	0.9	[93]
Hydropower	1		2450	80	0.9	[93]
Load-shedding		10^5				[87]
H_2 CCGT retrofit	1.785	15.8	182	25	0.59	[22][94] [96]
H_2 CCGT (new)	1.785	15.8	875	25	0.59	[22] [94]
H_2 OCGT (new)	1.785	19.3	450	25	0.42	[22] [94]

Table A.1: Included generators in the model, along with their technical and economical parameters.

Energy infrastructure	FOM	investment [EUR/MW/km]	lifetime	Reference
Pipelines & cables				
H2 pipeline	3	225	50	[97] [98]
HVAC	2	1160	45	[99]
HVDC submarine	0.35	3000	45	[100] [101] [102]
HVDC overhead	2	3800	45	[94]
Other				
HVDC inverter pair	2	1000000 (EUR/MW)	45	

Table A.2: Infrastructure components included in the model.

	This study and *W+B*[22]	DEA 2023 (2030) [27]	ESGC 2022 (2030) [103]	ENTEC (2030) [104]
PHS				
CAPEX [eu / kWh]	2274.8	4250	2207	470
FOM [%/kW y]	0.01	0.01	0.007	0.06
RTE	75.00%	75.00%	80.00%	0.7-0.85
lifetime	80	50	60	50-100
Li-ion storage				
CAPEX storage [eu/kWh]	125	150	270 - 400	150 - 350
CAPEX bicharger [eu/kW]	178	170	-	-
FOM [%/kW yr]	0.42%	0.62%	-	1%
RTE	0.88	0.92	0.85	0.85-0.89
Lifetime [years]	15	25	16	10-20
Flow battery storage				
CAPEX storage [eu/kWh]	168	290	304.713	370
CAPEX bicharger [eu/kW]	160	350	-	-
FOM [%/kW yr]	1.7648	2	4	1-2
RTE	0.7	0.78	0.65	0.7-0.85
Lifetime [years]	30	20	12	10-25
Mechanical storage				
CAPEX storage [eu/kWh]	50	92	45	112 - 450
CAPEX bicharger [eu/kW]	1500	957	-	-
FOM [%/kW yr]	1.1115	-	-	1
RTE	0.6	0.65	0.52	0.54 - 0.7
Lifetime	60	40	60	25 - 60
H_2 salt cavern			H2 underground system	
CAPEX [eu/kWh]	2.1	2.1	1083	2979
FOM [%/kW yr]	0	0		
RTE	1	0.99	0.31	0.2 - 0.4
Lifetime [years]	100	100	30	5 - 30
H_2 electrolyser				
CAPEX [eu/kW]	550	650		
FOM [%/kW yr]	0.04	0.02		
RTE	0.6217	0.705		
Lifetime [years]	25	25		
H_2 Fuel Cell				
CAPEX [eu/kW]	1164.04	1169.71		
FOM [%/kW yr]	0.05	0.05		
RTE	0.5	0.5		
Lifetime [years]	10	10		

Table A.3: Flexiblity solutions included, along with a additional research into the validity of the costs

B

McCormick envelope

In addition to the relaxation of the complimentarity variable, this thesis explores an alternative approach. Instead of introducing complementarity constraint δ, the objective function is made bilinear, converting the problem to be Non-linear, instead of MILP: Add another subscript j to denote that variables exist per time and per node (for all equations for that matter)

$$\text{min} C^{system} = \sum_t C_t^C + \sum_t C_t^O + \sum_t w_t C^M \tag{B.1}$$

$$w_t = d_t^+ d_t^- \tag{B.2}$$

The minimisation of wt ensures the simultaneous cycling of upward and downward cycling to be small, enforcing a similar type of logic as the complementarity constraint. For NLP's, McCormick envelopes are a widely used method for convex relaxation of bilinear terms in optimisation. First introduced by NAME McCormick, the relaxation provides a way to linearise non- convex bilinear constraints, allowing the problem to be solved using linear programming techniques. The logic essentially establishes concave over-estimators, and convex under-estimators for the NLP problem, approaching the optimum [105].
he addition of the McCormick envelope yields the following additional constraints[71]. For the under-estimators: inconsistent with subscripts...
The under-estimators of the function are represented by:

$$w_{j,t} \geq d_{j,t}^{+L} d_{j,t}^{-} + d_{j,t}^{+} d_{j,t}^{-L} - d_{j,t}^{+L} d_{j,t}^{-L} \tag{B.3}$$

$$w_{j,t} \geq d_{j,t}^{+U} d_{j,t}^{-} + d_{j,t}^{+} d_{j,t}^{-U} - d_{j,t}^{+U} d_{j,t}^{-U} \tag{B.4}$$

The over-estimators of the function are represented by:

$$w_{j,t} \leq d_{j,t}^{+U} d_{j,t}^{-} + d_{j,t}^{+} d_{j,t}^{-L} - d_{j,t}^{+U} d_{j,t}^{-L} \tag{B.5}$$

$$w_{j,t} \leq d_{j,t}^{+} d_{j,t}^{-U} + d_{j,t}^{+L} d_{j,t}^{-} - d_{j,t}^{+L} d_{j,t}^{-U} \tag{B.6}$$

Here, the $d_{j,t}^{+U/L}$ stand for the upper and lower bounds of the variable. Within the context of the bottom-up framework, these can be substituted with maximum discharging/charging capacities for the virtual battery in the framework.Now, the variable $w_{j,t}$ can be created, along with the above set of estimator

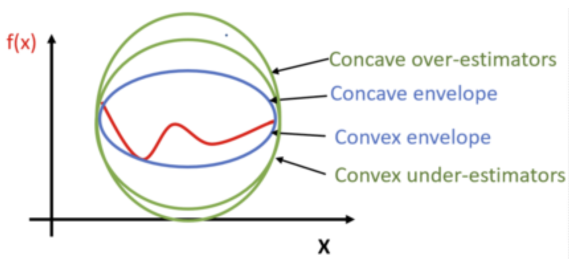

Figure B.1: McCormick envelope [105] constraints. If this variable is then added along with a penalty cost, a new, LP, objective function is found:

$$\text{min} C^{system} = \sum_{j,t} C^{C}_{j,t} + \sum_{j,t} C^{O}_{j,t} + P^{McC} \sum_{j,t} w_{j,t} \tag{B.7}$$

After further consideration, this method was deemed ineffective due to the formulation of the relaxation. This made this method unsuitable for further assessment. This method proved ineffective due to fundamental issues with the relaxation formulation, particularly in handling the non-linear relationship $w_t = d^+_t d^-_t$. The core challenge lies in attempting to linearise the constraint $xy = 0$, which presents several significant limitations when using McCormick linearisation. First, the equation $xy = 0$ creates a nonconvex feasible set that consists of two separate, disjoint convex regions.

Second, while McCormick linearisation is effective for rectangular domains, it struggles to accurately represent the disconnected nature of solutions where either x or y must be zero.

Finally, and perhaps most critically, the relaxation produces an outer approximation that is insufficiently tight, allowing solutions where both x and y can be non-zero. This violates the fundamental requirement of the original constraint and leads to solutions that, while mathematically valid within the relaxed formulation, are not feasible for the original problem.

C

Suitability matrix mapped per aggregation

DR characteristics and model requirements				Suitable formulation			
				Network scope and time-scale			
DR detail	**Aggregation of DR**	**Timely recovery**	**System flexibility role**	**Small & operational**	**mid-scope**	**Planning - (ESOMs)**	**Virtual battery suitability**
1 DR mechanism (e.g. Electric Vehicle)	disaggregated (Homogeneous)	Within time frame	equals recovery time	MINLP, NLP, MIP	MIP, LP	LP	Prone to over-simplification
Set of homogeneous DR actors	appliance aggregated (Homogeneous)	Within time frame	equals recovery time	MINLP, NLP, MIP	MIP, LP	LP	MIP/LP Morales
Economic entity	Aggregation of appliances (Heterogeneous)	x	short-mid term	LP	LP	LP	**Morales LP relaxation**/Wasserstein
Sector aggregated	sector aggregated (Heterogeneous)	x	short-mid term	LP	LP	LP	**Wasserstein VB**
DR top level aggregated	aggregated (Heterogeneous)	x	short-mid term	LP	LP	LP	**Wasserstein Top-down VB**

Table C.1: Blue cells correspond to homogeneous aggregation, red correspond to heterogeneous aggregation, green corresponds to DR relevant for this study, and the dotted line correspond to large-scale ESOMs

D

Computation times & solver settings

D.1. MIP Gurobi settings

```
n.optimize.solve_model(solver_name='gurobi', solver_options={
    'BarHomogeneous': 1,
    'crossover' : 0,
    'MIPGap' : 0.0003})
```

D.2. LP Gurobi settings

default pypsa-eur

```
    n.optimize.solve_model(solver_name='gurobi', solver_options={
        'method' : 2,
        'crossover' : 0,
        'BarConvTol' : 1e-6,
        'Seed': 123,
        'AggFill': 0,
        'PreDual': 0})
```

E

Additional sensitivities

		System details		NL System	
		Annualised cost (CAPEX+OPEX) [$e10^9$]	Total demand [TWh]	Annualised cost (CAPEX+OPEX) [$e10^9$]	Total demand [TWh]
NO DR	2011	107.192	2631.1566	9.164	170.930
	2012	116.519	2702.2765	10.492	170.930
	2013	115.662	2555.5	10.701	170.930
	2014	112.89	2696.8214	10.446	170.930
DR	2011	103.6445	2631.1566	10.139	170.930
	2012	113.2618	2702.276	12.048	170.930
	2013	112.419	2555.5	12.424	170.930
	2014	109.48	2696.8214	12.374	170.930

Table E.1: System details and NL System details: total system demand fixed for every year

While the results for this case also show how systems including DR generally have lower costs, the lowest maximum regret was found for a system without DR. This is different than the system stated in section 7.2. This discrepancy highlights the fact that the solutions are similar in robustness. It must be noted that since the demand of the optimised system is not kept consistent, the comparative analysis is a bit more cumbersome. A more comprehensive study, which could optimise for minimax regret, could yield interesting insights into the interplay between implicit and explicit flexibility investment decision-making.

		Regret costs **system**				
		2011	2012	2013	2014	Max.
NO DR	2011	0.00	22.12	23.68	15.81	23.68
	2012	6.5132	0.00	8.29	3.87	**8.29**
	2013	6.4796	20.37	0.00	35.16	35.16
	2014	2.9640	15.23	17.74	0.00	17.74
DR	2011	0.00	21.60	23.91	10.97	23.91
	2012	6.5829	0.00	8.41	4.41	8.41
	2013	7.3751	12.24	0.00	22.85	22.85
	2014	2.7558	14.60	17.04	0.00	17.04

Table E.2: System regret: total system demand fixed for every year

		Regret costs **NL**				
		2011	2012	2013	2014	Max.
NO DR	2011	0.00	5.92	-0.48	1.38	5.92
	2012	0.92	0.00	-0.40	-0.19	**0.92**
	2013	1.70	5.05	0.00	16.46	16.46
	2014	1.22	4.47	0.18	0.00	4.47
DR	2011	0.00	2.91	-0.81	-0.33	2.91
	2012	1.58	0.00	-0.32	-0.42	1.58
	2013	2.26	3.05	0.00	2.86	3.05
	2014	2.09	3.64	0.39	0.00	3.64

Table E.3: System regret: total system demand fixed for every year

E.1. System cost sensitivity 2013

In order to assess the **endogenous** parameters of the created model, another sensitivity can reveal the impact of DR This will be done by conducting a sensitivity analysis on two of the most important characteristics assigned to the DR operation: **Inconvenience costs (willingness-to-pay)**, and the **flexible share**.

Figures E.1, show how the system objective functions differs per increasing/decreasing flexible bandwidth α, and increasing decreasing Cost tier.

E.1.1. System cost sensitivities

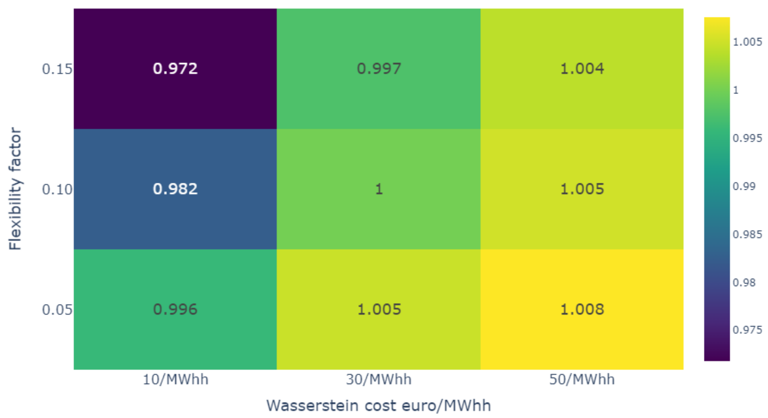

Figure E.1: Sensitivity of system cost to flexible bandwidth parameter (α) and Cost tier

Also, this procedure is repeated for the *Kleinhans* method

Figure E.2: Caption

The results show the standardised results in system cost, in reference to cost tier 3: 30 eu/ MWhh. From the above heatmaps, it becomes clear that the *Kleinhans* method is more susceptible to display larger changes in system costs due to changing network effects. This shows, that large-scale systems employing *Kleinhans* methodology thus are expected to find larger differences in system configuration, resulting in volatile results.

E.1.2. time-variant flexiblity

For this sensitivity, a timely dependent flexible share was tested. Considering results from [67], who pointed out that DR is less elastic at daytime hours and workdays.

	hours between 08:00 - 20:00	flex hours on working days (mon-fri)	other hours	mean flex over year
Rigid	0.1	0.1	0.1	0.1
Variable	0.104	0.135	0.080	0.1

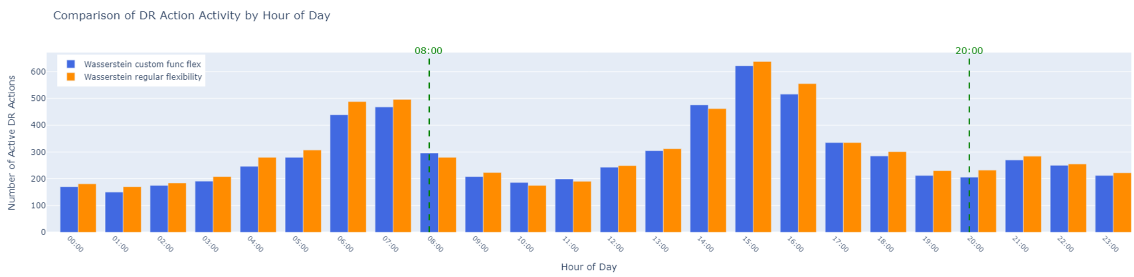

Figure E.3: Cost = 25 eu / MWhh

This figure shows that the reduced flexible share in night/morning hours effectively results in less flexible demand usage without the right price incentives.

F

Additional structures tight relaxation Morales

	Disaggregated, J=3 c_1 [€/MWh]			Aggregated c_2 [€/MWhh]
	Industrial	Tertiary	Residential	
Δt	12	6	2	
T	24	12	4	
ϵ	23	11	3	
Cost Tier 1	60	30	10	10
Cost Tier 2	120	60	20	20
Cost Tier 3	180	90	30	30
Cost Tier 4	240	120	40	40
Cost Tier 5	300	150	50	50

Table F.1: Standard cost parameters

F.1. Decreased cost difference

	Disaggregated, J=3 c_1 [€/MWh]		
	Industrial	Tertiary	Residential
Δt	12	6	2
T	24	12	4
Cost Tier X	**100**	**80**	**60**

Table F.2: Smaller cost difference per virtual battery

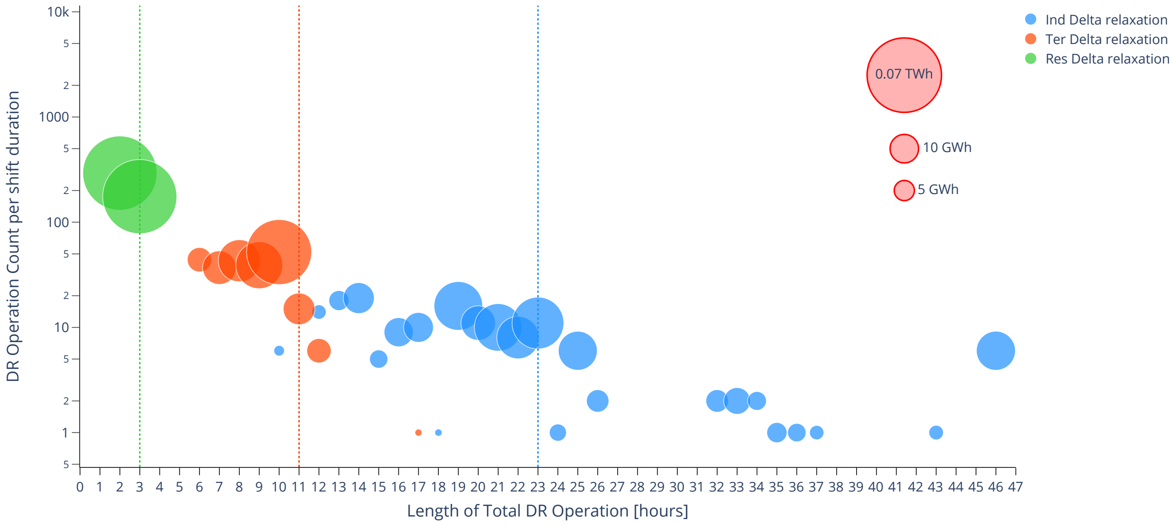

Figure F.1: Smaller cost difference per virtual battery

From figure F.1, clearly a larger share of energy is shifted in primarily the industry sector. This figure shows the ability of the bottom-up *Morales* framework to also account for different types of load-shifting processes.

F.2. Equal costs per virtual battery

	Disaggregated, J=3 c_1 [€/MWh]		
	Industrial	Tertiary	Residential
Δt	12	6	2
T	24	12	4
Cost Tier Y	**50**	**50**	**50**

Table F.3: Equal cost per virtual battery

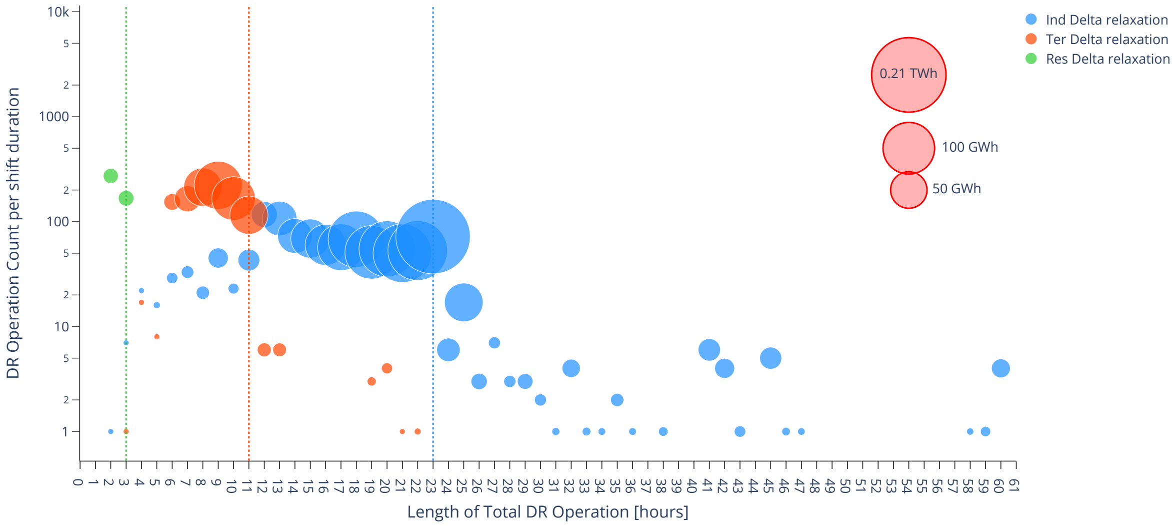

Figure F.2: Equal cost per virtual battery

For the equal cost framework shown in figure F.2. Since all virtual batteries have the same costs, most shifts for the industrial batteries make sense. Interestingly, however, timeshifts also occur for other virtual batteries.

F.3. Decreased timeframe difference

	Disaggregated, J=3 c_1 [€/MWh]		
	Industrial	Tertiary	Residential
Δt^Z	8	6	4
T^Z	16	12	8
Cost Tier 2	120	60	20

Table F.4: Different ratio in recovery times

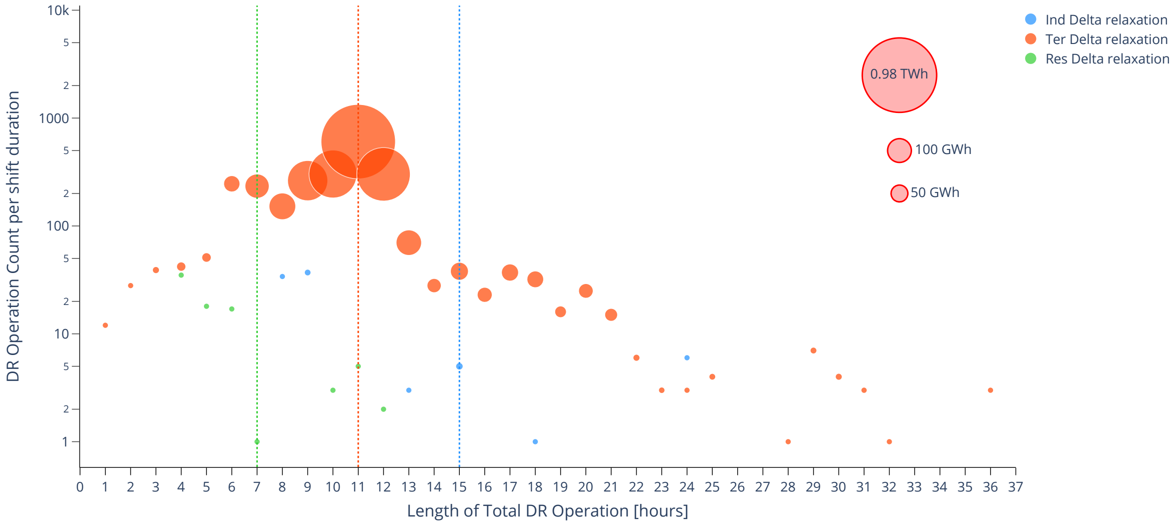

Figure F.3: Caption

From this figure, the load-shifting action is almost exclusively centred around shifts in the 11-hour range. This highlights, how the tight relaxation bottom-up *Morales* method is able to model DR processes with time-specific properties. IT should once again be noted, however, that there is still a significant amount of undue load recovery happening. Interestingly, the model does not use the industrial virtual battery for time durations over 11 hours.