

The Right Flex in the Right Place

Optimising the Spatial Distribution of Flexibility
in a Distribution Grid in 2050

SEN2331: CoSEM Master Thesis

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Master Thesis

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Project Duration:	December 2025 – May 2026
Faculty:	Technology, Policy and Management, Delft University of Technology

To be defended publicly on 6 May 2026

Cover: [1]

Preface

A year ago I started looking for a thesis topic. I knew I wanted something that would genuinely excite me, something I would not mind spending six months on. After searching around, I ended up at Francesco's office, who happened to have exactly that kind of project waiting: a collaboration with Stedin, combining modelling with real-world impact. It felt like the right fit from the start.

What I did not expect was how much I would enjoy it. Day after day, building a model, chasing results, and slowly turning it all into a coherent story. Six months later, I find energy transition more fascinating than ever, I am proud to call this my thesis.

None of this happened by itself. Francesco Lombardi, thank you for your inspiring way of supervising and for the genuine passion you bring to your work, it is contagious. Tim Alders, thank you for being there week after week with enthusiasm and a sharp eye, pushing this work to the level it is at now. Jafar Rezaei, thank you for offering a different perspective on the subject and helping me see energy modelling through a new lens.

I also want to thank Stedin and everyone I got to work with there. The depth of knowledge in that organisation is remarkable, and what struck me most was how openly people shared it, from quick coffee chats to being pointed in exactly the right direction at exactly the right moment. It made a real difference. The same goes for my fellow interns and students, who made what is an individual project feel like a shared one.

Beyond the hours at the office and at TU Delft, I have been lucky to have wonderful people at home. My parents, who always listen to my stories, and who have given me the confidence to find my own way. My housemates and friends, who kept my spirits up when I needed it most. And Pep, who was always ready to think along with me.

Enjoy reading ;)

*Daphne Piket
Delft, May 2026*

Summary

Electrification and renewable generation are pushing electricity peaks beyond what network expansion alone can accommodate, causing congestion. Expanding the grid to serve every conceivable peak load is costly, spatially constrained, and insufficient given the pace at which demand and supply patterns are changing. For Dutch distribution system operators (DSOs), flexibility technologies such as batteries and hydrogen systems are therefore increasingly recognised as a structural component of network planning. Their effectiveness depends on where they are deployed, because placing flexibility in the wrong location can worsen congestion rather than relieve it.

Planning where flexibility should be deployed requires a model that simultaneously represents regional network constraints and optimises across the broader electricity system. This is challenging to achieve, because more network detail increases computational complexity. National energy system models address this by abstracting from the distribution network detail, optimising flexibility on system-wide costs without capturing local congestion constraints. Bottom-up DSO models identify congestion at individual substations but cannot optimise flexibility across the network as a whole, leaving interactions between substations unresolved. How flexibility technologies can be spatially distributed across a network including High-Voltage (HV) and Medium-Voltage (MV) levels in a way that combines decision-relevant detail with computational tractability in order to generate robust planning insights for DSOs therefore remains unanswered.

This study addresses this gap by developing a spatial linear optimisation model for Stedin, a Dutch DSO, implemented in Calliope. Two model configurations are developed: an HV-only model, and an HV-MV model that extends this by incorporating MV topology. Both determine the cost-effective spatial distribution of flexibility technologies and grid expansions across Stedin's service area towards 2050. Computational feasibility is achieved by letting the planning purpose govern every modelling decision: MV topology is preserved while constraints irrelevant to long-term planning, such as voltage constraints, are excluded. The service area is divided into three provincial sub-models to keep each optimisation tractable. Planning insights are assessed along three dimensions of robustness: parametric robustness through scenario analysis varying technology costs, structural robustness through near-optimal solution space exploration using Modelling to Generate Alternatives (MGA), generating 113 configurations of near-equal cost, and attributed structural robustness by linking robust outcomes to specific network properties through statistical testing.

The first finding demonstrates that HV-level detail alone is insufficient for spatial flexibility planning. In the HV model, flexibility concentrates at high-voltage substations because MV demand is aggregated there, not because congestion occurs there. Once MV topology is included, flexibility shifts down to where network bottlenecks actually lie. A complementary finding is that a screening index derived from cost parameters and load forecasts identifies economically justified expansion candidates without requiring a full optimisation.

Parametric robustness analysis shows that flexibility locations remain stable across cost scenarios while the technologies deployed at those locations shift, making location decisions more robust than technology decisions under parametric uncertainty.

Structural robustness analysis reveals that not all parametrically robust locations are equally robust across the near-optimal solution space. Some attract flexibility only under specific cost assumptions, but the system can achieve similar costs by placing flexibility elsewhere. Others are not optional, where a substation cannot be expanded and existing capacity is insufficient, local flexibility is the only viable response regardless of cost. Where demand also persistently exceeds capacity, even the technology type becomes fixed. For grid expansion, the index ranks connections by how economically justified their expansion is relative to flexibility, and links with high index values are expanded consistently across configurations.

Modelling congestion at the network level where it actually occurs, while maintaining computational tractability, allows the location of flexibility and grid expansion to be determined from network structure rather than cost assumptions alone, providing robust spatial planning guidance for DSOs under long-term uncertainty.

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Introduction

1.1. Problem introduction

The Dutch energy system is undergoing major changes on the path towards climate neutrality by 2050. One of the main challenges is that the current grid capacity, particularly in the medium-voltage (MV) network, is not sufficient to support the large-scale electrification and growth in distributed generation required in the coming decades [2]. The increasing reliance on solar and wind power introduces strong fluctuations in energy supply. These variable renewable sources do not always produce electricity when demand is highest, nor necessarily where demand occurs [3, 4]. The combination of rising demand and increasing variability leads to growing grid congestion, situations where the network can no longer safely transport all electricity, and puts pressure on the security of supply [3].

This rising pressure on the electricity system directly affects the regional infrastructure. To accommodate growing peak loads and variability, grid operators face a substantial challenge: the MV network must expand by 35–45%, and the capacity of high-voltage (HV) and medium-voltage (MV) substations must at least double or triple by 2050 [4]. At the same time, fully accommodating all potential supply peaks would be neither technically nor socially desirable. If all theoretical renewable generation were to be absorbed, the Netherlands would require a grid capacity of approximately 120 GW, while the maximum national demand is only 45 to 50 GW. Such a system would be unaffordable and spatially infeasible [5].

Flexibility technologies are therefore a necessary part of the future energy system. They help maintain system balance by spreading peak loads and absorbing periods of low demand, thereby reducing the need for costly and time-consuming grid reinforcements [5, 6]. TenneT therefore advises securing sufficient flexibility and controllable capacity in time to safeguard security of supply [3].

Flexibility cannot be connected arbitrarily across the electricity grid. Its effectiveness depends strongly on where it is deployed. While the importance of flexibility is widely recognised, it is far less clear where it should be deployed and at what capacity [4]. Connecting flexibility without regard to regional network constraints can worsen congestion rather than relieve it. If deployed in the wrong locations, the required capacity at HV/MV substations may increase by up to 75 percent [4]. This distribution question is particularly relevant for Distribution System Operators (DSOs), who are responsible for maintaining a reliable regional electricity grid and must make cost-effective investment trade-offs between flexibility deployment and network expansions [7]. Various modelling approaches address this challenge from different perspectives.

Top-down models, such as the Energy Transition Model (ETM) used in the Integrated Infrastructure Outlook 2030–2050 (II3050), determine how much flexibility is needed at a national level and which technologies should provide it. However, they do not specify where within the electricity grid flexibility should be connected, at which network level, or at what capacity [4]. Because these models rely on national price signals and aggregated regional representations, they lack the spatial resolution needed to represent regional network capacity constraints. Follow-up studies, such as the optimisation model

by Bordignon, allocate flexibility at the level of HV substations, identifying the cost-optimal distributions at the national level but do not assess whether those locations are feasible within the MV network, nor how flexibility should be traded off against network expansions [8].

Bottom-up models used by DSOs, in contrast, focus on identifying local congestion and assessing which substations are likely to become overloaded in the future. However, these models typically evaluate flexibility as a local measure applied at the congested substation itself, without optimising its deployment across the wider MV network [7]. They do not account for energy balance interactions between substations or the possibility that flexibility deployed at alternative locations could provide a more effective or cost-efficient response. As a result, it remains unclear how flexibility should be spatially distributed across the MV network while maintaining overall system balance.

This results in a mismatch: top-down models optimise flexibility at the national level without capturing local HV–MV network constraints, while bottom-up DSO models identify local congestion points but lack a system-wide optimisation across the MV network. Addressing this mismatch is not straightforward. Combining system-wide optimisation with MV network detail significantly increases model complexity, making it computationally infeasible to include all relevant constraints [9]. A third problem adds to this: most energy system models produce a single cost-optimal solution that represents just one of many configurations achieving near-identical costs [10, 11]. Relying on it alone can create a false sense of certainty about which investments are necessary. For a DSO making long-term decisions under policy, technological and economic uncertainty, understanding which locations and technologies remain structurally robust across a range of plausible futures is at least as important as identifying the cheapest outcome. To address all three challenges, this thesis develops a spatial optimisation model for Stedin’s HV–MV network that integrates both system balancing and regional capacity constraints, and assesses the parametric, structural robustness of the resulting planning insights through scenario analysis and exploration of the near-optimal solution space.

1.2. Research questions

These three challenges define the planning problem this thesis addresses. Stedin and TU Delft initiated a joint research effort to investigate how spatial optimisation models can support long-term planning decisions for the distribution of flexibility technologies and grid expansions within the regional electricity network, leading to the following main research question:

How can flexibility technologies be spatially distributed across an HV–MV network in a way that combines decision-relevant detail with computational tractability in order to generate robust planning insights for DSOs?

To answer the main research question, the analysis is divided into four sub-questions:

- SQ1A:** How can a national HV network model be downscaled to a regional HV network representation?
- SQ1B:** How can MV-level network topology and capacity constraints be incorporated into an HV–MV optimisation model in a way that remains suitable for DSO decision-making?
- SQ2:** How does including MV-level network topology to an HV network model affect the cost-optimal spatial distribution of flexibility technologies?
- SQ3A:** How parametrically robust is the cost-optimal distribution of flexibility technologies in an HV–MV network under variations in key scenario assumptions?
- SQ3B:** How structurally robust is the cost-optimal distribution of flexibility technologies in an HV–MV network under near-optimal solutions?

To address these questions, the research is guided by two objectives:

Objective 1: Develop a spatially explicit optimisation model for DSO investment planning.

This objective is addressed by designing an integrated economic optimisation model that incorporates both HV and MV network topology and capacity constraints. The model is built in two stages: first by downscaling an existing national HV model to a regional representation (SQ1A), and then by extending this representation with MV-level network detail (SQ1B). The result is a computationally tractable tool that generates spatially differentiated investment recommendations for flexibility technologies and network expansion across the HV–MV network towards 2050.

Objective 2: Generate robust planning insights by analysing the model's solution space.

This objective is addressed in three ways. First, the spatial distribution of flexibility technologies produced by the HV and HV–MV models is compared to assess the impact of including MV network topology on the cost-optimal system (SQ2). Second, scenario analysis evaluates parametric robustness by testing how changes in key cost assumptions affect the spatial distribution of flexibility technologies (SQ3A). Third, near-optimal solution space exploration using SPORES identifies locations and technologies that remain structurally robust across a wide range of near-optimal solutions, and statistical testing links each robust outcome to the specific network property that drives it (SQ3B). Together, these analyses translate model results into planning-relevant insights for DSOs operating under uncertainty.

1.3. Link to CoSEM master program

This thesis aligns with the Master's programme in Complex Systems Engineering and Management (CoSEM) at Delft University of Technology, within the Energy specialisation. The spatial planning of flexibility technologies and grid expansions in regional electricity networks is not a purely technical problem. The decisions that DSOs face, lie at the intersection of public and private values: Stedin carries a legal obligation to maintain a reliable electricity supply for society, while simultaneously operating under the economic constraint of cost-effective investment. These values do not always point in the same direction, and navigating that tension requires more than technical optimisation alone.

The research reflects this through three components that build on one another. First, informal consultations with Stedin ground the research in planning practice: they directly shape the modelling scope, the choice of network representation, and the decisions about what to include or abstract away. These are not purely technical decisions, as each abstraction carries consequences for how useful the model is to a DSO in practice. Second, the optimisation model forms the technical core of the thesis. Most importantly, it goes beyond producing a single cost-optimal solution. The mathematically optimal configuration may in practice be unreachable due to policy constraints, spatial resistance, or institutional barriers. A near-optimal solution that is actually implementable is then more valuable than a theoretical optimum that is not. Third, expert interviews with an electrotechnical expert, a data expert, and a system strategist serve as verification. They assess whether the modelling choices and outcomes are credible and meaningful from a practical planning perspective.

Together, these components reflect CoSEM's emphasis on developing solutions that are not only technically credible but also decision-relevant, generating insights that are robust under uncertainty and communicable to planners who must make decisions without knowing exactly how the future will unfold.

1.4. Report Outline

The remainder of this report is structured as follows. Chapter 2 provides the theoretical and empirical background for this thesis. It introduces the structure of the Dutch electricity network, the challenge of congestion in distribution networks, and the location-dependent value of flexibility. A review of existing modelling approaches concludes with the key limitations that motivate the modelling choices made in this thesis. Chapter 3 presents the research design and justifies the modelling strategy. It defines the spatial scope, operationalises the research questions into specific analytical steps, and introduces the SPORES method for near-optimal solution space exploration. Chapter 4 describes the mathematical structure of the optimisation model, covering the decision variables, the objective function, and the system constraints. Chapter 5 details the implementation in Calliope, covering the network representation, demand and generation data, technology cost assumptions, and the experimental setup. Chapter 6 presents the findings in sequence: model development, comparison of investment outcomes, scenario

analysis, and near-optimal solution space exploration. Chapter 7 interprets the results, reflects on modelling choices and limitations, and provides implications for DSOs and possible future research directions. Chapter 8 answers the main research question and summarises the key contributions to academic knowledge.

2

Context

This chapter provides the background necessary to understand the planning challenge addressed in this thesis. It begins by introducing the structure of the Dutch electricity network and the role of each voltage level. It then explains how congestion arises in distribution networks and why the value of flexibility is strongly dependent on location. Finally, it reviews existing modelling approaches for the spatial distribution of flexibility technologies and identifies the limitations that motivate the modelling choices made in this thesis.

2.1. Structure of the electricity network

The Dutch electricity grid is organised into three voltage levels: high-voltage (HV), medium-voltage (MV), and low-voltage (LV). Each level has a distinct role in getting electricity from generation to end users [12].

At the highest level, the HV transmission network (110–380 kV) transports large amounts of electricity over long distances between power plants, international connections, and regional substations. This network is operated by TenneT, the Dutch transmission system operator [13]. High voltage is used for long-distance transport because it minimises energy losses. At HV–MV substations, transformers step down the voltage from transmission to distribution level, and electricity enters the regional MV network (10–66 kV). This network is operated by regional DSOs, such as Stedin, and distributes electricity to cities, industrial areas, and local connection points [13]. At the local level, a second transformation at MV–LV substations brings the voltage down to 400 V for delivery to households, businesses, and other small users [13]. Figure 2.1 illustrates this hierarchical structure.

Within the Stedin service area, the distribution network connects to the TenneT transmission system specifically through 150 kV substations fed by the 380 kV grid. This thesis therefore focuses on this interface and the underlying MV network down to 10 kV. Understanding where the network can and cannot handle peak loads at these voltage levels is the starting point for the spatial planning problem this thesis addresses. Other HV levels, such as 110 kV, are not present in the Stedin network and fall outside the scope of this study.

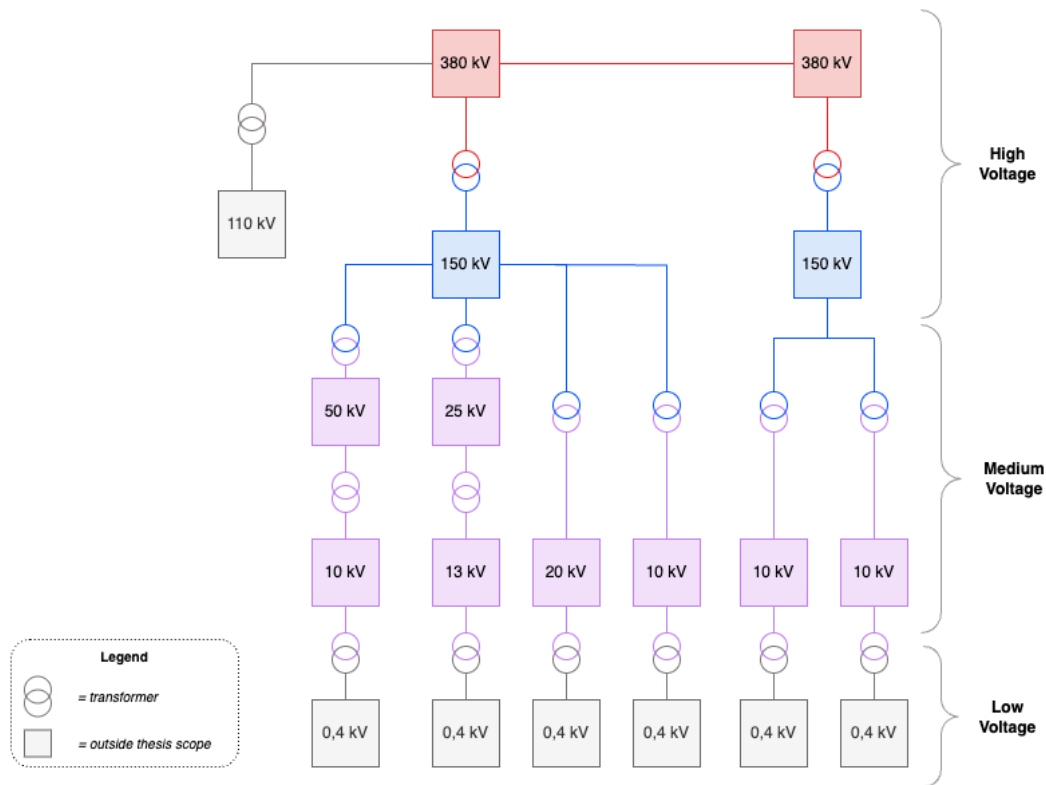


Figure 2.1: Hierarchical structure of the Dutch electricity grid by voltage level.

Transmission and distribution networks also differ in physical structure. The HV network is typically meshed, meaning multiple paths exist between any two points. This ensures that if one component fails, electricity can still flow via an alternative route [13]. The MV network is typically built as a ring but operated radially. Under normal conditions, a switch in the ring is kept open, so power flows in one direction from the substation outward. If a fault occurs, the switch can be closed and the fault isolated, restoring supply via the alternative route. The different structures are shown in Figure 2.2.

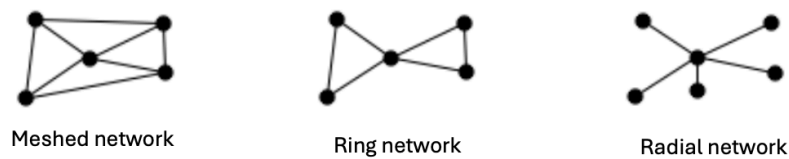


Figure 2.2: Types of network structures [13]

In the Netherlands, the MV network is divided among several regional DSOs, each responsible for operating and developing the distribution grids in a defined service area. One of these is Stedin, which operates the network in large parts of Zuid-Holland, Utrecht, and Zeeland. Figure 2.3 shows the geographic distribution of DSOs across the country.



Figure 2.3: Distribution System Operator in the Netherlands [14]

2.2. Congestion in distribution networks

The capacity of these networks is determined by the substations and the cables that connect them. The key substations are those where electricity is transformed between voltage levels. At HV–MV substations, transformers step down the voltage from the transmission network to the distribution network. Within the MV network, cables connect these substations to lower-level substations where a further transformation takes place [13]. Each transformer has a maximum power rating beyond which it overheats, and each cable is similarly limited in how much current it can carry. When demand or generation at a specific substation or cable exceeds these limits, the network can no longer transport electricity safely. This is called network congestion [15, 16].

Congestion is becoming an increasingly urgent problem. The electrification of heating, transport, and industry is driving up electricity demand, while the rapid growth of solar and wind generation makes supply more variable and weather-dependent [15]. Importantly, demand and generation follow different patterns throughout the day. Electricity demand peaks at predictable moments, such as mornings and evenings, while renewable generation depends on weather conditions and may peak at different times of the day. At some moments high demand combines with little solar or wind output, while at others large amounts of renewable generation meet low demand [17]. Both situations can create sharp and temporary peaks in network loading [17]. Figure 2.4 illustrates how different electricity uses, like household demand, electric vehicle charging, and solar generation combine into an aggregated load profile with such peaks.

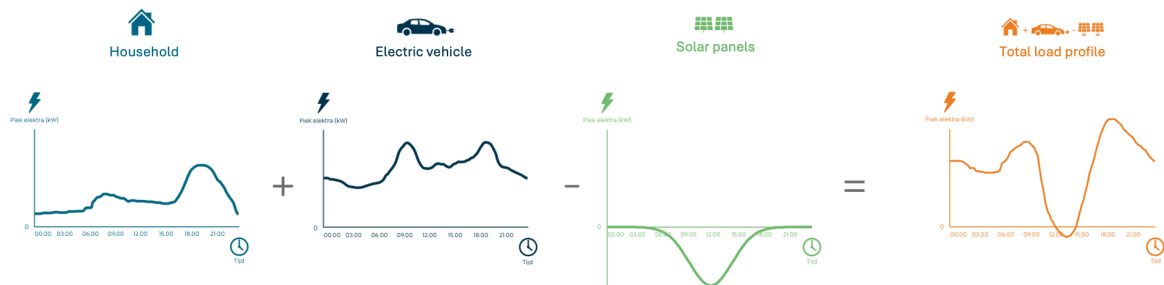


Figure 2.4: Aggregated electricity load profile [18]

When these peak loads exceed the technical limits of a network component and congestion occurs and

action is required [15]; traditionally, this means reinforcing or expanding the grid. But because these peaks are temporary, they can also be managed by shifting when electricity is consumed, stored, or produced. Technologies that enable this such as batteries, demand-side flexibility, and power-to-hydrogen systems are referred to as flexibility technologies. However, the effectiveness of these technologies depends strongly on where in the network they are deployed.

2.3. Location dependent value of flexibility

The literature shows that flexibility in the electricity system fulfils two functions, each with its own value dynamics [19][16]. For system balancing, flexibility helps align national supply and demand. In this role, the location of the flexibility technologies is less important. Its value is mainly determined by temporal variation, system price signals, and technological characteristics [16].

For congestion management, the opposite applies: the value of flexibility is highly location-dependent [19]. The more precise the location information, the more targeted the mitigation [19]. The effectiveness of flexibility is therefore directly linked to whether it is deployed at locations where its activation can relieve the capacity constraints at the congestion point [20]. Deploying flexibility based solely on system-balancing signals can even worsen the congestion. When these signals reflect national supply and demand without accounting for local network conditions, they can unintentionally increase power flows through already congested parts of the network [16].

2.4. Modelling paradigms

A way to determine where flexibility should be deployed is through energy system models. However, many different modelling approaches exist, differing in their objective, the level of network detail they represent, and the type of questions they are designed to answer.

The first widely used approach for analysing future energy systems we will discuss is energy system optimisation modelling. In these models, the energy system is represented as an optimisation problem in which the model determines the most cost-effective combination of technologies and infrastructure needed to meet energy demand while respecting technical and policy constraints [21, 10]. This typically includes both investment decisions, such as how much generation or storage capacity to build, and operational decisions regarding how these technologies are dispatched over time. Such models are used to analyse long-term energy transitions and to explore how changes in technology costs, fuel prices, or policy measures affect the structure of future energy systems. Examples of modelling frameworks used for this purpose include Calliope, PyPSA and Tulipa.

A second modelling paradigm is optimal power flow (OPF) modelling, which focuses on the physical behaviour of electricity networks. OPF models determine the optimal dispatch of generation and other resources while respecting the grid's electrical constraints. These models typically incorporate AC or DC power-flow formulations and explicitly represent network limits, such as line capacities and voltage constraints [22]. As a result, OPF approaches are widely used for operational planning and congestion management studies. Some frameworks, such as PyPSA, can operate across both system optimisation modelling and OPF, depending on the modelling setup chosen.

A third category consists of simulation-based grid models, which analyse network behaviour under pre-defined system configurations. Instead of determining optimal decisions, these models simulate the flows and operational states of the network for a given scenario of generation, demand and flexibility technologies. Network operators commonly use simulation tools to assess potential congestion or voltage violations in detailed network studies. Examples include DigSILENT PowerFactory and OpenDSS [23, 24].

Other modelling approaches, such as agent-based models or heuristic planning tools, are occasionally used to analyse flexibility markets or simplified network planning processes. However, these approaches are less commonly applied to large-scale optimisation of flexibility deployment and are therefore not considered further in this study.

These paradigms are applied at different spatial scales and for different planning purposes, which shapes how they can be used to analyse the spatial distribution of flexibility technologies in electricity networks.

2.5. Modelling approaches for the spatial distribution of flexibility

The modelling paradigms discussed above provide different perspectives on the analysis of electricity systems. In the context of congestion management, however, the key question is not only how flexibility technologies operate within the system, but also where it should be deployed within the network to relieve capacity constraints. Consequently, a growing body of literature examines the spatial distribution of flexibility technologies within electricity networks.

In practice, different modelling paradigms are applied at different spatial scales. Energy system optimisation models are typically used to analyse the deployment of flexibility across transmission networks or national energy systems, with a focus on long-term planning and technology investment. In contrast, optimal power flow and simulation-based grid models are more frequently applied at the distribution level, where detailed network physics and operational constraints play a central role.

As a result, the literature on spatial flexibility deployment can broadly be divided into two strands: transmission-level optimisation studies and distribution-level network studies. The following sections review these modelling approaches in more detail and subsequently examine the current planning methodologies used by DSOs.

2.5.1. Transmission-level flexibility distribution models

In earlier work by Bordignon [8], the open-source framework Calliope was used to develop an optimisation model of the Dutch HV substations. The model included the full HV topology (283 substations and 359 lines at 110380 kV) and optimised the spatial distribution of four different flexibility technologies towards 2050.

The model identifies where and how much flexibility is economically most efficient, considering transmission capacity constraints represented through simplified Net Transfer Capacities (NTC). Using the SPORES methodology, the study generated not only a single cost-optimal distribution but also many near-optimal alternatives, enabling the identification of robust recommendations for the locations of flexibility technologies.

Although the model provides valuable insights at the national, HV level, it has three important limitations. First, it does not represent the MV topology, where most congestion occurs [25, 9]. As a result, optimisation at the HV level may identify locations that appear optimal at the transmission level, while the corresponding solutions cannot be realised within the capacity constraints of the underlying MV network. Second, the model uses a low temporal resolution with four-hour time blocks and covers only half a year, which limits its ability to fully capture both the operational value of short-cyclic flexibility, such as batteries, and seasonal effects. Third, the model assumes a fixed network capacity and includes no options for grid reinforcement or expansion. As a result, it cannot determine whether reinforcing or expanding the grid would be more effective or more cost-effective than deploying flexibility technologies.

Similar insights at the transmission and national scale are provided by other large-scale optimisation models, such as PyPSA-Eur [26], derived national PyPSA models [27, 28], and planning frameworks developed by the European Commission's Joint Research Centre [29]. These models optimise the spatial deployment of generation, storage, and flexible demand across national or European transmission networks, and capture congestion effects using DC power-flow formulations. While they offer spatial resolution at the HV level and valuable insights into the distribution of flexibility, they abstract from the internal topology and capacity constraints of MV distribution networks.

These studies demonstrate how optimisation models can identify cost-effective flexibility deployment at the transmission level. However, because the internal structure of distribution networks is typically abstracted for computational reasons, these models cannot explicitly represent the capacity constraints of MV networks. These models therefore provide spatial resolution at the transmission level, but do not represent the internal topology and capacity constraints of MV distribution networks.

2.5.2. Distribution-level flexibility distribution models

In addition to national and transmission models, research also examines flexibility at the distribution level, particularly within MV networks. These studies typically evaluate flexibility as an alternative to

traditional grid reinforcement and focus on mitigating congestion at individual power lines or substations [30, 31, 32].

To make such analyses computationally tractable, most distribution models use simplified or convexified formulations of power-flow physics, such as SOCP relaxations or linearised AC OPF [33, 34, 35]. These formulations are sufficiently accurate for short-term operational studies at local scale, where constraints are typically limited to a single substation or power line. However, this modelling approach typically results in analyses that focus on isolated bottlenecks rather than the MV network as a whole. Consequently, such studies do not assess how flexibility should be allocated across all MV substations within a DSO service area, nor how interventions at one substation affect power flows and capacity constraints at neighbouring substations [34, 32]. In addition, many studies consider only one type of flexibility, often batteries, leaving potential complementarities or trade-offs between technologies unexamined. [33, 36, 31].

While these approaches provide detailed insights into local congestion management, they are typically not structured to optimise the allocation of flexibility across all substations within a DSO service area simultaneously, analysing isolated network components rather than the spatial distribution of flexibility across the MV network as a whole.

2.5.3. Practical planning models

Stedin also applies a long-term planning process to assess future grid development and determine necessary network reinforcements and expansions themselves [7]. While this process ultimately leads to investment decisions, the focus here is limited to the analytical steps relevant for projecting future grid loading and identifying capacity shortages.

The starting point of Stedin's planning process is the set of nationally coordinated scenarios developed by Netbeheer Nederland (NBNL). These scenarios provide consistent assumptions on demand growth, electrification, decentralised generation and system developments towards 2050. The Koersvaste Middenweg (KM) scenario is used as a reference for estimating future electricity demand, generation growth and regional connection needs. These national scenarios are translated into Stedin-specific projections by incorporating regional characteristics and expected market developments.

Based on these regionalised scenarios, Stedin develops load forecasts for individual substations within its service area. These projections describe expected substation loading in 2050 and form the basis for capacity assessment. Projected loading levels are then compared with the available transformer capacity at the substation level. This analysis is performed using an internal planning model and focuses primarily on transformer constraints. Network interactions among substations, power line capacities, and the explicit MV network topology are not considered in this step. As a result, the assessment identifies individual substations where projected loading exceeds available capacity. The projected loading results are validated by regional grid planners responsible for specific geographic areas. These planners assess the plausibility of forecasts based on local knowledge and recent developments. The validated substation-level analyses are subsequently translated into master plans that describe the required network reinforcements or expansions for each area. These master plans are then bundled into a consolidated investment plan.

Overall, this planning logic is substation-based and reinforcement-oriented. It identifies where transformer capacity is insufficient and designs network expansions accordingly. However, it does not optimise other mitigation measures across substations, nor does it evaluate the spatial distribution of flexibility within the MV network. In response to these limitations, Stedin is developing new tools to improve the assessment of congestion mitigation measures beyond conventional reinforcement. While these tools represent a step towards a broader evaluation of alternatives, they remain primarily focused on congestion at individual substations. They do not yet provide a network-wide optimisation framework that allocates congestion management measures across the grid while accounting for network constraints, national system balance, and interaction effects between substations.

Taken together, the three approaches reviewed above address different aspects of the spatial planning problem. Transmission-level optimisation models determine cost-effective flexibility distributions at the system level but abstract from MV network constraints. Distribution-level models capture local network physics but analyse isolated bottlenecks rather than the network as a whole. Practical plan-

ning tools identify where substation capacity is insufficient but do not optimise flexibility deployment across substations or account for interactions between them. None of the three approaches combines system-wide optimisation with MV network topology in a way that supports DSO investment decisions across the full service area. The following section examines the modelling limitations that explain why this combination has not yet been achieved.

2.6. Limitations of existing modelling approaches

Three limitations recur across the modelling approaches reviewed above and together explain why combining system-wide optimisation with MV network detail remains an open challenge: the computational cost of representing spatial and temporal detail simultaneously, the sensitivity of model outcomes to uncertain input assumptions, and the risk of drawing planning conclusions from a single cost-optimal solution. The following subsections discuss each limitation in turn.

2.6.1. Model simplification and computational tractability

Modelling future energy systems requires balancing sufficient network detail for meaningful insights with computational tractability, ensuring that optimisation problems remain solvable within reasonable computational time and memory requirements. On the one hand, a detailed, physically realistic network representation is needed to identify reliable, implementable solutions [35, 25]. On the other hand, modelling elements such as AC physics, high temporal resolution, and explicit MV and LV topologies create computational limitations that make realistic optimisation problems nearly impossible to solve [35, 9]. This trade-off appears across nearly all modelling approaches, from national and transmission models to distribution models [9, 25].

This need for model detail is especially important for congestion analysis, since congestion occurs at individual substations and power lines rather than at the national scale [25, 9]. With insufficient spatial resolution, models may overlook local congestion bottlenecks or identify flexibility as optimal at the system level, even though it cannot be applied under regional capacity constraints or may create additional congestion [25, 20]. Similarly, temporal resolution is critical for representing short-cyclic flexibility, whose value depends on hourly or sub-hourly dynamics that are lost under strong temporal aggregation.

However, representing this level of spatial and temporal detail significantly increases model complexity and computation time. Jacquier et al. (2025) demonstrate that simulating even a single year using full AC power flow in an HV–MV network model can require many hours of computation [9]. This makes long-term planning studies difficult to perform in practice. Even in models specifically designed to combine HV and MV network detail, simplifications remain necessary: Jacquier et al. (2025) for example rely on DC power flow instead of full AC formulations, represent only a limited number of MV networks, and exclude LV networks entirely. Their approach reflects a broader pattern in the literature, where computational complexity motivates the use of various simplification techniques. Standard techniques include spatial clustering, temporal reduction using representative days [25, 37], and simplified power-flow formulations that neglect losses or reactive power [25, 38]. These simplifications enable large-scale optimisation but introduce new drawbacks. When network capacity constraints are aggregated or ignored, solutions may appear mathematically optimal but could be infeasible within a lower network layer [20, 25]. As a result of these modelling simplifications, system-level balancing and local network capacity constraints are often analysed separately, limiting insight into interactions between transmission and distribution networks [39].

2.6.2. Uncertainty in model assumptions

Energy system models rely on a large number of assumptions about future developments, including technology costs, energy demand, fuel prices, and policy conditions [10]. Because these factors depend on socio-economic, technological, and geopolitical developments, their future values are inherently uncertain. As a result, model outcomes are strongly influenced by the assumptions chosen for these input parameters. The literature commonly distinguishes between parametric and uncertainty. Parametric uncertainty refers to uncertainty in the numerical values of model inputs, such as future electricity prices or technology investment costs. Uncertainty arises from modelling choices and simplifications in the representation of the energy system [40]. While previous sections primar-

ily addressed technical simplifications related to network representation and computational tractability, models also simplify institutional and behavioural aspects of energy systems. Factors such as behavioural responses, regulatory constraints, or stakeholder preferences are often difficult to represent quantitatively and are therefore only partially captured in optimisation models [40, 11].

Despite the importance of these uncertainties, they are often only partially addressed in energy system modelling studies. When uncertainty is explicitly considered, common approaches include sensitivity analysis, Monte Carlo simulations, stochastic optimisation, and robust optimisation. These methods typically explore how variations in input parameters affect model outcomes and therefore mainly address parametric uncertainty. Uncertainty, is harder to address, as it cannot be resolved by varying input parameters alone [40]. Modelling to Generate Alternatives (MGA) can be used to address part of this uncertainty by searching for alternative configurations that may account for objectives that are difficult to capture in the model [11]. Remaining uncertainty can be further reduced by involving practitioners with knowledge of the modelled system [40].

This highlights the importance of critically evaluating and verifying modelling assumptions against practical planning knowledge, particularly when the outcomes of energy system models inform real-world planning decisions.

2.6.3. Single optimal solution problem

Even when model assumptions are fixed, another limitation arises from the way optimisation results are typically interpreted. Many energy system optimisation studies focus on identifying a single cost-optimal solution for a given scenario. While this provides insights into economically efficient system configurations, it may hide the existence of multiple alternative system designs that perform almost equally well [11]. In large-scale energy system models, the cost function often exhibits a relatively flat optimum, meaning that substantially different technology portfolios or spatial distributions can lead to only marginally higher system costs [41]. Consequently, the cost-optimal solution does not necessarily represent a unique or robust outcome. Relying on a single optimal configuration may therefore create a misleading sense of certainty regarding future system designs.

Recent studies, therefore, emphasise the importance of exploring near-optimal solutions to understand the diversity of feasible system configurations better and to assess the robustness of planning insights under uncertainty [10, 42, 11]. For example by identifying which locations or technologies appear consistently across a large set of near-optimal alternatives. This can be done most effectively using MGA, an example of this approach is the SPORES methodology applied in the transmission-level model by Bordignon (2025) [8, 43]. However, such robustness analyses have not yet been widely applied in models that explicitly represent both HV and MV network topology and grid constraints.

The three limitations reviewed in this chapter are not independent. Computational tractability constrains how much network detail can be included; limited network detail produces planning signals that do not reflect where congestion occurs; and without robustness analysis, even accurate signals may not be actionable under uncertainty. Addressing any limitation in isolation leaves the other two unresolved. This combination defines the gap this thesis addresses and motivates the modelling approach developed in Chapter 3.

Methodological Approach

This chapter describes the methodological approach used to answer the research questions introduced in Chapter 1. It motivates the choice of an energy system optimisation approach, introduces the Calliope modelling framework, defines the spatial scope of the analysis, and translates the research questions into a modelling strategy. The chapter concludes by formulating the methodological requirements that guide model development and serve as a reference framework for evaluating whether the resulting models are suitable for DSO planning.

3.1. Research design

This section motivates the choice of an energy system optimisation approach, defines the spatial scope of the analysis, and translates the research questions into the methodological steps that structure the remainder of the study.

3.1.1. Motivation modelling approach

Chapter 2 reviewed three modelling paradigms relevant to the spatial distribution of flexibility: energy system optimisation models, OPF models, and simulation-based grid models [21, 22]. Each paradigm is suited to a different planning purpose. The question is therefore not which paradigm is technically superior, but which aligns with the specific planning problem this thesis addresses.

The central challenge for Stedin is to determine, before assets are installed, where in the HV–MV network flexibility technologies and network expansions should be placed to manage congestion cost-effectively towards 2050. This is an investment planning problem under uncertainty, in which multiple technology options compete across a large number of locations simultaneously. OPF models and simulation-based tools are not designed for this type of problem: they require a predefined system configuration as input, whereas the cost-optimal configuration is precisely what needs to be determined [22, 23, 24]. An energy system optimisation model, by contrast, treats investment decisions as outputs: given cost parameters, network topology, and demand projections, it determines the least-cost combination of technologies and expansions across the network [21, 10].

A further reason to adopt an optimisation approach concerns the trade-off between flexibility and network expansion, which is a central planning question for Stedin. Evaluating this trade-off requires that both options compete within the same model under consistent cost assumptions. OPF and simulation-based tools are not structured to produce this comparison as part of the optimisation itself, since they take the installed system as given rather than determining it [22, 23]. For these reasons, an energy system optimisation approach is adopted as the methodological foundation of this study.

Calliope modelling framework

To implement this approach, the open-source energy system modelling framework Calliope [44] is selected, building on the existing national-scale optimisation model of the Dutch high-voltage network developed by Bordignon (2025), also in collaboration with Stedin [8]. Using this model as a starting

point ensures consistency with prior work on the spatial distribution of flexibility in the Dutch electricity system, and provides a network structure that can be extended towards a regional HV–MV representation. Section 3.1.3 elaborates on how this extension is implemented. A visualisation of the national model scope is shown in Figure 3.1.

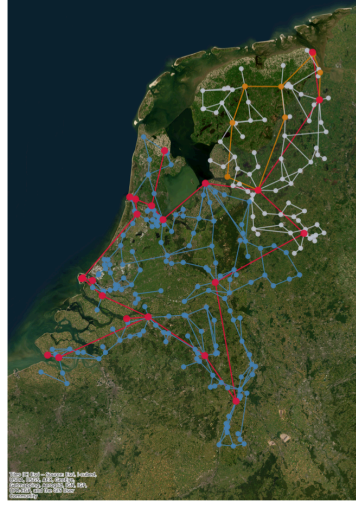


Figure 3.1: National HV Calliope model scope [8]

Linear optimisation

Calliope represents an energy system as a linear optimisation problem in which the model determines the most cost-effective configuration of technologies and infrastructure while satisfying system constraints. The energy system is described by decision variables, an objective function, and constraints. Decision variables represent quantities the model optimises, including installed technology capacities and carrier flows over time.

The objective function represents the quantity minimised by the model, corresponding to total annualised system costs, where all investment costs are converted into annual equivalents based on asset lifetime and interest rate, allowing the model to optimise across a single representative year. Constraints represent the physical and operational limits of the system, including energy balance equations, capacity limits, and transmission constraints. Model parameters, such as technology costs, demand profiles, and network capacities, define the numerical values that shape the optimisation problem.

Within Calliope, these relationships are formulated as:

$$\begin{aligned} \min_x \quad & c^T x \\ \text{s.t.} \quad & Ax \leq b \\ & x \geq 0 \end{aligned} \tag{3.1}$$

where x represents the vector of decision variables, c contains the associated cost coefficients, A represents the constraint matrix, and b represents the constraint limits.

The constraints define the feasible solution space, containing all combinations of decision variables that satisfy the model requirements. Geometrically, this feasible region can be interpreted as a convex polyhedron in the decision space. A key property of linear optimisation problems is that, if an optimal solution exists, it lies on the boundary of the feasible region, specifically at one of its vertices. Optimisation algorithms such as the simplex method exploit this property by moving along the edges of the feasible region until the optimal vertex is reached [45], as illustrated in Figure 3.2.

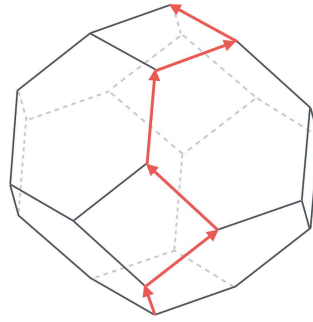


Figure 3.2: Geometric interpretation of a linear optimisation problem. The optimisation algorithm moves along the edges of the feasible region until the optimal solution is reached at one of the vertices [45].

This property makes linear programming particularly suitable for large-scale optimisation problems such as energy system models, where thousands of variables and constraints must be solved simultaneously. In practice, however, the simplex method becomes computationally inefficient as problem size grows, and large-scale models instead rely on interior point barrier methods [46]. These methods navigate through the interior of the feasible region rather than along its edges, and scale more favourably with problem size. In this study, the resulting optimisation problems are solved using Gurobi's barrier solver, integrated within Calliope.

3.1.2. Spatial scope

The spatial scope of this study is limited to the service area of DSO Stedin, covering the Dutch provinces of Zuid-Holland, Utrecht, and Zeeland. To analyse flexibility technologies across both transmission and distribution levels, the scope includes substations operating between 150 kV and 10 kV. Within the Stedin service area, the following voltage levels are present: 150 kV, representing the interface between the TenneT transmission system and the Stedin distribution network, as well as 66 kV, 50 kV, 30 kV, 25 kV, 23 kV, 21 kV, 13 kV, and 10 kV.

The analysis focuses on the system configuration in 2050, consistent with the long-term planning horizon used in Stedin's internal planning practice and the KM scenario developed by Netbeheer Nederland [2].

3.1.3. Methods and research questions

The main research question is structured so that answering the individual sub-questions leads to the overall answer. Therefore, this section explains which methodological steps were taken to address each sub-question.

Methods and sub questions

The starting point of this research is the national high-voltage optimisation model developed by Bordignon [8]. Answering the main research question requires first downscaling this model to a regional representation of the Stedin service area, and subsequently extending it with MV-level network detail. The first step is addressed by the following sub-question.

SQ1A How can a national HV network model be downscaled to a regional HV network representation?

HV Network modelling

Addressing this question requires defining the geographical boundaries of the regional model while maintaining consistency with the national electricity system. A methodological approach is required that represents HV substations within the Stedin service area in detail, while the remainder of the Dutch electricity system is represented in aggregated form. This approach preserves the interaction between the regional network and the national electricity system while maintaining computational tractability. The outcome is a regional HV model representing the Stedin service area, shown in Figure 3.3, which serves as the starting point for SQ1B.

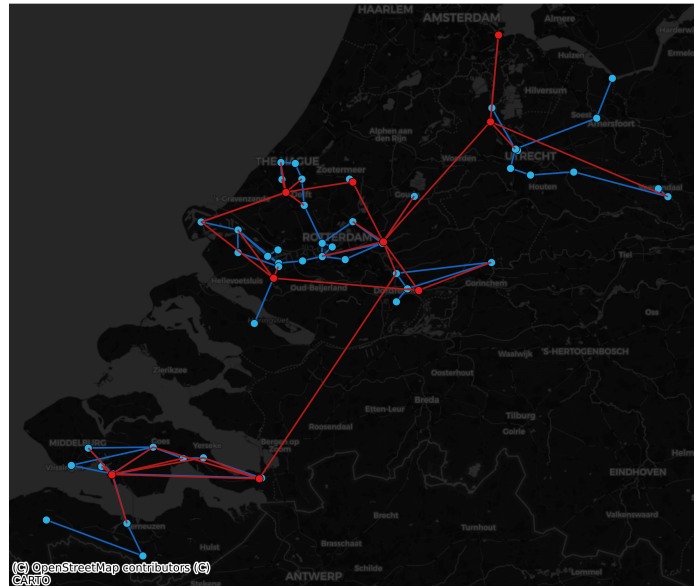


Figure 3.3: Regional HV Calliope model scope

SQ1B How can MV-level network topology and capacity constraints be incorporated into an HV-MV optimisation model in a way that remains suitable for DSO decision-making?

HV-MV Network modelling

Answering this question requires extending the regional HV model with MV network detail. Since modelling the full MV topology significantly increases model complexity, a modelling approach is required that incorporates the relevant MV network structure and capacity constraints while maintaining an appropriate level of abstraction for DSO decision-making. An important methodological consideration is that the available planning datasets already contain simplifications relative to the physical network. Identifying which abstractions are already in the data and which additional simplifications are required forms a central part of the modelling process. The choices made in this translation are described in Chapter 5 and justified in Appendix A.

The increase in model size resulting from adding MV network detail also introduces a tension between temporal resolution and computational tractability: running the HV-MV model at full hourly resolution proved infeasible within available computational resources. The implications of this tension and the resampling strategy adopted to address it are discussed in Section 5.5. The resulting HV-MV model scope is illustrated in Figure 3.4, and the provincial subdivision used to maintain computational tractability is shown in Figure 3.5.

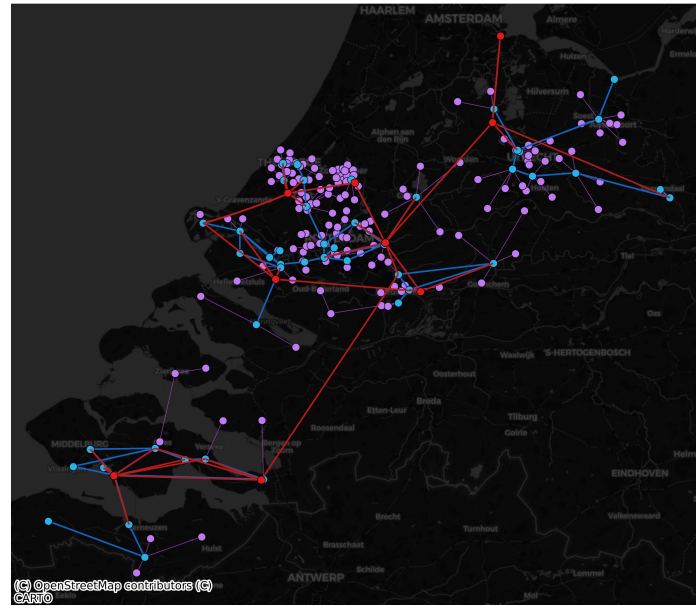


Figure 3.4: Regional HV-MV Calliope model scope

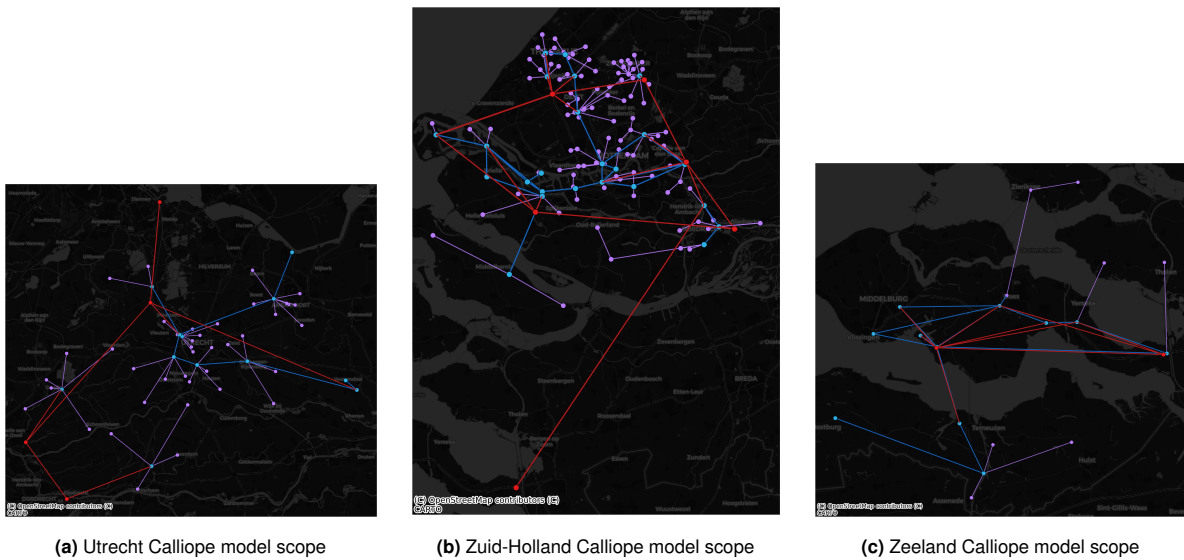


Figure 3.5: Provinces Calliope model scope

SQ2 How does including MV-level network topology in an HV network model affect the cost-optimal spatial distribution of flexibility technologies?

Before the outcomes of the HV and HV-MV models can be compared, the raw results from the optimisation runs are processed and organised into a subset of outputs covering the spatial distribution of flexibility technologies, installed capacities per node, network expansion investments, and overall system costs. This comparison produces a set of spatial patterns describing where flexibility is deployed and why. These patterns form the basis for a set of hypotheses. These are preliminary explanations of the mechanisms driving the observed distributions, grounded in the network properties and cost logic visible in the results. These hypotheses are examined further under parametric uncertainty in SQ3A and subsequently tested for structural robustness across near-optimal solutions in SQ3B.

SQ3A How parametrically robust is the cost-optimal distribution of flexibility technologies in an HV–MV network under variations in key scenario assumptions?

Scenario analysis

Since this study looks ahead to 2050, the model's input parameters are unavoidably uncertain. A scenario analysis is conducted in which two key technology cost parameters, identified together with Stedin, are varied to evaluate how the spatial distribution of flexibility technologies changes under different system conditions. The results are used to refine and extend the hypotheses identified in SQ2.

SQ3B How structurally robust is the cost-optimal distribution of flexibility technologies in an HV–MV network under near-optimal solutions?

As discussed in Section 2.6.3, optimisation models typically identify a single cost-optimal solution for a given set of assumptions. However, energy system optimisation problems often exhibit a relatively flat optimum, meaning that multiple system configurations may exist with costs very close to the optimal solution. Relying solely on a single optimal distribution can therefore be misleading when formulating planning recommendations. To address this, the near-optimal solution space is explored (see Figure 3.6 and the related highlight box for further details). This goes beyond standard structural robustness testing: the goal is not only to establish whether a planning decision is structurally robust across configurations, but also to explain why, an approach referred to in this thesis as attributed structural robustness.

The near-optimal exploration is applied to the Utrecht provincial model only. Running the full SPORES analysis for the HV–MV model and for all the provinces is computationally infeasible within the available time and resources. A single province is therefore selected as the analytical focus. Utrecht is chosen because it currently experiences some of the most severe congestion within the Stedin service area, with capacity shortages on both the TenneT transmission network and the regional distribution network affecting large parts of the province [47]. This makes it a planning-relevant test case for the near-optimal analysis.

Near-optimal solution space

The near-optimal solution space contains all feasible solutions whose total system cost remains within a predefined margin of the optimal solution. Formally, a solution x is considered near-optimal if it satisfies:

$$f(x) \leq (1 + \epsilon)f(x^*) \quad (3.2)$$

where $f(x^*)$ represents the cost of the optimal solution and ϵ represents the allowed cost slack. The cost slack is the maximum percentage increase in total system cost that is still considered acceptable relative to the optimal solution. The resulting constraint defines a subset of the feasible solution space containing all system configurations whose total cost remains close to the optimum.

Figure 3.6 illustrates this concept. The left panels shows the objective function $f(x)$ as a function of the decision variables x with the near-optimal region defined as all solutions whose cost remains within the allowed slack ϵ above the optimum $f(x^*) = c^*$. The right panel projects this near-optimal region onto the two-dimensional decision-variable space, where each point represents a different combination of technology investment. The green shaded area contains all configurations that are both feasible and near-optimal.

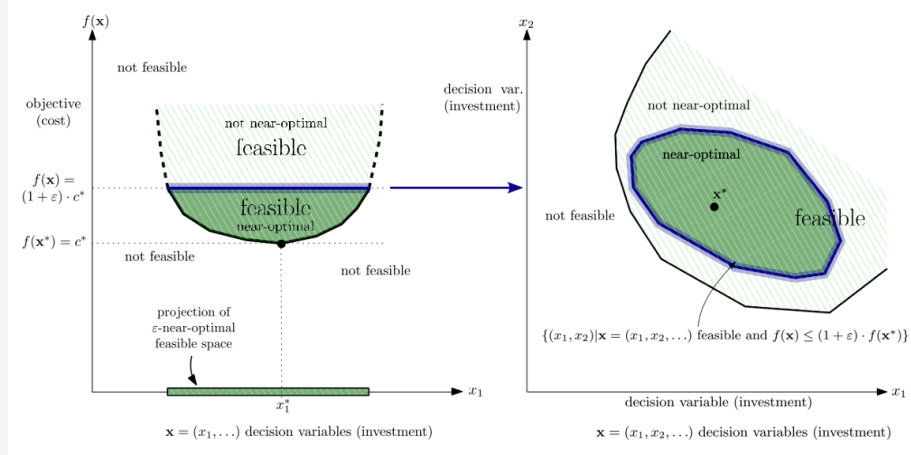


Figure 3.6: Conceptual near-optimal solution space [10]

Near-optimal exploration using MGA and SPORES

To explore the near-optimal solution space, the Modelling to Generate Alternatives (MGA) approach is applied using the SPORES methodology (Spatially-explicit Practically Optimal RESULTS). SPORES generates multiple alternative solutions within the predefined cost slack, searching for configurations that are as spatially and technologically diverse as possible. By analysing which technology-location combinations consistently appear across solutions, structural robust planning options can be identified. MGA addresses part of the structural uncertainty in energy system models by identifying alternative configurations that may better reflect objectives or constraints that are difficult to quantify in the optimisation function, such as stakeholder preferences or spatial planning restrictions [11]. The remaining structural uncertainty, related to modelling choices and abstractions that cannot be captured in the near-optimal space, is addressed through expert interviews, as described in the following section.

Two complementary SPORES strategies are applied. The first is a broad exploration of the near-optimal solution space, in which flexibility technologies are randomly weighted to generate diverse system configurations. Rather than minimising total system costs, each SPORE minimises a weighted sum of installed capacities across technologies and locations, subject to the near-optimality constraint that total system costs remain within the predefined cost slack:

$$\min Y = \sum_j \sum_i w_{ij} X_{ij}^{\text{cap}} \quad (3.3)$$

where X_{ij}^{cap} represents the capacity of technology i installed at location j , and w_{ij} represents penalty weights applied to technologies at each location. These penalty weights are updated after each SPORE: technologies that were heavily deployed in previous solutions receive higher penalties, making it increasingly costly for the solver to select the same configurations again. This produces a diverse set of near-optimal solutions that together cover a broad range of the solution space.

While the broad exploration generates diverse configurations across the solution space, it does not systematically reveal the extreme boundaries of what is feasible within the cost slack. The second strategy is therefore an intensified exploration that pushes the solver towards these boundaries for each flexibility technology individually. The objective function is extended with an intensification term:

$$\min Y_2 = a \sum_j \sum_i w_{ij} X_{ij}^{\text{cap}} \pm b \sum_j \bar{X}_{ij}^{\text{cap}} \quad (3.4)$$

where $\bar{X}_{ij}^{\text{cap}}$ represents the capacity of a specific target technology. The parameter b controls the strength of the intensification. A negative value of b encourages the solver to maximise the deployment of the target technology; a positive value pushes the solver towards minimising its deployment while remaining within the allowed cost slack.

Together, the broad and intensified strategies enable exploration of both the diversity and the boundaries of the near-optimal solution space, supporting the classification of planning insights as defined in Table 3.1.

Table 3.1: Classification of measures based on frequency across near-optimal solutions.

Frequency	Category	Interpretation
90%	No-regret	Measures that appear consistently across near-optimal solutions.
60% – 90%	Robust	Measures that are stable across most model configurations.
40% – 60%	Moderate	Measures with moderate sensitivity to other design decisions within the system.
< 40%	Limited	Measures that vary strongly depending on other design decisions within the system.

These frequency categories establish how structural robust a planning decision is across near-optimal solutions, but do not explain the source of that robustness. A location may consistently attract flexibility because the network leaves no alternative, or because current cost assumptions happen to favour it, two situations that call for very different planning responses. To make this distinction, the frequency classification is combined with statistical testing of network properties. This second step constitutes what this thesis refers to as *attributed structural robustness*: the analysis of whether the stability of planning insights across near-optimal solutions is driven by identifiable network properties, established by statistically testing hypotheses across SPORES. Decisions whose stability is confirmed in this way are translated into modelling principles. A principle is a planning-relevant conclusion that hold regardless of how the broader system is configured.

Some hypotheses established through model comparison cannot be tested across near-optimal configurations, because the SPORES analysis network representation is fixed. Where the underlying pattern cannot be confirmed, these hypotheses remain observations, and should be interpreted as descriptions of model behaviour rather than structurally robust planning conclusions.

Expert interviews

Scenario analysis and near-optimal exploration together address parametric and part of the structural uncertainty in the model outcomes. However, structural uncertainty related to modelling choices and abstractions cannot be fully resolved through either approach [40]. To address this remaining structural uncertainty, three interviews are conducted with Stedin experts to evaluate whether the model structure, assumptions, and results are consistent with practical planning knowledge.

The selection of experts is based on the key components of the modelling framework. A data specialist with expertise in load forecasting and network topology is consulted on the translation of planning data into model inputs. An electrical engineering expert with expertise in transformers and network capacity constraints reviews the technical representation of substations and network limitations. A system strategist with a broader perspective on long-term network development assesses the spatial implications of the model outcomes and their alignment with practical planning approaches.

Each expert participates in one semi-structured interview conducted after the model structure and assumptions have been defined. The key modelling choices are shared with the experts prior to the interviews to facilitate focused discussion of specific assumptions and simplifications. The interviews serve as a verification step to assess whether the structure, assumptions, and results of the models provide decision-relevant insights for DSO planning practice. The transcripts are included in Appendix B.

Methods and main research question

The sub-questions introduced in this section each address a distinct methodological challenge that must be resolved before the main research question can be answered. Together, they form a structured research strategy in which each step builds on the outputs of the previous one.

The first two sub-questions establish the base models. **SQ1A** addresses the downscaling of the national HV model to a regional representation of the Stedin service area, ensuring that the model captures the relevant transmission-level topology while remaining consistent with the national electricity system. **SQ1B** extends this model by incorporating MV-level network topology and capacity constraints, producing a model that is both spatially detailed and computationally tractable for DSO decision-making.

With the models in place, **SQ2** examines what changes when MV network detail is included: how the cost-optimal spatial distribution of flexibility technologies shifts relative to an HV-only representation, and what mechanisms drive that redistribution. The findings from this comparison form the basis for the robustness analyses that follow.

SQ3A and **SQ3B** assess the robustness of the resulting planning insights from two complementary perspectives. **SQ3A** tests parametric robustness by examining how the spatial cost-optimal distribution changes under alternative technology cost assumptions. Together with **SQ2**, this produces a set of hypotheses about where flexibility is needed and why. **SQ3B** then tests these hypotheses for structural robustness across near-optimal configurations, through the attributed structural robustness analysis introduced above. By combining all three analyses it becomes possible to distinguish planning decisions that are enforced by network topology from those that are driven by cost assumptions or model simplifications.

Together, these steps provide the basis for answering the main research question. Figure 3.7 summarises the overall research strategy and illustrates how each sub-question contributes to the main research question, with the colour coding indicating which part of the main question each sub-question addresses.

How can flexibility technologies be spatially distributed across an HV–MV network in a way that combines decision-relevant detail with computational tractability in order to generate robust planning insights for DSOs?

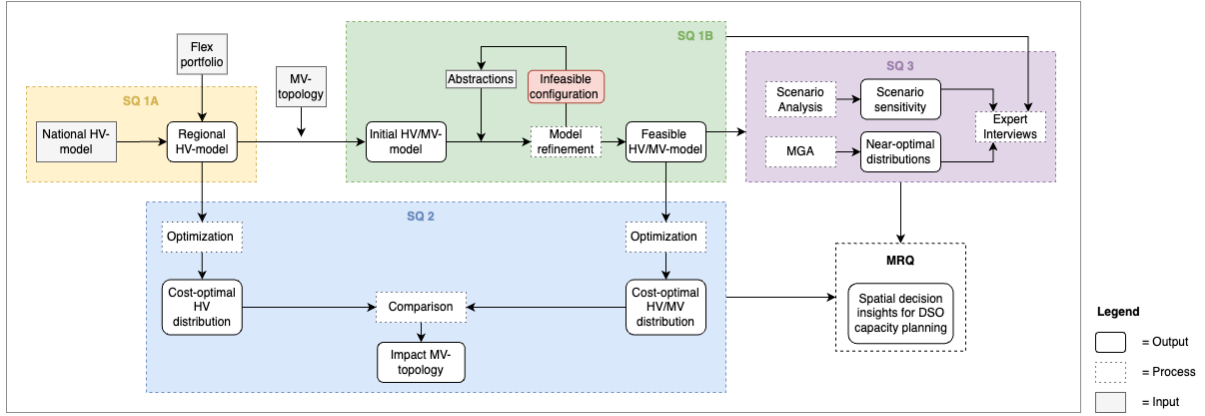


Figure 3.7: Research Strategy

3.2. Methodological requirements

To ensure that the developed model remains relevant for DSO planning practice, a set of methodological requirements is defined prior to model development. These requirements serve as guiding principles for model design and are derived from the knowledge gap and modelling limitations identified in Chapter 2. In particular, the literature highlights challenges related to the representation of spatial network constraints, computational tractability, and the robustness of optimisation outcomes.

Based on these insights, the following requirements are formulated:

- R1 **Spatial decision granularity:** The model should represent flexibility deployment at the HV and MV substation levels to produce location-specific planning insights meaningful for distribution network planning.
- R2 **Network feasibility:** The model should explicitly represent MV network capacity constraints to improve the physical feasibility of optimisation results within the distribution grid.
- R3 **System consistency:** Regional flexibility deployment should remain consistent with the national electricity system by maintaining interaction with the wider HV network and the overall supply-demand balance.
- R4 **Technology competition:** Multiple flexibility technologies should be represented simultaneously to enable different technologies to compete within the models, avoiding biases that arise when only a single technology is considered.
- R5 **Computational tractability:** The modelling approach should remain computationally tractable to allow multiple model runs
- R6 **Robustness of results:** The analysis should explore the near-optimal solution space to assess whether planning insights depend on a single cost-optimal configuration.
- R7 **Temporal representation:** The model should represent temporal variation sufficiently to capture the operational value of flexibility technologies and the occurrence of congestion events in the electricity network.

These requirements define the methodological conditions for modelling the HV and HV-MV service areas. They guide the development of the optimisation models and provide a reference framework for evaluating whether the resulting model structure remains suitable for generating decision-relevant insights for DSO planning.

4

Model Formulation

This chapter describes the mathematical structure of the optimisation model through three components: decision variables, an objective function, and system constraints. Each component is discussed in turn.

4.1. Model structure

The electricity system of the Stedin service area is represented as a network-based energy system model implemented in the Calliope framework. The system is described through three core building blocks: nodes, technologies, and carrier flows.

Nodes represent spatial locations in the network and correspond to substations in this study. Within each node, technologies can be installed that supply, consume, convert, store, or transmit energy. Technologies therefore represent the physical components of the system, including batteries, conversion technologies, transmission links, and demand sinks. Energy moves between and through these components as carrier flows, with electricity as the primary carrier. Additional carriers, such as hydrogen, are introduced when conversion technologies are included.

The model evolves over a series of discrete time steps, allowing technology operation and energy flows to vary over time. At each time step, the model determines the optimal dispatch of technologies while respecting the physical and operational constraints [48]. Figure 4.1 illustrates this conceptual structure.

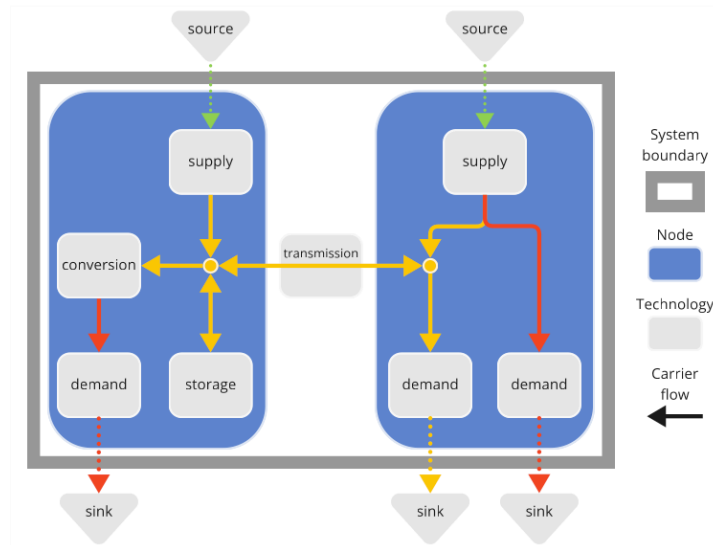


Figure 4.1: Conceptual representation of an energy system model consisting of nodes, technologies, and carrier flows [48]

Building on this representation, the optimisation model determines the cost-optimal configuration and operation of the electricity system through three components: decision variables, the objective function, and system constraints. These components determine the feasible solution space and how the cost-optimal solution is identified. Each component is discussed in the sections that follow.

4.2. Decision variables

The decision variables represent the quantities that the optimisation model determines to minimise total system costs, subject to the system constraints. These variables span two categories: investment decisions and operational decisions.

Investment decisions concern the installed capacity of flexibility technologies and the expansion of network capacity at specific locations within the HV–MV network. Operational decisions determine how these installed technologies are utilised over time, capturing the charging and discharging behaviour of storage technologies as well as the power flows between substations.

4.2.1. Flexibility technologies

The flexibility technologies included in the model are selected based on three overarching flexibility needs identified in the Netbeheer Nederland scenarios [2]:

1. Short-term balancing of electricity supply and demand
2. Energy carrier conversion between electricity and other energy carriers
3. Provision of dispatchable capacity during periods of high demand or low renewable generation

Short-term balancing is represented by two battery storage technologies. *Lithium-ion batteries* provide fast-response storage suited to mitigating intra-day fluctuations in renewable generation and local network congestion. *Vanadium redox flow batteries* complement this by providing storage over multiple hours to days, making them better suited to capture multi-day imbalances between supply and demand.

Energy carrier conversion and dispatchable capacity provision are captured through *power-to-hydrogen* and *hydrogen-to-power* technologies. Power-to-hydrogen technologies (electrolyser) convert surplus electricity into hydrogen during periods of high renewable generation, reducing network congestion while transferring energy to another carrier. Hydrogen-to-power reconverts hydrogen into electricity during periods of high demand or low renewable output.

Together, these four technologies form a flexibility portfolio that captures the key operational roles of flexibility in future electricity systems. The portfolio is not intended to be exhaustive but rather to represent the main flexibility functions relevant to congestion management in the HV–MV network and system balance. By including multiple technologies, the model allows different flexibility technologies and grid expansions to compete within the optimisation, avoiding biases that arise when only a single technology is considered (R4).

4.3. Objective function

The optimisation models minimise total system costs subject to all technical and operational constraints. These costs include investments in flexibility technologies and network infrastructure, operational and maintenance costs, and costs associated with energy imports and unmet demand.

The objective function minimises the total system costs across all time steps t , network nodes n , and technologies $techs$:

$$\min \sum_{t,n,tech} [C^{inv} \cdot \Delta flow_cap + C^{inv} \cdot \Delta storage_cap + C^{om} \cdot flow_cap + C^{flow_out} \cdot f_{out} + C^{flow_in} \cdot f_{in}] \quad (4.1)$$

The decision variables include the installed capacity of technologies ($flow_cap$), capacity expansions ($\Delta flow_cap$ and $\Delta storage_cap$), and the carrier flows into and out of technologies (f_{in} and f_{out}). Ta-

ble 4.1 summarises the individual cost components and the corresponding technologies and parameters used in the model implementation.

Table 4.1: Cost components included in the objective function

Term	Technology	Parameter
Cable investment	Transmission links	<code>cost_flow_cap_per_distance</code>
Transformer investment	Transmission links (stations)	<code>cost_flow_cap</code>
Battery investment	battery_flow, battery_system	<code>cost_storage_cap</code>
Hydrogen investment	power_2_h2, gas_2_power	<code>cost_flow_cap</code>
Operation & maintenance	batteries, gas_2_power	<code>cost_om_annual</code>
Hydrogen import costs	import_h2	<code>cost_flow_in</code>
Lost load penalty	lost_load	<code>cost_flow_out</code>

Unmet demand is represented by a lost-load penalty, a high cost assigned to any electricity demand that cannot be met, ensuring that the model prioritises meeting electricity demand under all circumstances.

4.4. System constraints

The objective function is subject to a set of constraints that enforce the physical and operational limits of the electricity system. These constraints can be grouped into five categories: energy balance, network capacity, technology operation, storage, and spatial constraints. The parameters used to define these constraints are described in detail in Section 5.4.

Energy balance

The energy balance constraint ensures that electricity supply equals demand at every network node and time step. All electricity entering a node through generation, imports, or storage discharge must equal the electricity leaving the node through demand, exports, or storage charging:

$$generation + imports + storage_{discharge} = demand + exports + storage_{charge} \quad (4.2)$$

Network capacity constraints

Electricity flows between nodes are bounded by the transmission capacity of network links and transformers. This is particularly relevant for congestion analysis, as congestion emerges when power flows approach or exceed these limits [15]. Power flows between two nodes are constrained by the installed transmission capacity:

$$f_{n_1, n_2, t} \leq flow_cap_{n_1, n_2} \quad (4.3)$$

The model can invest in expanding the transmission capacity of network links, subject to a minimum and maximum expansion limit per link:

$$flow_cap_{min} \leq flow_cap \leq flow_cap_{max} \quad (4.4)$$

This allows the model to determine whether network expansion is economically preferable to deploying flexibility technologies at a given location.

Technology operation constraints

Technology-specific constraints define the operational boundaries of individual technologies, reflecting characteristics such as storage utilisation limits and sink capacities:

- `storage_loss`: hourly self-discharge losses in storage technologies

- `sink_use_max`: upper bound on the use of sink technologies, such as hydrogen export

These constraints ensure that the operational behaviour of technologies remains consistent with their technical characteristics.

Storage constraints

Storage constraints track how the stored energy level evolves over time. Charging increases the stored energy, while discharging reduces it. A storage technology cannot discharge more energy than is currently stored. The evolution of the stored energy is expressed as:

$$SOC_t = SOC_{t-1} + charge_t - discharge_t \quad (4.5)$$

where SOC_t represents the amount of energy stored at t . Three additional parameters bound the operation of storage technologies:

- `flow_cap_per_storage_cap_max`: limits the ratio between power capacity (MW) and energy capacity (MWh), reflecting the physical discharge rate of a battery.
- `storage_discharge_depth`: limits the fraction of total battery capacity that can actually be used, reflecting that fully depleting a battery reduces its lifespan.
- `storage_initial`: sets the initial state of charge at the start of the modelling period.

These constraints ensure that storage technologies operate within realistic physical limits.

Spatial constraints

Calliope allows spatial constraints to be applied at the node level through the parameter `area_use_max`, which limits the total spatial footprint of technologies installed at a given location. In this study, the spatial constraint is set to infinity because no detailed spatial planning data are available at the substation level. The constraint remains part of the model structure and can be activated in future analyses when spatial limitations on technology deployment become available.

5

Model Implementation

This chapter describes how the optimisation model is implemented in the Calliope modelling framework. It begins by introducing the two model configurations used in this study: the regional HV model and the extended HV–MV model. It then describes the choices made in representing the network, covering the node structure, topology, capacity constraints, and coupling with the broader Dutch electricity system. Subsequently, it describes how demand and generation are represented, the technology data and cost assumptions used, and the temporal resolution of the model. The chapter concludes with the experimental setup used to address each sub-question.

5.1. Model configurations

This study applies two model configurations to analyse the spatial distribution of flexibility technologies across the Stedin service area. Each configuration represents a different level of network detail and spatial scope.

The regional *HV model* represents the HV network within the Stedin service area at 150 kV. This voltage level forms the top layer of the Stedin distribution network and one of the lower layers of the TenneT transmission system. The rest of the Dutch electricity system is represented in aggregated form through the 380 kV nodes, as described in Section 5.2.4. This model serves as the starting point for the HV–MV extension.

The *HV–MV model* extends the regional HV model with a representation of the MV network, covering voltage levels from 66 kV down to 10 kV. Representing the full Stedin service area at this level of detail results in a (332-node & 363-link) model that proved infeasible as a single integrated problem. Numerical instability in the Gurobi barrier solver, arising from decision variables, was only partially resolved through cost rescaling and solver adjustments. The HV–MV network is therefore implemented as three separate provincial models, each covering one province within the Stedin service area: Zuid-Holland, Utrecht, and Zeeland. Each provincial model represents the full HV–MV network topology of its province, while interactions with the other provinces are captured through a single aggregated node. This subdivision allows the near-optimal solution space to be explored at the provincial level (R5 & R6). The consequence is that the provincial results represent independently optimised solutions rather than segments of a system-wide optimum; this limitation is discussed in Section 7.3.

The following sections describe how the network is represented across these model configurations, covering the network layers, topology, capacity constraints, and abstractions applied.

5.2. Network representation

This section describes how the electricity network is represented in the model. It covers the definition of nodes and their spatial structure, the network topology, the representation of capacity constraints, and the coupling with the broader Dutch electricity system. Together, these choices determine where congestion can occur in the model and where flexibility technologies and network expansions can be

deployed.

5.2.1. Substations

In the model, each node corresponds to a substation within the electricity network. Stedin's network datasets apply two different definitions of a substation. In the operational network data, a substation is defined as a physical location: a single site may contain transformers operating at multiple voltage levels, sharing the same geographic coordinates and GIS code. In the planning datasets, each voltage level within a physical site is assigned a distinct substation code.

This study adopts the planning-based definition, in which each substation code corresponds to a single voltage level and is represented as a separate node in the model. This allows each voltage level to be distinguished within the network hierarchy, which is necessary for correctly assigning capacity constraints to the links between them, and ensures that flexibility deployment can be assessed at the level of individual HV and MV substations (R1).

HV substations form the highest layer of the network and form the connection point between the TenneT transmission system and the Stedin distribution network. The HV layer consists of 10 substations operating at 380 kV and 47 substations operating at 150 kV. These substations are included in all model configurations. *MV substations* form the distribution layer and cover voltage levels ranging from 66 kV down to 10 kV. Within the Stedin service area, this includes 274 substations across the three provinces, which are only represented in the HV–MV models.

The *hydrogen node* represents the point at which hydrogen can be stored, imported into, and exported from the system. Since the focus of this study is on the electricity network, the hydrogen transport infrastructure is not explicitly modelled. Instead, a single centralised hydrogen node is included as a modelling abstraction that allows hydrogen to be incorporated as an energy carrier in the optimisation model (R4&R5).

Table 5.1 provides an overview of the number of nodes per network layer and voltage level in the HV–MV model. The HV model only includes the 380 kV and 150 kV nodes. A complete overview of all substations is provided in Appendix I.

Table 5.1: Number of nodes per voltage level in the HV–MV model

Network layer	Voltage level	Number of nodes
HV	380 kV	10
	150 kV	47
MV	66 kV	2
	50 kV	30
	30 kV	1
	25 kV	31
	23 kV	28
	21 kV	8
	13 kV	26
	10 kV	148
H2 hub	–	1
Total		332

For the provincial models, substations operating at 150 kV and below are assigned to the province in which they are located based on their geographic coordinates. Substations located outside the focus province are aggregated into a single node representing that province. The assignment of 380 kV

substations follows a different approach, described in Section 5.2.4. The Utrecht provincial model, which is used for the further analysis, comprises 73 150 kV/ MV substations and 83 links within and connected to the MV network.

Topologically isolated substations

Not all substations present in Stedin's datasets are included in the model. Two categories of substations are excluded because including them would add model complexity without generating additional planning insights. The first consists of newly planned substations for which no demand or generation forecasts are available. The second consists of substations that are fed from outside the Stedin network: these substations are not part of the internal HV–MV topology, meaning that flexibility deployed at these locations cannot interact with the rest of the network and therefore cannot contribute to congestion relief elsewhere in the grid. A list of excluded substations is provided in Appendix I.

5.2.2. Network topology

The connections between HV substations are based on the national high-voltage network map and follow the topology of the existing transmission network [49]. The geographic coordinates of HV substations are also derived from this map. Links that normally connect 150 kV substations within and outside the Stedin service area are instead connected to the nearest 380 kV node. Since transmission lines in Calliope are represented as straight lines between nodes, a path length correction factor of 1.2 is applied to account for the actual routing of cables in the field. Figure 5.1 illustrates the difference between the Calliope network representation and the actual high-voltage network map.

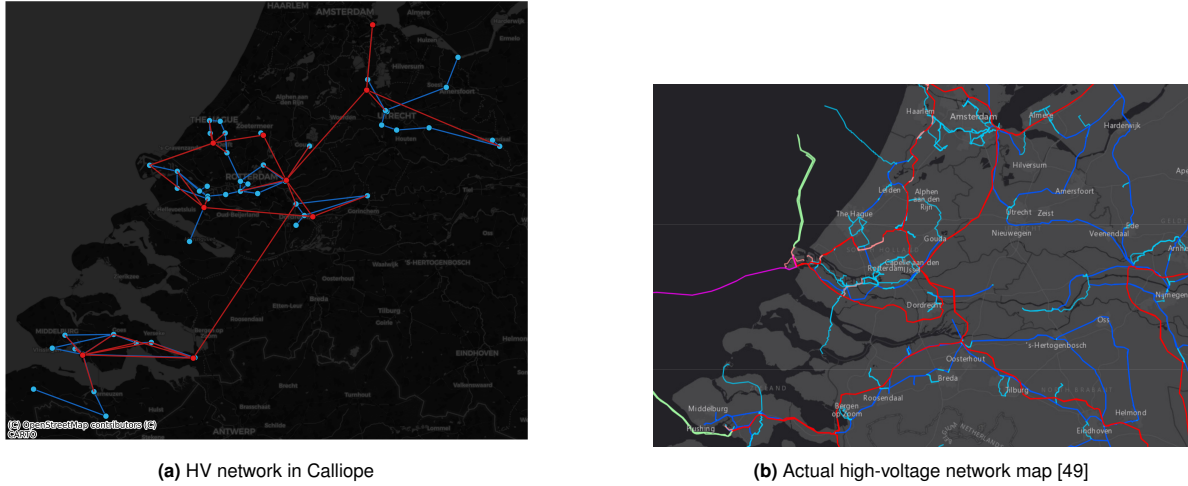


Figure 5.1: Comparison between the Calliope HV network representation and the physical high-voltage network map. In both graphs, red lines indicate 380 kV connections. In (a) dark blue lines indicate 150 kV connections. In (b) both tints of blue lines indicate 146–170 kV connections.

As discussed in Section 2.1, MV networks are typically built as a ring but operated radially. The MV network within the Stedin service area is also operated radially, meaning each substation is connected to exactly one upstream substation. This radial structure is reflected in Stedin's internal planning dataset, which forms the basis for the demand and generation inputs of this study, and is therefore adopted as the MV network structure in the model. The radial topology is also a necessary condition for representing capacity constraints correctly within the model (R2, as discussed in Section 5.2.3). In a radial network, each substation has a single path to the rest of the grid, which means that the capacity of a substation can be directly assigned to the single link connecting it to the upstream network. This follows from the fact that Calliope cannot assign capacity constraints to nodes. In a meshed network, multiple links connect to the same node, making it challenging to assign substation capacity to individual links in a realistic way.

Table 5.2 provides an overview of the number of links per voltage level combination in the HV–MV model. The HV model contains only the 380–380 kV, 380–150 kV, and 150–150 kV connections. A complete overview of all links is provided in Appendix I.

Table 5.2: Network links per connection type in the HV–MV model (excluding H2 hub connections)

From	To	Count	Min dist. (km)	Max dist. (km)
380 kV	380 kV	8	0.0	36.7
380 kV	150 kV	30	0.2	56.8
150 kV	150 kV	51	0.6	34.6
150 kV	66 kV	1	0.0	0.0
150 kV	50 kV	18	0.0	1.9
150 kV	30 kV	1	0.0	0.0
150 kV	25 kV	18	0.0	1.4
150 kV	23 kV	8	0.0	0.0
150 kV	21 kV	5	0.0	0.0
150 kV	10 kV	21	0.0	0.0
66 kV	66 kV	1	2.0	2.0
66 kV	25 kV	1	0.0	0.0
66 kV	23 kV	1	0.0	0.0
50 kV	50 kV	12	3.0	16.2
50 kV	21 kV	1	6.6	6.6
50 kV	13 kV	24	0.0	14.3
50 kV	10 kV	49	0.0	12.7
25 kV	25 kV	12	0.4	4.0
25 kV	23 kV	14	0.0	5.8
25 kV	21 kV	1	0.0	0.0
25 kV	13 kV	1	3.6	3.6
25 kV	10 kV	68	0.0	10.4
23 kV	23 kV	5	1.4	3.7
23 kV	13 kV	1	10.2	10.2
23 kV	10 kV	4	0.0	0.4
21 kV	21 kV	1	13.6	13.6
21 kV	10 kV	1	0.0	0.0
10 kV	10 kV	5	0.9	2.9
Total		363		

In the provincial models, the network links are preserved as closely as possible. Links that originally connected substations across provincial boundaries are retained, but their endpoints outside the focus province are redirected to the aggregated provincial node. These links also retain their original capacity, as described in Section 5.2.3.

Each node in the model is connected to the hydrogen hub via a hydrogen transmission link. This allows every substation to potentially host power-to-hydrogen or hydrogen-to-power technologies regardless of its location in the network. Modelling the hydrogen transport infrastructure would require assumptions about a network whose future layout is uncertain, and would introduce a separate planning problem beyond the scope of this study. Connecting all nodes directly to a single centralised hub is therefore a simplification that allows hydrogen to function as an energy carrier in the optimisation without compromising computational tractability or losing focus from the main research question (R5).

5.2.3. Capacity representation

In Calliope, capacity constraints cannot be applied directly to nodes. All capacity limits are therefore represented through the links connecting substations. In principle, transformers could be modelled as

conversion technologies, with each voltage level represented as a distinct carrier that the transformer converts between. However, this would substantially increase model complexity without providing tangible benefits for the planning questions addressed in this study (R5).

The model distinguishes between two types of links: transformer connections, which link substations at different voltage levels and represent the physical transformers in the network, and transmission cables, which link substations at the same voltage level and represent the physical cables between them.

In practice, grid congestion can arise when the loading of any network component exceeds its capacity limit, including both transformers and cables [4, 7]. In Stedin's long-term planning practice, load forecasts are primarily assessed against transformer capacity at substations, as this is the dominant binding constraint in the distribution network [7]. This study therefore treats transformer capacity as the primary constraint for congestion.

Representation of transformer (substation) capacity via links

Since transformer capacity is treated as the primary constraint for congestion, the capacity of the transformer between two substations is assigned to the link connecting the downstream substation to its upstream substation. This is feasible because the MV topology is radial: each substation has exactly one upstream connection, and all power flowing through a substation passes over a single link. Setting the flow capacity of that link equal to the transformer capacity ensures that the model cannot select solutions requiring more power to pass through the substation than its transformers can physically handle (R2).

For 380-150 kV links, the capacity is set equal to the transformer capacity of the connected 150 kV substation, denoted T_i . In four cases, a 150 kV substation is connected to two 380 kV nodes. In these cases, both links are assigned the same transformer capacity T_i , resulting in a total capacity of $2 \times T_i$. As a consequence, the effective import capacity from the TenneT network can exceed the physical transformer capacity of the substation itself. This modelling abstraction may therefore slightly relax the local network constraint at these nodes and influence where the model allocates flexibility resources.

Existing substation capacities are derived from a Stedin dataset of N-1 safe substation capacities. The N-1 criterion means that the network must remain operational even if one component fails: the N-1 safe capacity therefore represents the maximum load a substation can handle while remaining able to absorb the loss of a single component. Each substation capacity in this dataset reflects the limiting component at that substation. In consultation with Stedin, the transformer is identified as the dominant limiting component in the distribution network in the majority of substations. The substation capacities are therefore assigned to the upstream links as transformer capacities. These capacities are expressed in MVA and converted to MW using an assumed power factor of 0.95.

Electricity transmission link capacity

In the MV network, substation capacity can be assigned to the upstream link for all connections. However, this approach is not applicable to transmission cables between 150 kV substations, since the 150 kV network has a meshed structure in which a substation may have multiple upstream connections. For these links, the minimum flow capacity is based on the thermal limit of a single 150 kV circuit:

$$\text{flow_cap}_{\min} = \sqrt{3} \cdot U \cdot I \cdot \cos \varphi \quad (5.1)$$

where $U = 150$ kV, $I = 0.8$ kA, and $\cos \varphi = 0.95$ is the assumed power factor.

Transmission lines between 380 kV substations are left unbounded, as the national transmission network operated by TenneT is not the focus of this study.

Hydrogen transmission link capacity

The capacity of hydrogen links is set to infinity, ensuring that hydrogen transport between nodes and the hydrogen hub is never the binding constraint in the optimisation. This reflects the modelling choice to abstract from hydrogen transport infrastructure.

Capacity expansion

To enable a trade-off between deploying flexibility technologies and network expansion, the model allows optimisation-driven capacity expansion at substations with available connection space. The number of expansion slots indicates how many additional transformers can be installed at a substation and varies by transformer type, as shown in Table 5.3.

To determine the available expansion capacity per substation, the number of transformers currently installed at each substation is derived from Stedin's network dataset. Transformers are assigned to the substation at the secondary voltage level, meaning that a transformer stepping down from 150 kV to 50 kV is counted at the 50 kV substation. The number of installed transformers is then compared to the maximum number of slots available at that substation, giving the number of remaining expansion slots available for investment.

The dataset includes two- and three-winding transformers. A two-winding transformer connects one primary voltage level to one secondary voltage level. A three-winding transformer connects one primary side to a secondary and tertiary voltage level simultaneously, for example, stepping down from 150 kV to both 50 kV and 10 kV in a single unit. Physically, such a transformer has one shared capacity limit that is distributed across its secondary and tertiary windings. In the model, it occupies a single physical slot and its capacity is assigned to the link at the secondary voltage level.

Table 5.3: Transformer capacity, expansion slots, transformer investment costs, and associated cable investment costs.[18]

Type	Cap. (MW)	Max slots	kEUR/MW	kEUR/MW/km
150/380 kV	475	4	210.53	3000
150/50 kV	118.75	4	75.79	800
150/25 kV	90.25	4	77.56	800
150/23 kV	87.40	3	80.09	800
150/21 kV	85.50	3	76.02	800
150/10 kV	73.15	3	88.86	800
66/23 kV	66.50	2	105.26	800
50/21 kV	66.50	2	105.26	800
50/13 kV	47.50	2	126.31	800
50/10 kV	38.00	2	157.89	800
25/23 kV	28.50	3	157.89	800
25/21 kV	28.50	3	157.89	800
25/13 kV	23.75	3	168.42	800
23/13 kV	23.75	3	168.42	800
25/10 kV	21.38	3	187.13	800
23/10 kV	21.38	3	187.13	800
21/10 kV	21.38	3	187.13	800

Capacity expansion is implemented in Calliope via three parameters per link: `flow_cap_min` sets the existing capacity of the substation, `flow_cap_max` sets the existing capacity plus the maximum expandable capacity defined as the number of available slots multiplied by the capacity per transformer, and `cost_flow_cap` and `cost_flow_cap_per_distance` set the investment cost per MW of additional capacity, covering transformer and cable costs. This allows the optimisation model to determine whether capacity expansion is needed, where it should occur, and what scale is economically optimal. By bounding expansion through the available transformer slots, the model ensures that all network investments remain physically realisable within the existing substation infrastructure (R2).

Since the model is a linear optimisation, capacity expansion is treated as a continuous variable, meaning the model can invest in fractional transformer units. While this does not fully reflect real investment decisions, which would require binary or integer variables, it is a simplification to preserve computational tractability (R5). This introduces a tension with the physical feasibility requirement (R2), as continuous expansion does not capture the discrete nature of real transformer investments.

5.2.4. Representation of the rest of the Dutch system

The model focuses on the Stedin service area but accounts for the broader Dutch electricity system to ensure a realistic supply-demand balance. As discussed in Section 2.3, flexibility fulfils two functions: supporting national system balance and mitigating local congestion. To capture both functions within a single model, the regional network is coupled to the national electricity system through the 380 kV nodes (R3). These nodes function as a black box interface between the TenneT transmission system and the Stedin distribution network: they absorb and supply electricity according to a predetermined national demand and supply profile, without the internal dynamics of the national grid being simulated. The derivation of this profile is described in Section 5.3.2. Flexibility technologies can be deployed at any node in the model, including the 380 kV nodes, meaning the model partially captures the interaction between regional congestion management and national system balancing. This approach ensures consistency with the national system (R3) while limiting computational complexity (R5).

The selection of 380 kV nodes differs per model configuration. In the HV and HV–MV models, all ten 380 kV nodes directly connected to the Stedin network are included, based on the national high-voltage network map [49]. For the three provincial models, only the 380 kV nodes directly connected to substations within the respective province are retained: two for Zeeland, four for Utrecht, and seven for Zuid-Holland. Some 380 kV substations appear in multiple provincial models, but this has no consequence as the national electricity profile is distributed equally across the included nodes.

The national grid profile is distributed equally across all included 380 kV nodes, each carrying an equal share of the total national demand and supply. Concentrating the full national load in a single node creates a large difference in demand between nodes, which causes numerical instability in the Gurobi solver. Equal distribution preserves the overall system balance without introducing additional flexibility (R5).

5.3. Demand and generation representation

This section describes how electricity demand and generation are represented in the model. It covers the substation-level load forecasts used for the Stedin service area, and the national demand and supply profiles used to represent the rest of the Dutch electricity system. Together, these inputs define the temporal demand and generation patterns for each substation in the model.

5.3.1. Substation-level load forecasts

The demand and generation inputs for the Stedin service area are based on substation-level load forecasts provided by Stedin for the year 2050. These forecasts are developed by Stedin based on the 'Koersvaste Middenweg' scenario of the Energy Transition Model (ETM) [50], translating national scenario assumptions into load projections at the level of individual substations within the Stedin service area. Flexibility options are excluded from this dataset, and Stedin applies additional assumptions to create a dataset suitable for long-term grid planning studies. These assumptions are described in Appendix C.

Each forecast represents the aggregated electricity demand and generation of a substation and all downstream substations connected to it in the network hierarchy. For each substation, a net load profile is derived by subtracting supply from demand at each timestep, and subsequently separated into a non-negative demand time series and a non-negative supply time series for use as model inputs. As a result, a substation has either a net demand or a net supply at any given hour, implicitly assuming that local generation first serves local demand before any surplus or deficit is exchanged with the rest of the network.

For the HV model, this aggregated net load profile is used directly at each 150 kV node, since no downstream substations are modelled. For the HV–MV model, downstream substations are repre-

sented as separate nodes. Using aggregated forecasts directly would result in each substation's load being counted multiple times across the network. To resolve this, a net node profile is calculated for each substation by subtracting the aggregated profiles of all directly connected downstream substations from the substation's aggregated profile:

$$P_{\text{node},t} = P_{\text{substation},t} - \sum_{c \in \text{children}} P_{c,t} \quad (5.2)$$

This produces a profile representing only the demand and generation at the substation itself, excluding the contributions of downstream substations that are explicitly modelled. For the lowest-level substations in the model, no subtraction is applied. Their profiles therefore include the aggregated load of the low-voltage network below them, which is not explicitly represented in the model.

For the provincial models, substations outside the focus province are not modelled individually. Instead, their aggregated 150 kV substation profiles are summed into a single net load profile per timestep, which is assigned to the aggregated provincial node.

5.3.2. National demand and supply

The national 380 kV substations require a different approach to demand and supply representation than the Stedin substations. Since no substation-level forecasts from Stedin are available for these substations, national electricity demand and supply profiles are derived directly from the ETM KM 2050 scenario [51]. This is the same source Stedin uses for its substation-level forecasts. However, Stedin supplements the ETM data with additional regional assumptions to translate the national scenario to individual substations, as described in Section 5.3.1. As a result, the two datasets may differ in their temporal patterns despite sharing the same underlying scenario. To verify that they are sufficiently aligned to be used side by side in the model, a consistency check is performed, the results of which are presented in Appendix C.

To avoid double counting, the electricity demand and supply already represented by the modelled Stedin substations is removed from the national ETM profile by subtracting the provincial ETM profiles for Zuid-Holland [52], Utrecht [51], and Zeeland [53]. Flexibility technologies are excluded from this calculation so that their installed capacities remain a decision of the optimisation model rather than a predefined input.

This subtraction involves two simplifications. First, the provincial ETM profiles are assumed to fully correspond to the Stedin service area, whereas Zuid-Holland is partly served by Liander. The subtracted profile therefore covers a slightly larger area than is modelled, which is accepted as a modelling limitation. Second, the resulting residual profile includes the effects of international imports and exports, which are not modelled as separate decision variables. Treating imports, exports, and the broader national electricity market as predetermined reflects the perspective of a DSO, for whom cross-border electricity flows are an external system condition. This modelling choice also limits the optimisation space, keeping the problem computationally tractable (R5).

5.4. Technology data and cost assumptions

This section describes the technical and economic parameters used to represent the flexibility technologies and network investment options in the model. The model includes four flexibility technologies: two battery storage technologies, an electrolyser for power-to-hydrogen conversion and a hydrogen gas turbine for hydrogen-to-power conversion. In addition, hydrogen can be imported at a fixed price, exported up to a maximum annual volume, and stored without capacity limit.

The parameters for each technology are listed in Tables 5.5–5.10. The majority of parameters are derived from the Danish Energy Agency technology catalogue [54, 55, 56]. Following a consultation with a Stedin expert on batteries and electrolysers, several parameters were updated to better reflect expected technology performance in the Dutch context; these are indicated by their respective sources in the tables. A description of each parameter is provided in Table 5.4.

Table 5.4: Description of technology parameters used in the models

Parameter	Unit	Description
lifetime	yr	Technical lifetime of the technology
flow_out_eff	–	Discharge or output conversion efficiency
flow_in_eff	–	Charge or input conversion efficiency
flow_cap_per_storage_cap_max	h^{-1}	Maximum ratio of power capacity to energy capacity; inverse equals minimum autonomy duration
storage_discharge_depth	–	Minimum allowable state of charge (1 = fully discharged)
storage_loss	h^{-1} or day^{-1}	Fractional self-discharge loss per unit time
storage_cap_max	MWh	Maximum installed energy capacity
storage_initial	–	Initial state of charge at the start of the modelled year
cost_storage_cap	kEUR/MWh	CAPEX per unit of energy capacity
cost_flow_cap	kEUR/MW	CAPEX per unit of power capacity
cost_om_annual	kEUR/MW/yr	Annual fixed operations and maintenance cost
cost_om_annual_investment	yr^{-1}	Annual fixed O&M expressed as a fraction of total CAPEX
flow_ramping	h^{-1}	Maximum change in output per hour as a fraction of installed capacity
cost_flow_in	kEUR/MWh	Variable cost per unit of energy consumed (e.g. import price)
resource_use_max	MWh	Maximum cumulative resource use over the modelled period
cost_interest_rate	–	Discount rate used to annualise capital costs
lost_load: cost_flow_out	kEUR/MWh	Penalty cost for unserved energy; ensures load shedding is a last resort
area_use_per_flow_cap	m^2/MW or m^2/MWh	Spatial footprint per unit of installed power or energy capacity

Table 5.5: Parameters for the vanadium redox flow battery (battery_flow)

Parameter	Value	Unit	Source
lifetime	25	yr	[55]
flow_out_eff	0.91	–	[55]
flow_in_eff	0.91	–	[55]
flow_cap_per_storage_cap_max	0.08	h^{-1}	[55]
storage_discharge_depth	0.11	–	[55]
storage_loss	6.25×10^{-5}	h^{-1}	[55]
cost_storage_cap	320	kEUR/MWh	[55](lower bound)
cost_om_annual	2.92	kEUR/MW/yr	[55]
area_use_per_flow_cap	65	m^2/MWh	[57]

Table 5.6: Parameters for the lithium-ion battery system (battery_system)

Parameter	Value	Unit	Source
lifetime	17	yr	[58]
flow_out_eff	0.985	–	[55]
flow_in_eff	0.975	–	[55]
flow_cap_per_storage_cap_max	0.25	h ⁻¹	[55]
storage_discharge_depth	0.11	–	[55]
storage_loss	4.17×10^{-5}	h ⁻¹	[55]
cost_storage_cap	162	kEUR/MWh	[58]
cost_om_annual	8.67	kEUR/MW/yr	[55]
area_use_per_flow_cap	30	m ² /MWh	[57]

Table 5.7: Parameters for the power-to-hydrogen electrolyser (power_2_h2)

Parameter	Value	Unit	Source
lifetime	25	yr	[54]
flow_out_eff	0.653	–	[54]
cost_flow_cap	370	kEUR/MW	[59]
cost_om_annual_investment_fraction	0.04	yr ⁻¹	[54]
area_use_per_flow_cap	100	m ² /MW	[60]

Table 5.8: Parameters for the (natural) gas turbine (gas_2_power)

Parameter	Value	Unit	Source
lifetime	25	yr	[56]
flow_out_eff	0.57	–	[56]
flow_ramping	0.80	h ⁻¹	[56]
cost_flow_cap	904.78	kEUR/MW	[56]
cost_om_annual	3.34	kEUR/MW/yr	[56]

Table 5.9: Parameters for hydrogen storage (storage_h2)

Parameter	Value	Unit	Source
storage_cap_max	∞	MWh	Model choice
flow_in_eff	0.99	–	Model choice
flow_out_eff	1.00	–	Model choice
storage_loss	0.01	day ⁻¹	Model choice
storage_initial	0.50	–	Model choice

Hydrogen storage capacity is unbounded to allow the model to freely determine how much hydrogen needs to be

stored to balance supply and demand over time. This reflects the assumption that hydrogen storage infrastructure can be scaled to meet system needs, and avoids imposing a capacity constraint that cannot be justified and would distort the optimisation. The storage is initialised at 50% of its installed capacity to avoid boundary effects at the start and end of the modelled year. A cyclic storage constraint ensures that the state of charge at the end of the year equals that at the beginning, preventing the model from drawing on stored energy that would not be available in a multi-year setting.

Table 5.10: Parameters for hydrogen import and export

Parameter	Value	Unit	Source
<code>cost_flow_in (import_h2)</code>	0.126	kEUR/MWh	[61]
<code>resource_use_max (export_h2)</code>	50,000	MWh	Model choice

Hydrogen can be imported at a fixed price and exported up to a maximum annual volume of 50,000 MWh. No revenue is assigned to hydrogen export, as the goal of the model is to optimise congestion management rather than to maximise hydrogen production. This ensures that hydrogen export functions only as an outlet for surplus hydrogen rather than becoming a dominant driver of the optimisation. This penalty also partially offsets a modelling simplification applied to hydrogen. Because the hydrogen distribution network is modelled without capacity constraints, the model implicitly assumes that hydrogen can be transported freely across the system, overstating the availability of distribution infrastructure relative to reality. The export penalty introduces a modest disadvantage that helps balance this simplification. The import price reflects the baseline cost of green hydrogen [61].

Table 5.11: Global model parameters

Parameter	Value	Unit	Source
<code>cost_interest_rate</code>	0.01	—	Model choice [62]
<code>lost_load: cost_flow_out</code>	10,000,000	kEUR/MWh	Model choice
<code>curtailment: resource_use_max</code>	∞	MWh	Model choice

Three global parameters apply across all model configurations. The interest rate of 1% is used to annualise capital costs. The lost load penalty assigns an extremely high cost to any unmet electricity demand. This ensures that the model always finds a feasible solution by treating lost load as a last resort, preventing unmet demand from distorting the optimisation. Curtailment is unbounded, meaning the model can shed any amount of excess electricity generation when no other option is available. Since no separate generation categories are modelled, the net supply at each node represents the combined output of all local generation. In the 2050 KM scenario, this generation consists primarily of renewable sources, so curtailment represents the shedding of excess renewable generation.

Network investment costs consist of two components: a fixed cost per MW of additional capacity reflecting the investment in transformers, and a distance-dependent cost per MW per kilometre reflecting the associated cable works. Both components are included in the `cost_flow_cap` and `cost_flow_cap_per_distance` parameters and are listed per transformer type in Table 5.3.

5.5. Temporal representation

The HV model is run at hourly temporal resolution as the baseline. For the HV–MV model, running at full hourly resolution is computationally infeasible, a more limited temporal representation is therefore required. Time clustering is tested as a potential approach to reduce computational load while preserving temporal variation. However, time clustering disrupts the seasonal charge and discharge patterns that hydrogen storage depends on for long-term system balancing, making it unsuitable for a model in which hydrogen operates as a seasonal storage technology. Temporal resampling is therefore adopted instead. Although resampling reduces the temporal resolution of individual time steps, it retains sequential time steps and preserves the seasonal variation necessary for hydrogen storage. The test results supporting this choice are presented in Appendix D.

The HV–MV model and the HV model used for comparison in Section 6.3 and the Utrecht HV–MV provincial model

used for the SPORES analysis in Section 6.5 are run at three-hour resampling. The effect of temporal resampling on model outcomes is assessed in Section 6.2.

5.6. Implementation in Calliope

The optimisation model is implemented using Calliope 0.7.0 [48], an open-source energy system modelling framework that represents energy systems as linear optimisation problems. Calliope is built on top of Pyomo and interfaces with commercial and open-source solvers. In this study, the Gurobi solver is used.

The model is defined entirely by a set of YAML configuration files that specify the technologies, nodes, network links, and input datasets. This modular structure keeps the model transparent and easy to adapt: swapping datasets, adjusting parameters, or running different model configurations requires only targeted changes to the relevant files. The model is built and solved using Python, which allows the models to be run via a Jupyter notebook for local testing, or as a standalone script for batch execution on the Delft Blue supercomputer. The overall file structure of the model is described below.

The following subsections describe the main components of the model implementation, including the model configuration, technology definitions, node structure, and transmission links.

The model directory is organised as follows:

```
HV_model/
model_run.ipynb          # Notebook to build and solve the model
spores_algorithm.py      # SPORES batch execution script
environment.yml          # Conda environment specification
model/
  model.yaml             # Top-level configuration (solver, imports)
  techs.yaml             # Technology definitions and parameters
  nodes.yaml             # Node definitions with coordinates
  transmission.yaml      # Electricity transmission links
  transmission_h2.yaml   # Hydrogen links to H2 hub
  imports.yaml           # References to timeseries input files
  custom_math/
    spores_slack.yaml    # Custom SPORES slack constraint
  scenarios/
    scenarios.yaml       # Override definitions for scenarios
    spores.yaml          # SPORES mode configuration
  techs/
    link_150_150_corrected_distance.csv
    link_150_380_flowcapmin.csv
  timeseries/
    demand_supply_380.csv # National residual profile
    |                     # divided by the number of 380 kV nodes
    demand_supply_GOP_150.csv # Substation-level profiles
    ...                   # (one file per node)
```

5.6.1. Model file

The core model configuration is defined in the `model.yaml` file. This file references all other YAML files that define technologies, nodes, transmission links, and input datasets via the `import` section.

Solver settings are specified in the `solve` section of the model configuration. The Gurobi solver is used with the barrier method (`Method: 2`), which improves numerical stability for large-scale optimisation problems. Crossover is disabled to avoid additional numerical adjustments after the barrier solution converges. Presolve routines are enabled to reduce model size before optimisation, and multi-threading across six CPU threads is used to accelerate computation. Numerical tolerances are set to ensure stability and convergence, covering feasibility, optimality, and barrier convergence. A zero threshold is applied to treat values close to zero as zero, preventing numerical artefacts in the results.

The `model.yaml` file used in the model is shown in Listing 5.1.

Listing 5.1: `model.yaml` file used for this research

```
1 import:
2   - "techs.yaml" # Model's technologies
3   - "nodes.yaml" # Model's nodes
```

```

4 - "transmission_h2.yaml" # Model's links between substations and h2 hub
5 - "transmission.yaml" # Model's links between nodes
6 - "imports.yaml" # Model's input data
7 # - "scenarios/scenarios.yaml" # Model's scenarios
8 # - "scenarios/spores.yaml" # Model's SPORE scenarios
9
10 config:
11   init:
12     name: HV model / HV--MV model / Zeeland model / Utrecht model / Zuid-Holland model
13     calliope_version: 0.7.0
14
15   #   resample:
16   #     timesteps: 2h
17
18   build:
19     ensure_feasibility: true
20     mode: plan
21
22   solve:
23     solver: gurobi
24     zero_threshold: 1e-10
25
26     solver_options:
27       # BarHomogeneous: 1 # used when numerical trouble arises
28       Presolve: 2
29       Threads: 6
30       Method: 2
31       Crossover: 0
32       FeasibilityTol: 1e-3
33       OptimalityTol: 1e-4
34       BarConvTol: 1e-4

```

5.6.2. Import file

External input data are specified in the `imports.yaml` file. This file tells the model where to find the input data it needs, by linking each dataset to the relevant nodes and technologies in the model. The input data are stored as CSV files and include three types of information. First, hourly demand and supply time series for each substation, which describe how much electricity is consumed and generated at each location throughout the year. Second, the distances between connected substations, corrected for the actual routing of cables using the correction factor described in Section 5.2.2. Third, the existing transformer capacities at the 150 kV substations, which are used to set the minimum transmission capacity and the distance-dependent investment costs for network expansion.

Listing 5.2 shows a simplified example of how datasets are imported and assigned to model nodes and technologies.

Listing 5.2: Example of imported datasets in the Calliope model

```

1 data_tables:
2
3   link_150_capacity:
4     data: techs/link_150_150_corrected_distance.csv
5     rows: techs
6     columns: parameters
7
8   supply_DIM_380:
9     data: timeseries/demand_supply_380.csv
10    rows: timesteps
11    columns: [techs]
12    select:
13      techs: [supply_power]
14    add_dims:
15      nodes: [DIM_380]
16      parameters: source_use_equals

```

5.6.3. Technology file

The `techs.yaml` file defines the technical and economic parameters of all technologies the models include. For each technology, a block specifies the Calliope technology type (such as storage, conversion, or supply) along with the associated parameters covering efficiency, storage characteristics, lifetime, and investment and operational costs. Visualisation properties, such as the colours used in result plots, are also specified here.

Listing 5.3 shows an example of the technology definition for the vanadium redox flow battery.

Listing 5.3: Example technology definition for a vanadium redox flow battery in the Calliope model

```

1 techs:
2   battery_flow:                                # Vanadium Redox Battery
3     name: "Battery_□Flow"
4     base_tech: storage
5     cyclic_storage: true
6     carrier_in: power
7     carrier_out: power
8     color: "#7B1FA2" #Purple
9     template: interest_rate_setter
10    lifetime: 25                                # [years]
11    flow_out_eff: 0.91
12    flow_in_eff: 0.91
13    flow_cap_per_storage_cap_max: 0.08          # 12.5h autonomy
14    storage_discharge_depth: 0.11              # 89% usable capacity
15    storage_loss: 0.0000625                    # [1% per hour]
16    cost_storage_cap:
17      data: 320                                # kEUR per MWh
18      index: monetary
19      dims: costs
20    cost_om_annual:
21      data: 2.92                                # kEUR per MW per year
22      index: monetary
23      dims: costs
24    area_use_per_flow_cap: 65                   # m2 per MWh
25
26 ...

```

5.6.4. Node file

The `nodes.yaml` file defines the spatial structure of the model by specifying all nodes, their geographic coordinates, and the technologies that can be installed at each location.

To avoid repeating the same configuration for every node, templates are used. A template defines a standard set of technologies that can be assigned to multiple nodes at once. For example, the `standard_node_techs` template assigns the default set of technologies available at the substations, including demand, curtailment, battery storage, and hydrogen conversion technologies. A separate template is defined for the hydrogen hub node, covering hydrogen storage, import, and export. Each node entry then references the appropriate template and specifies its geographic coordinates.

Listing 5.4 shows a simplified example of the node definitions used in the model.

Listing 5.4: Example node and template definitions in the Calliope model

```

1 templates:
2
3   standard_node_techs:
4     techs: {lost_load, supply_power, curtailment, demand_power,
5            battery_flow, battery_system, power_2_h2, gas_2_power}
6
7   h2_hub_techs:
8     techs: {storage_h2, export_h2, import_h2}
9
10 nodes:
11
12   h2_hub:
13     longitude: 4.555121
14     latitude: 51.702665
15     template: h2_hub_techs
16
17   WT_380:
18     latitude: 52.0159
19     longitude: 4.3067
20     template: standard_node_techs
21     available_area: inf
22
23 ...

```

5.6.5. Transmission files

Network links between nodes are defined in two separate transmission files: one for electricity and one for hydrogen. This separation reflects the different modelling assumptions applied to each carrier.

Hydrogen transmission

Since the hydrogen pipeline network is not modelled explicitly, all nodes are connected to the central hydrogen hub through a single shared transmission template. This template specifies hydrogen as both the input and output carrier. Individual links then connect each node to the hub using this template. Listing 5.5 shows an example of this structure.

Listing 5.5: Example hydrogen transmission links

```

1 templates:
2   transmission_h2:
3     name: "Hydrogen_pipeline"
4     base_tech: transmission
5     carrier_in: hydrogen
6     carrier_out: hydrogen
7     colour: "#E6E6E6"
8
9   techs:
10    WT_380_to_h2_hub:
11      template: transmission_h2
12      link_from: WT_380
13      link_to: h2_hub
14
15    BWK_380_to_h2_hub:
16      template: transmission_h2
17      link_from: BWK_380
18      link_to: h2_hub
19    ...

```

Electricity transmission

Electricity transmission links account for both power flows and capacity constraints, and allow the model to invest in network expansion where economically optimal. Two types of templates are defined. Standard transmission templates cover connections between substations at the same voltage level, specifying the carrier type, lifetime, and distance-dependent cable costs. Expansion templates cover transformer connections between voltage levels and include investment costs for the transformers per MW of additional capacity and distance-dependent cable costs.

Individual links are defined by referencing the appropriate template and specifying the origin (`link_from`) and destination node (`link_to`). Links are bidirectional by default, allowing power to flow in both directions. For expandable transformer links, the minimum and maximum flow capacity are also specified, defining the existing capacity and the maximum allowed expansion. When the two values are equal, no expansion is possible at that substation. Listing 5.6 shows a simplified example.

Listing 5.6: Example electricity transmission templates and links

```

1 templates:
2   transmission_150kv:
3     name: "150_kV_AC_power_transmission"
4     base_tech: transmission
5     carrier_in: power
6     carrier_out: power
7     colour: "#2CB1E6"
8     lifetime: 40
9     cost_flow_cap_per_distance:
10      data: 3000
11      index: monetary
12      dims: costs
13   ...
14 # Expansion templates
15   transmission_150_50_exp:
16     name: 150/50 kV trafo expansion
17     base_tech: transmission
18     carrier_in: power
19     carrier_out: power
20     colour: '#FFC107'

```

```

21     lifetime: 40
22     cost_flow_cap:
23         data: 75.79
24         index: monetary
25         dims: costs
26
27     ...
28 techs:
29 # Links 150-150 substations
30     BRK_150_to_ULW_150:
31         template: transmission_150kv
32         link_from: BRK_150
33         link_to: ULW_150
34         one_way: false
35
36     ...
37 # Links MV substations
38     UMW_150_to_UMW_50:
39         template: transmission_150_50_exp
40         link_from: UMW_150
41         link_to: UMW_50
42         one_way: false
43         flow_cap_min: 190.0
44         flow_cap_max: 427.5
45
46     ...

```

5.6.6. Scenario files

Scenarios and SPORES runs are implemented using Calliope's override function. An override allows specific parameters, technologies, or input datasets to be modified without changing the underlying model structure. This means that the base model only needs to be defined once, and each scenario or SPORES configuration is defined as a separate override file that adjusts only the relevant parameters.

SPORES are not a default functionality of Calliope but are implemented as an external algorithm, adopted from the Calliope-NL repository [63]. The SPORES workflow consists of two steps. First, the cost-optimal model is solved as normal. The total system cost of this solution is then used to define a cost slack of 15%, within which all subsequent SPORES solutions must remain. Second, the model is solved iteratively. In each iteration, a penalty score is assigned to technologies and locations that were deployed in the previous solution, making it less attractive for the model to select the same configuration again. This pushes the model towards alternative configurations of near-equal cost. The penalty scores accumulate across iterations, progressively steering the model away from previously explored parts of the solution space. The specific SPORES configurations and scoring methods applied in this study are described in Section 5.7.3.

5.6.7. Running the model

The model is built and solved using the Calliope Python API. The three main steps are:

1. **Initialise:** load the model configuration from `model.yaml` using `calliope.read_yaml()`, optionally passing an `override_dict` to apply a time subset or scenario override;
2. **Build:** call `model.build()` to construct the optimisation problem;
3. **Solve:** call `model.solve()` to invoke Gurobi and retrieve the results.

This workflow can be executed either interactively via the Jupyter notebook `model_run.ipynb` for local testing and analysis, or as a stand-alone Python script for batch execution on Delft Blue. Results are exported either to NetCDF format using `model.results.to_netcdf()` for storage and result analysis in Python, or to CSV format using `model.to_csv()`.

5.7. Experimental setup

To answer the research questions, several model runs were performed, organised into four experiments. All runs were executed on the Delft Blue supercomputer of TU Delft.

5.7.1. SQ2 - Comparison Analysis

To answer SQ2, three model runs are performed and compared. The regional HV model is solved at full hourly resolution over the year 2050, serving as the primary reference for the cost-optimal spatial distribution of flexibility

technologies under HV-only network constraints. The same HV model is then solved at two-hour and three-hour resampling. Comparing these three configurations isolates the effect of temporal resampling on system costs and spatial distribution before introducing MV network topology. The subsequent comparison between the HV model at three-hour resolution and the HV–MV model at three-hour resolution then isolates the effect of including MV network topology. This stepwise approach ensures that differences in outcomes between the HV and HV–MV models can be attributed to network topology rather than temporal resolution.

From each run, the following outputs are extracted and analysed: total annualised system costs, installed capacity per flexibility technology per substation, network expansion investments per link, and the distribution of flexibility technologies across voltage levels. Where relevant, dispatch patterns and network loading are also examined to explain the spatial outcomes.

5.7.2. SQ3A - Scenario analysis

A scenario analysis is performed to assess the parametric robustness of the cost-optimal distribution of flexibility technologies to key techno-economic uncertainties (R6). Two alternative scenarios are defined, each modifying the relative attractiveness of hydrogen-based and battery-based flexibility options.

High hydrogen import price scenario

The price of imported hydrogen is one of the main uncertainties in the model. Although hydrogen is expected to become cheaper over time, the extent and speed of this cost reduction remain highly uncertain. Johnsen et al. note that hydrogen cost projections have long relied on assumptions of rapid scale-up and learning effects, whereas actual costs remain strongly determined by electricity prices, engineering requirements, and transport and storage costs [64]. This scenario therefore represents a pessimistic case in which the expected decline in hydrogen prices does not materialise. Available sources indicate that current hydrogen production costs still vary widely but remain relatively high [65, 66, 67]. Based on this uncertainty range, the hydrogen import price in this scenario is increased from 0.126 kEUR/MWh [61] to 0.3 kEUR/MWh

Accelerated battery cost reduction scenario

Battery storage costs have declined rapidly over the past decade due to technological improvements, economies of scale, and large investments in manufacturing capacity [68]. Studies suggest that costs could decrease by around 40% between 2023 and 2030 as innovation in battery chemistries and manufacturing continues [69]. To account for the possibility that battery technologies improve faster than assumed in the baseline model, this scenario reduces the investment costs of both battery technologies by 50% relative to the baseline assumptions: the cost of `battery_flow` is reduced from 320 kEUR/MWh to 160 kEUR/MWh, and the cost of `battery_system` from 162 kEUR/MWh to 81 kEUR/MWh. This represents a case in which technological learning and manufacturing scale-up accelerate cost declines beyond baseline assumptions.

5.7.3. SQ3B - Near-optimal solution space exploration

The SPORES methodology is applied to the Utrecht HV–MV provincial model to explore the near-optimal solution space and assess the stability of the hypotheses developed in SQ2 and SQ3A. The analysis consists of two steps. First, a set of 113 SPORES is generated to map the diversity and boundaries of the near-optimal solution space, producing deployment frequencies for each substation and network link. Second, these frequencies are related to network properties through statistical hypothesis testing, constituting the attributed structural robustness analysis introduced in Section 3.1.3.

SPORES configuration

The SPORES methodology is applied using a cost slack of 15%, as justified in Appendix E. The solution space is explored through 113 SPORES organised into nine batches as summarised in Table 5.12: one broad exploration batch of 25 SPORES using random penalty weights, and eight intensified batches of 11 SPORES each, pushing the solver towards the maximum or minimum deployment of each of the four flexibility technologies. From each SPORE, installed capacity per technology per node, network expansion per link, and investment costs are extracted.

Intensification strength

The intensification strength b in the intensified SPORES objective (Equation 3.4) controls the degree to which the solver is pushed towards the maximum or minimum deployment of a target technology. If b is much smaller than $a \cdot w_{ij}$, the diversity term dominates and intensification has little effect. On the other hand, if b is much larger than $a \cdot w_{ij}$, the intensification term dominates, and all SPORES are pushed towards the boundary without sufficient diversity. To achieve a meaningful balance between both terms, b must therefore be of similar magnitude to $a \cdot w_{ij}$, which scales with the investment cost of the target technology.

To achieve this balance, b is scaled proportionally to the investment cost of each technology:

Table 5.12: Overview of SPORES batches used in the analysis

Batch	Type	N SPORES	SPORE IDs
batch_main	Broad exploration	25	1–25
bat_flow_max	Intensify MAX battery_flow	11	26–36
bat_flow_min	Intensify MIN battery_flow	11	37–47
bat_system_max	Intensify MAX battery_liion	11	48–58
bat_system_min	Intensify MIN battery_liion	11	59–69
p2h2_max	Intensify MAX power_2_h2	11	70–80
p2h2_min	Intensify MIN power_2_h2	11	81–91
gas2power_max	Intensify MAX h2_2_power	11	92–102
gas2power_min	Intensify MIN h2_2_power	11	103–113
Total		113	

$$b = \text{global factor} \times \frac{\text{cost_flow_cap}_{\text{tech}}}{\text{cost_flow_cap}_{\text{min}}} \quad (5.3)$$

The cheapest technology (battery_system, 162 kEUR/MW) is used as the reference. The global factor is set to 2, providing sufficient intensification pressure while preserving solution diversity. The resulting intensification parameters are summarised in Table 5.13.

Technology	cost_flow_cap (kEUR/MW)	Ratio to reference	Effective b
battery_system	162	1.00	1
battery_flow	320	1.98	2
power_2_h2	370	2.28	2
gas_2_power	904.78	5.48	6

Table 5.13: Technology-specific intensification weights used in the SPORES experiments.

Statistical testing of the hypotheses

The deployment frequencies produced by SPORES establish how structurally robust each planning decision is across near-optimal configurations, but do not explain the source of that stability. To move from frequency classification to attributed structural robustness, each hypothesis is tested statistically using the SPORES output. Five statistical tests are applied, each selected based on the nature of the variables and the relationship being examined. The observations in all tests are individual MV substations. Because substations are connected in a shared radial network, they are not fully statistically independent. This is acknowledged as a limitation of the analysis.

All tests use a significance threshold of $p < 0.05$. A p-value below this threshold indicates that, under the assumption that no true effect exists the probability of obtaining a result at least as extreme as the one observed is less than 5%. When the p-value falls below 0.05, this assumption becomes difficult to maintain, and the result is considered statistically significant.

The hypotheses referenced in this section (hypothesis 3, hypothesis 6, hypothesis 7, and hypothesis 10) are formulated from the cost-optimal and scenario results in Chapter 6. They are named here to make the link between each statistical test and its corresponding hypothesis explicit and their full formulations are given in Sections 6.3 and 6.4.

Kruskal-Wallis test

Before drawing planning conclusions from the 113 SPORES, it is necessary to establish whether the nine batches produce different outcomes. If the intensified batches steer results in a measurably different direction, they cannot be treated as an unbiased sample of the near-optimal solution space. The Kruskal-Wallis test assesses this

by comparing the distributions of key metrics across all nine batches simultaneously, without assuming that the data follow a normal distribution [70]. It does so by ranking all observations across batches and testing whether the mean ranks are equal. A significant result indicates that at least one batch produces outcomes that differ consistently from the others.

The Kruskal-Wallis test is used here for validation of the sampling strategy rather than for testing a substantive planning hypothesis. For this reason, no post-hoc pairwise comparisons are performed: the relevant question is whether batch effects exist at all, not which specific batches drive them. The effect size is reported as η^2 , calculated as $(H - k + 1)/(n - k)$, where H is the test statistic, k is the number of groups, and n is the total number of observations. This indicates what proportion of variance in each metric is attributable to which batch a SPORE belongs to. The test statistic H reflects how much the mean ranks of the batches differ from what would be expected if all batches were drawn from the same distribution: a larger H indicates greater differences between batches.

Fisher's exact test and logistic regression

Two tests are combined to assess whether no-regret classification as defined in hypothesis 3 can be attributed to identifiable network properties. Specifically, the tests examine whether substations that simultaneously lack upstream expansion capacity and experience high demand pressure are significantly overrepresented among no-regret nodes. Demand pressure is defined as the percentage of annual hours in which demand exceeds the upstream link capacity.

Fisher's exact test first establishes whether the joint presence of these two conditions is significantly associated with no-regret classification. It does so by testing the association in a 2×2 contingency table, where rows distinguish whether a substation meets both network conditions and columns distinguish whether it is classified as no-regret. Fisher's exact test is preferred over the chi-squared test because the chi-squared test relies on an approximation that requires a minimum number of observations in each cell. When expected cell counts fall below five, this approximation becomes unreliable. Fisher's exact test calculates the exact probability of the observed table directly, without relying on this approximation, and is therefore the appropriate choice when cell counts are small [71].

Fisher's exact test establishes whether the association is significant, but does not quantify the independent contribution of each network property. A binary logistic regression is therefore estimated to assess this [72]. Logistic regression is appropriate when the outcome variable is binary (a substation either qualifies as no-regret or it does not) and estimates the probability of that outcome as a function of multiple predictors simultaneously. The model takes the form:

$$P(\text{no-regret}) = \frac{1}{1 + e^{-(\alpha + \beta_1 x_1 + \beta_2 x_2)}} \quad (5.4)$$

where x_1 represents the absence of upstream expansion capacity (binary) and x_2 represents demand pressure, defined as the percentage of annual hours in which demand exceeds the upstream link capacity.

Each coefficient, β_1 and β_2 , reflects the effect of one predictor on the probability of no-regret classification, while the other predictor is held constant. This allows the contribution of each network property to be assessed independently, even if the two predictors are correlated with each other in the data. Results are reported as odds ratios with 95% confidence intervals. An odds ratio expresses how much more likely a substation is to be classified as no-regret when one predictor changes, while the other predictor is held constant. An odds ratio greater than one indicates a positive association with no-regret classification; an odds ratio of one indicates no association.

Mann-Whitney U test

The Mann-Whitney U test is applied to compare two independent groups of substations on a continuous outcome variable [73]. The test ranks all observations together and assesses whether one group tends to receive higher positions in that ranking than the other, without assuming a normal distribution. Two comparisons are made. The first tests hypothesis 6: whether substations that receive an electrolyser have significantly more annual surplus hours than substations that do not. The second tests hypothesis 7: whether substations with an electrolyser show significantly longer uninterrupted surplus blocks than those without. In both cases, the distribution of the outcome variable is right-skewed across substations, as shown in Appendix F, which confirms that a non-parametric test is appropriate.

Both tests are applied one-sided. A two-sided test would detect any systematic difference in surplus hours between substations with and without electrolyzers, regardless of direction. The underlying economic reasoning, however, is directional: an electrolyser is only viable where surplus exposure consistently exceeds a minimum operational threshold, so a substation with fewer surplus hours than the reference group would not attract one.

The relevant question is therefore not whether the two groups differ, but whether substations with electrolyzers have more surplus hours than those without. A significant result would indicate that substations with electrolyzers do have more surplus hours than those without.

The effect size is reported as the rank-biserial correlation r , calculated as $r = 1 - (2U)/(n_1 * n_2)$, where U is the Mann-Whitney statistic and n_1 and n_2 are the group sizes. This ranges from 1 to +1 and expresses the degree to which the values of one group dominates those of the other in the ranking.

Spearman correlation

The Spearman rank correlation measures the strength of association between two variables based on their ranks rather than their raw values [74]. It is applied to assess hypothesis 10: whether a substation's flexibility deployment frequency and the variability of its technology mix are related properties. A significant positive correlation would indicate that substations that consistently attract flexibility also tend to attract the same technology, while a non-significant result would suggest that location stability and technology stability are independent. Spearman correlation is used because SPORES outcomes are determined by binding network constraints and penalty weights rather than by a process that produces normally distributed values, and rank-based correlation does not assume that the relationship between the two variables is linear. The correlation coefficient ρ is the effect size.

The correlation coefficient is defined as:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (5.5)$$

where d_i is the difference between the ranks assigned to observation i on each of the two variables, and n is the total number of observations. The coefficient ρ ranges from -1 to $+1$, where values near $+1$ indicate a strong positive association and values near zero indicate no consistent directional relationship.

Phi coefficient and Wilcoxon signed-rank test

To assess whether flexibility and network expansion act as substitutes at the substation level, two complementary tests are applied. The phi coefficient measures the association between two binary variables [75]. For each substation, it captures whether flexibility deployment and upstream link expansion tend to co-occur across SPORES or to exclude each other:

$$\phi = \frac{n_{11}n_{00} - n_{10}n_{01}}{\sqrt{(n_{11} + n_{10})(n_{01} + n_{00})(n_{11} + n_{01})(n_{10} + n_{00})}} \quad (5.6)$$

where n_{11} represents SPORES in which both flexibility and expansion are present, n_{00} represents SPORES in which neither is present, and n_{10} and n_{01} represent the mixed cases. A negative phi indicates that the two responses tend not to co-occur (substitution), while a positive phi indicates they tend to appear together (complementarity). The phi coefficient is computed separately for each substation, producing one phi value per substation. The resulting set of values is then examined as a distribution, with the median used to characterise whether substitution is a structural pattern at the network level. A negative median phi across all substations would indicate that substitution is a structural pattern in the network as a whole, rather than an incidental finding at a few individual locations.

The Wilcoxon signed-rank test then assesses whether the median phi across all substations differs significantly from zero [76]. It does so by ranking the absolute deviations of phi values from zero and testing whether positive or negative deviations dominate, without assuming that the phi values are normally distributed. The distribution of phi values across substations is bounded and left-skewed, as shown in Appendix F, which confirms that a parametric test is unsuitable. The median phi value serves as the summary effect size.

6

Results

This chapter presents the results of the modelling experiments and answers the four sub-questions introduced in Chapter 1. Together, the sub-questions build towards an answer for the main research question.

The chapter is structured in four parts, each corresponding to a methodological step in the research strategy. The first part (Section 6.1) addresses SQ1A and SQ1B by describing how the regional HV model was constructed and how MV-level network topology and capacity constraints were incorporated.

The second part (Sections 6.2 and 6.3) addresses SQ2. Section 6.2 first examines the effect of temporal resampling, ensuring that differences between the two model configurations can be attributed to network topology rather than temporal resolution. The comparison in Section 6.3 then identifies how including MV network detail changes where and how much flexibility is deployed, and formulates a set of hypotheses that capture the main drivers of the observed spatial patterns. The third part (Section 6.4) addresses SQ3A through a scenario analysis. Two alternative assumptions on technology costs are tested to assess whether the spatial distribution identified in the cost-optimal solution is parametrically robust. The scenario results are used to complement the hypotheses.

The fourth part (Section 6.5) addresses SQ3B by applying the SPORES methodology to explore the near-optimal solution space. For each hypothesis from SQ2 and SQ3A that can be evaluated without varying the network representation, the analysis proceeds in two steps. First, deployment frequencies across the near-optimal configurations determine whether the hypothesis holds structurally. Second, where a structural pattern is identified, statistical testing assesses whether it can be attributed to a specific network property. Hypotheses confirmed through both steps are elevated to principles which serve as the basis for the recommendations to Stedin.

6.1. Results model development: SQ1A and SQ1B

The first two sub-questions concern the development of the spatial optimisation models used in this study. Together, they establish the modelling foundation on which the analyses in Sections 6.3 – 6.5 are built. The answers to SQ1A and SQ1B are therefore not quantitative results but descriptions of the modelling decisions made, the trade-offs considered, and an evaluation of whether the resulting models satisfy the methodological requirements defined in Section 3.2.

6.1.1. Downscaling to a regional HV model (SQ1A)

SQ1A How can a national HV network model be downscaled to a regional HV network representation?

First, the 150 kV substations within the Stedin service area were identified from Stedin's internal network database. These substations formed the spatial backbone of the regional model, from which the network topology was constructed using the national high-voltage network map as a reference [49]. This topology provided the connections between substations and their geographic coordinates. A correction factor of 1.2 was applied to all links to account for the actual routing of cables in the field. Second, the remainder of the Dutch electricity system was represented in aggregated form via the 380 kV nodes that directly connect to the Stedin network. These nodes act as a black-box, with national demand and supply profiles from the ETM KM 2050 scenario distributed evenly across them [50]. This preserves system-level consistency without simulating the internal dynamics of the national grid. Third, substation-level load forecasts provided by Stedin, derived from the same scenario, serve as the demand

and generation inputs for all 150 kV substations. This ensures that the regional model remains consistent with the planning assumptions Stedin uses internally.

The resulting model represents 10 substations at 380 kV and 47 substations at 150 kV, connected through the topology of the existing high-voltage network. Flexibility technologies can be deployed at all substations, and network expansion is possible at all 380/150 kV transformer links and 150/150 kV transmission links. This model serves as the baseline configuration against which the effect of including MV network topology is assessed in Section 6.3.

6.1.2. Incorporating MV network topology (SQ1B)

SQ1B How can MV-level network topology and capacity constraints be incorporated into an HV–MV optimisation model in a way that remains suitable for DSO decision-making?

Chapter 5 describes in detail how MV-level topology and capacity constraints were translated into the model. What that process revealed is that suitability for DSO decision-making depends on a design rule: the planning purpose must serve as the primary criterion for every abstraction decision, determining which detail is decision-relevant rather than which detail is technically possible to include.

In practice, this principle operated along two dimensions. The first concerned constraint selection. Transformer capacity was treated as the primary binding constraint, consistent with how Stedin assesses capacity in its own planning practice. All substation capacities in the dataset are expressed as N-1 safe values, which justifies using them directly as binding constraints in the model [B.1.1B]. The net node profile method was confirmed as the only workable approach given the structure of Stedin's planning data [B.2.1A]. Operational constraints not relevant at a 2050 planning horizon were excluded. Where the planning-relevance of a specific technical detail was unclear, Stedin experts were consulted. A complete overview of all modelling choices and their justification is provided in Appendix A.

The second dimension concerned model structure. The full HV–MV model covering the entire Stedin service area proved too large to solve reliably. Reducing the number of technologies was not considered, as technology competition is central to the decision-relevant output of the model. Two solutions were therefore combined: the model was divided into three provincial sub-models, preserving the full network detail and technology portfolio while keeping each optimisation problem solvable, and three-hour temporal resampling was applied.

The resulting model satisfies the core methodological requirements defined in Section 3.2: flexibility deployment is assessed at individual HV and MV substation level (R1); transformer constraints are enforced through the radial link structure (R2); system-level consistency is preserved via the 380 kV interface (R3); all four flexibility technologies compete simultaneously (R4); the provincial subdivision keeps the model solvable within reasonable computation time (R5); the near-optimal solution space can be explored at the provincial level (R6); and three-hour temporal resampling was found to have limited impact on planning insights, satisfying the temporal resolution requirement (R7), as discussed in the next section.

6.2. Preliminary: Effect of temporal resampling

Before comparing the HV and HV–MV model configurations, this section examines the effect of temporal resampling, ensuring that differences between the two configurations can be attributed to network topology rather than resolution (R7). Three temporal resolutions are compared: the HV model at full hourly resolution (HV 1h), at two-hour resampling (HV 2h), and at three-hour resampling (HV 3h). Table 6.1 summarises the investment outcomes across all three configurations, with HV (1h) serving as the reference.

Table 6.1: Effect of temporal resampling on investment outcomes. Percentage differences are calculated relative to the HV (1h) reference model.

Metric	HV (1h)	HV (2h)	HV (3h)
Total costs (M€/yr)	24.78	24.75 (-0.1%)	24.73 (-0.2%)
Network expansion (MW)	414	427 (+3.1%)	415 (+0.2%)
Total flexibility (MW)	38,194	37,617 (-1.5%)	35,617 (-6.8%)
Vanadium Redox Flow (MW)	24	8 (-66.7%)	6 (-75%)
Lithium-ion (MW)	15,108	14,957 (-1%)	14,754 (-2.3%)
Electrolyser (MW)	6,787	6,554 (-3.4%)	5,916 (-12.8%)
H2-to-Power (MW)	16,274	16,098 (-1.1%)	14,941 (-8.2%)
Spatial correlation – Pearson (min.)	1	0.964	0.967
Spatial correlation – Spearman (min.)	1	0.923	0.925

Effect of temporal resampling on deployment and dispatch

The effect of temporal resampling is small for total system costs and network expansions, but more pronounced for some flexibility technologies.

The general mechanism is straightforward: longer averaging intervals smooth out short-duration fluctuations in demand and generation. Technologies that derive their value from those fluctuations are therefore underestimated when resampling is applied. For the vanadium redox flow battery, weekly mean discharge at two-hour and three-hour resolution drops close to zero, while the hourly reference shows slightly higher but still marginal dispatch (Figure 6.1a). This has limited practical significance, as installed capacity remains marginal across all resolutions. For the electrolyser (Figure 6.1c) the weekly mean discharge is slightly lower at longer intervals. The capacity reduction has two possible causes. First, resampling removes short surplus peaks that would otherwise make electrolyser investment viable at specific substations. Second, the decline in hydrogen-to-power capacity reduces hydrogen demand, which lowers the value of local hydrogen production and further suppresses electrolyser investment. The two effects reinforce each other.

The lithium-ion battery behaves differently. Three-hour resampling actually tracks the hourly reference more closely than two-hour resampling as seen in Figure 6.1b. This is because the battery's cycle length requires at least four hours at maximum power. A two-hour interval cuts through discharge events at the midpoint and underestimates their amplitude, while a three-hour interval avoids this misalignment. The larger time step therefore introduces less error here, not more.

Hydrogen-to-power shows a different pattern. Its dispatch profile, shown in Figure 6.1d, shifts only slightly downward with longer averaging intervals. What does change is the installed capacity, which falls by 8.2% at three-hour resampling. Averaging over three hours lowers the peak demand level that H2P must deliver below the one-hour peak, reducing the required capacity. However, because H2P operates over sustained periods rather than isolated moments, the total energy delivered over those periods remains the same. Resampling therefore reduces the required peak capacity without meaningfully affecting total dispatch.

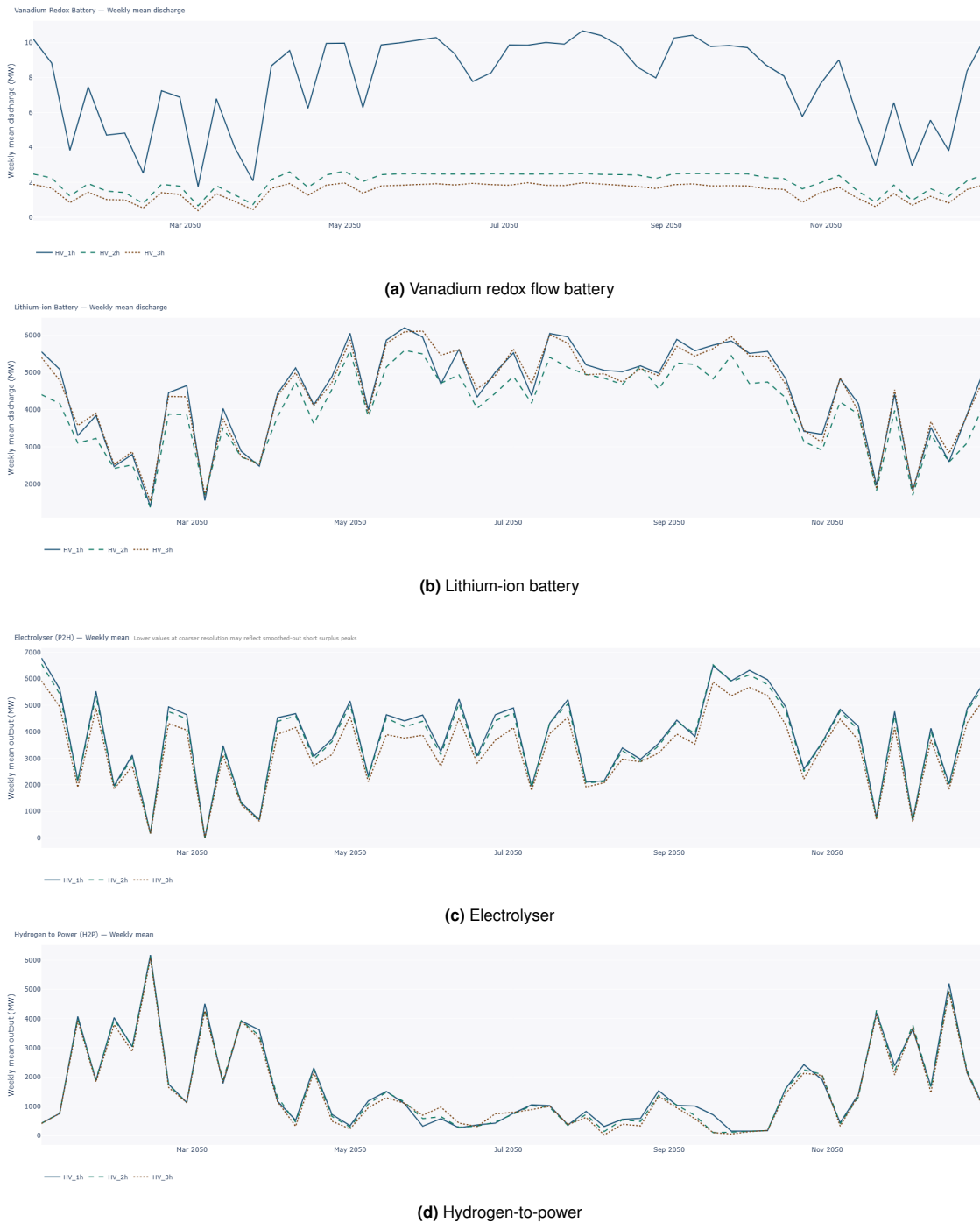


Figure 6.1: Weekly mean discharge profiles for flexibility technologies under HV (1h), HV (2h), and HV (3h) temporal resolutions throughout 2050.

Effect of temporal resampling on spatial distribution

The spatial distribution of flexibility investments remains stable across temporal resolutions. Two complementary correlation measures are used to assess this. The Pearson correlation captures whether the absolute capacity levels per substation remain consistent across resolutions [77]. While the Spearman correlation captures whether the ranking of substations from highest to lowest investment remains stable, regardless of the absolute levels [74]. Across all technologies, Pearson correlations are at minimum 0.96, and Spearman correlations at minimum 0.92. This confirms that both the scale of investment per substation and the relative ordering of substations remain largely consistent across temporal resolutions. The 10 substations attracting the largest flexibility investments are identical across all three configurations.

Temporal resolution selection

Three-hour resampling is adopted throughout this study primarily because full hourly and two-hour resolution is computationally infeasible at HV–MV scale. The spatial distribution of flexibility investments remains stable across all tested resolutions, which means the planning-relevant signals this study aims to produce are preserved. Absolute capacity levels of electrolyzers and hydrogen-to-power should, however, be interpreted with caution, as three-hour resampling underestimates the installed capacity of these technologies.

6.3. Impact of MV network topology on cost-optimal spatial distribution

This section addresses SQ2:

SQ2 How does including MV-level network topology in an HV network model affect the cost-optimal spatial distribution of flexibility technologies?

6.3.1. Overall system outcomes

Table 6.2 compares the key investment outcomes for the HV and HV–MV model configurations. These aggregate differences are small, this means that including MV network detail does not substantially change the overall scale of investment required to manage congestion in Stedins service area towards 2050. What does change is how that investment is distributed across the network. The following sections examine this redistribution at three levels: across voltage levels, across technologies, and in terms of network expansion.

Table 6.2: Comparison between the HV and HV–MV model configurations. Percentage differences are calculated relative to the HV model. Network expansion is calculated as $\text{flow_cap_diff} / 2$ to correct for bidirectional links.

Metric	HV	HV–MV	Δ
Total costs (M€/ yr)	24.73	25.27	(+2.2%)
Network expansion (MW)	414	797	(+93%)
Total flexibility (MW)	35,617	37,562	(+5.5%)
of which 380 kV (MW)	17,305	17,286	-0.1%
of which Stedin area (MW)	18,312	20,276	+10.7%
Vanadium redox flow (MW)	6	0	(-100.0%)
Lithium-ion (MW)	14,754	14,938	(+1.2%)
Electrolyser (MW)	5,916	7,097	(+20%)
Hydrogen-to-Power (MW)	14,941	15,527	(+3.9%)

The 5.5% increase in total flexibility is itself a finding worth noting. In the HV model, electricity surplus at one MV substation and deficits at another are aggregated onto the 150 kV level, where they partially cancel each other out. Once MV topology is introduced, each substation must independently balance supply and demand within its own transformer constraints, and what appeared as a small net imbalance at 150 kV requires separate local responses.

Hypothesis 1

Including MV network topology increases total installed flexibility capacity relative to an HV model, because each MV substation must respect its own transformer constraints independently. Aggregating MV demand at the 150 kV level masks these individual constraints and therefore understates the total need for local flexibility deployment and network expansion.

One observation worth noting is that vanadium redox flow batteries are almost absent from both model configurations. The reason is not that redox batteries are technically unsuitable, but that they serve a system function that closely overlaps with that of lithium-ion batteries. Since lithium-ion is significantly cheaper, it consistently outcompetes redox in the cost-optimal solution, leaving no role for redox to fill, a pattern that becomes fully visible only in the near-optimal solution space and is discussed in Section 6.5.

6.3.2. Flexibility shift in voltage-level distribution

Figure 6.2 shows how this redistribution is distributed across voltage levels.

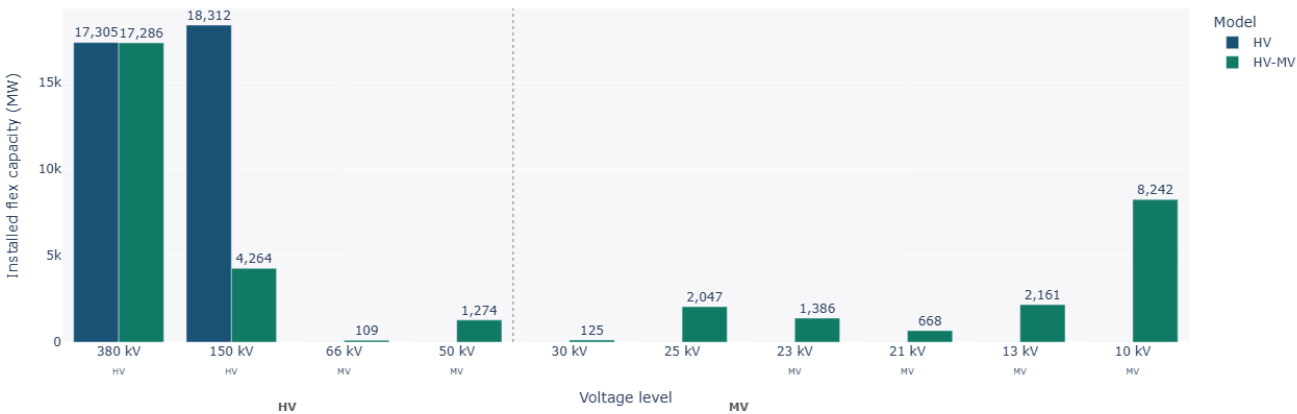


Figure 6.2: Installed flexibility capacity per voltage level for the HV and HV–MV models

When MV topology is introduced, the decline in flexibility at HV levels is concentrated at the 150 kV layer, while the 380 kV layer remains almost unchanged. Together, approximately 14 GW of flexibility disappears from the 150 kV level and approximately 16 GW appears across the MV levels. The total flexibility capacity in the system increases as a result.

The decline at 150 kV follows from the aggregation mechanism described above. In the HV model, no network level below 150 kV exists, so flexibility can only be placed at the substations where demand and supply imbalances appear in the model: the 150 kV and 380 kV nodes. Once MV topology is introduced, those imbalances are reassigned to the lower-voltage substations where the demand and supply actually originate. Because many of the transformer links connecting 150 kV to those substations are already operating at full capacity, flexibility placed at 150 kV cannot reach the MV level. The model therefore places flexibility directly at the MV substations. What the HV model identifies as the optimal location for flexibility is not where the network physically limits the flow of electricity, but where the model can see the imbalances.

Hypothesis 2

When MV network topology is included, flexibility shifts to the substations where demand and supply imbalances actually originate. Without MV topology, these imbalances are aggregated at the nearest 150 kV node, making that node appear as the cost-effective location for flexibility deployment. The spatial distribution produced by an HV model therefore reflects where imbalances are visible in the model, not where they physically occur in the network.

Figure 6.3 confirms that this redistribution is not limited to individual substations but reflects the mechanism: all 150 kV substations lose flexibility while a broad group of MV substations gains it.

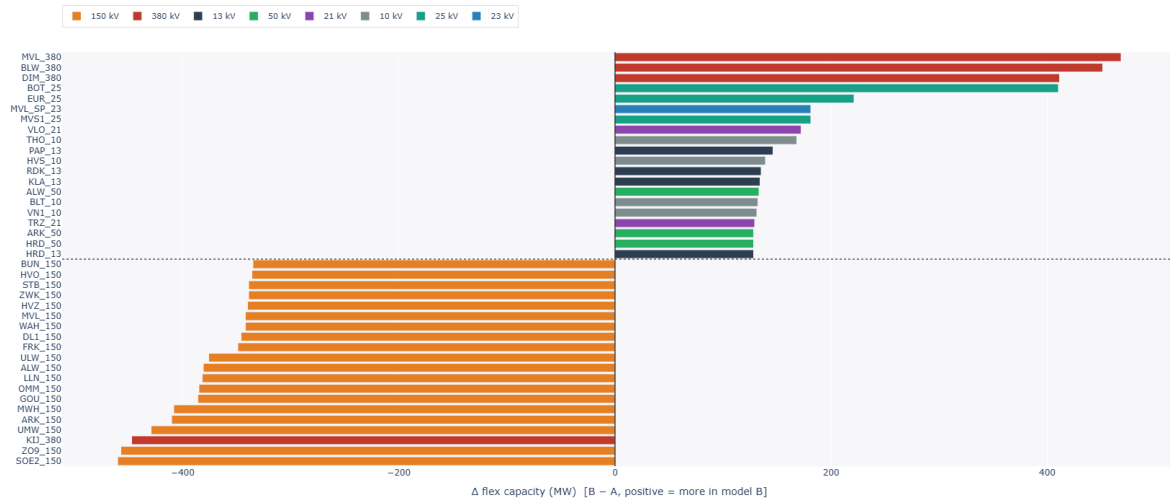


Figure 6.3: Top shifted substations, showing the change in installed flexibility capacity between the HV and HV–MV model ($\Delta \text{flex capacity (MW)} = \text{HVMV} - \text{HV}$).

Two cases illustrate the two sides of this redistribution. The first shows where flexibility disappears and why. SOE_150 shows the largest flexibility decline of 460 MW. In the HV model, this substation carries the aggregated demand of all downstream MV substations, making it an attractive location for hydrogen-to-power and lithium-ion deployment. Once MV topology is introduced, that demand redistributes to the underlying substations where it actually originates. The saturated and non-expandable link to the downstream 50 kV substation means flexibility cannot be passed downward, so it is placed directly at each MV substation instead (Tables 6.3 and 6.4).

Table 6.3: Downstream network connections of substations SOE_150 in the HV–MV model.

From	To	cap_min (MW)	cap (MW)	Δ exp.	Room?
SOE_150	SOE_50	256	256	–	No
SOE_150	SOE2_10	28	29	–	Yes
SOE_50	LEU_10	51	51	–	Yes
SOE_50	SOE2_10	49	49	–	Yes
SOE_50	AF5_10	38	38	–	Yes
SOE_50	AF3_10	38	38	–	Yes
SOE_50	BAA_10	29	29	–	Yes
SOE_50	AF2_10	27	27	–	Yes
SOE_50	SDZ_10	23	23	–	Yes
SOE_50	AF4_10	19	19	–	Yes

Table 6.4: Flexibility distribution along the SOE_150 hierarchy in HV and HV–MV models.

Station	HV total	HV–MV total	Δ total	Δ VRB	Δ Li-ion	Δ Electrolyser	Δ Hydrogen-to-Power
SOE_150	516	55	(-460)	–	(-94)	–	(-366)
SOE_50	–	56	(+56)	–	(+11)	–	(+45)
SOE2_10	–	59	(+59)	–	(+11)	–	(+48)
LEU_10	–	63	(+63)	–	(+15)	–	(+49)
AF1_10	–	56	(+56)	–	(+11)	–	(+45)
AF5_10	–	93	(+93)	–	(+26)	–	(+66)
AF3_10	–	61	(+61)	–	(+11)	–	(+50)
BAA_10	–	104	(+104)	–	(+27)	–	(+77)
AF2_10	–	68	(+68)	–	(+17)	–	(+51)
SDZ_10	–	65	(+65)	–	(+15)	–	(+50)
AF4_10	–	55	(+55)	–	(+11)	–	(+44)

The second case shows where flexibility appears and why. BOT_25 was invisible in the HV model but gains 410 MW of flexibility once MV topology is introduced. This substation serves large industrial connections in the Botlek area

with peak demand of approximately 200 MW. Because the transformer link between BOT_150 and BOT_25 has no expansion slots available (Table 6.5), flexibility placed higher in the network cannot reach this substation, and local deployment is the only available response.

Table 6.5: Downstream network connections of substation BOT_150 in the HV–MV model.

From	To	Cap_min (MW)	Cap (MW)	Δ exp.	Room?
BOT_150	BOT_25	185	185	–	No
BOT_25	BOT_23	23	51	+28	Yes
BOT_25	BOT_10	11	32	+21	Yes

Together, these two cases illustrate the two mechanisms that drive the spatial redistribution of flexibility: the reassignment of aggregated demand to its actual origin, and saturated upstream transformer links that make local flexibility deployment unavoidable.

Hypothesis 3

MV substations that combine high peak demand with no available upstream expansion capacity consistently attract flexibility in the cost-optimal solution. The absence of upstream expansion capacity makes local flexibility the only available response regardless of how the rest of the system is configured. High peak demand determines the scale of that local response.

The 380 kV level does not follow this pattern. The 380 kV substations function as the black-box interface with the national electricity system and carry no aggregated MV demand from Stedin's underlying network. Their role is therefore not affected by the introduction of MV topology: the system balancing function they serve persists regardless of how demand is distributed across the underlying network. This explains why flexibility at 380 kV remains constant across both model configurations.

6.3.3. Shift across flexibility technologies

The shift in flexibility deployment is not uniform across technologies. While the previous section described how the total amount of flexibility shifts across voltage levels, this section examines which technologies drive this redistribution and whether different technologies respond differently to the introduction of MV network topology. Figure 6.4 compares the spatial distribution of electrolyzers, hydrogen-to-power, and lithium-ion batteries between the HV and HV–MV models. Figure 6.5 further disaggregates these patterns by province and voltage level.

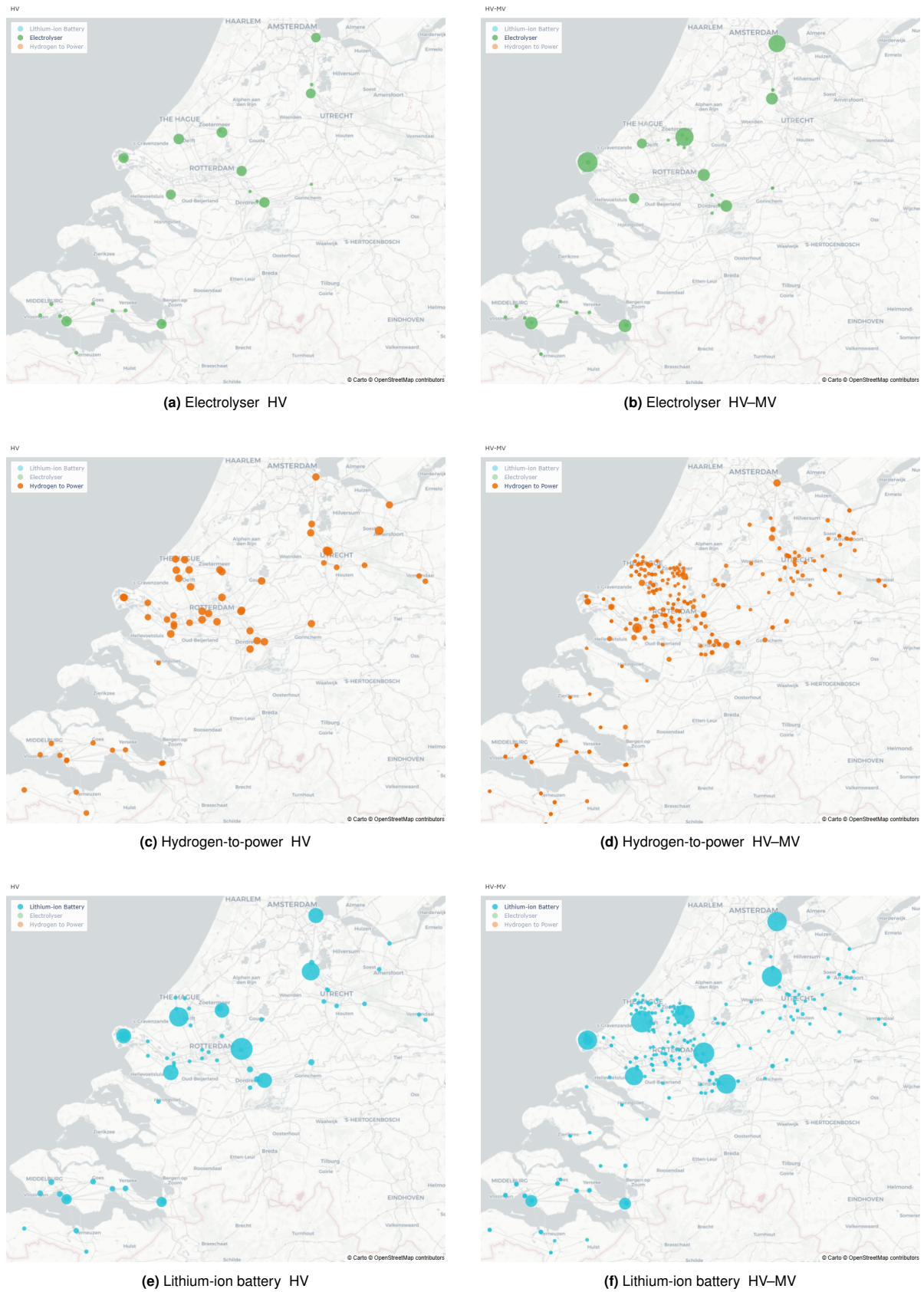
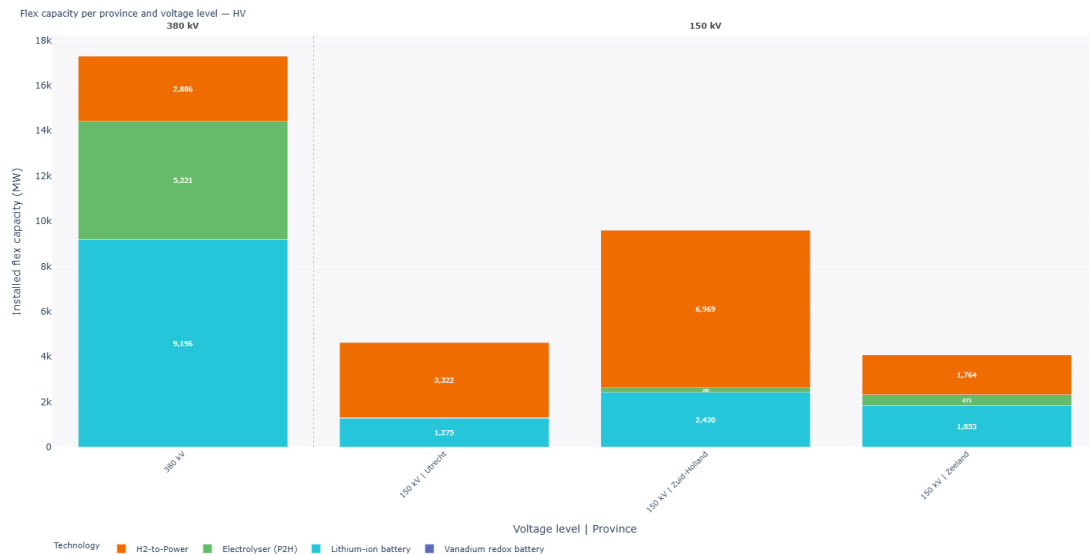
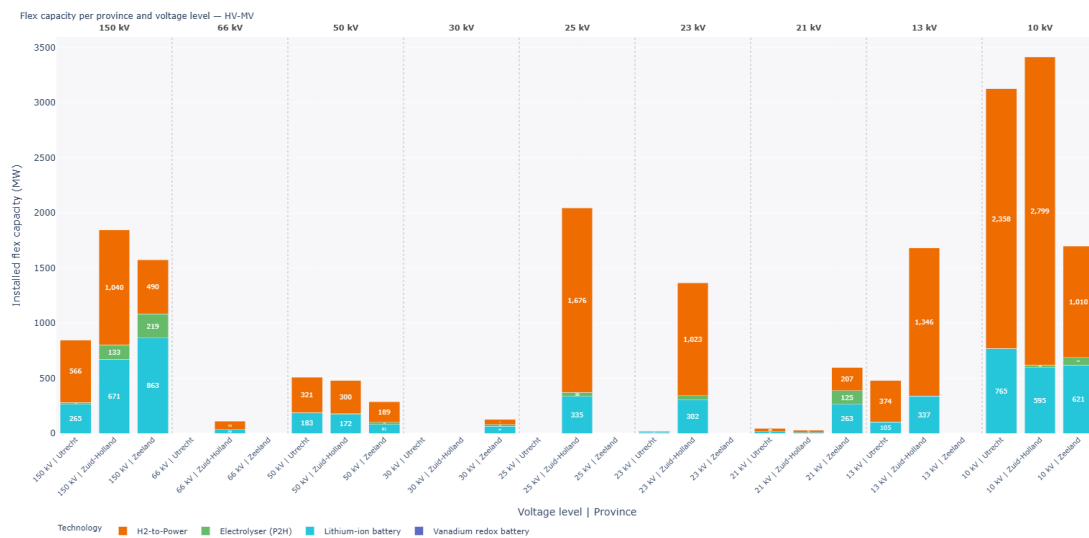


Figure 6.4: Comparison of technology deployment between HV and HV-MV configurations.



(a) HV model



(b) HV–MV model. The 380 kV capacities in this model are **lithium-ion** (9,245 MW), **electrolyser** (6,387 MW), and **hydrogen-to-power** (1,653 MW)

Figure 6.5: Installed flexibility capacity by province and voltage level in the HV and HV–MV model.

Three patterns stand out. Hydrogen-to-power and lithium-ion batteries shift deeper into the network, while electrolyser deployment remains concentrated at 380 kV in both models. The following sections examine each technology in turn.

Hydrogen-to-power and batteries

Hydrogen-to-power and lithium-ion batteries both shift deeper into the network when MV topology is introduced, but the reason for that shift differs between the two technologies.

In the HV model, it is cost-effective to distribute hydrogen-to-power capacity across both 380 kV and 150 kV. Because demand peaks at these two levels do not coincide exactly, the two levels can complement each other via the 380/150 kV links: when demand is low at one level, capacity installed there can help serve peaks at the other. This shared capacity arrangement reduces the total installed capacity needed across both levels combined.

Once MV topology is introduced, net demand at 150 kV falls as it redistributes to its actual origin at MV level. The complementary relationship between 380 kV and 150 kV disappears as a result, and hydrogen-to-power capacity at 380 kV is reduced to what is needed for national system balancing alone. At the same time, capacity at MV level increases substantially: each MV substation must now independently serve its own local demand peaks,

and where upstream transformer links are saturated, local deployment is the only available response. The total hydrogen-to-power capacity in the system therefore shifts from a shared arrangement across two high-voltage levels to a distributed deployment across many individual MV substations, each constrained by its own upstream transformer capacity.

Lithium-ion batteries show a more selective shift. Capacity at 380 kV remains almost unchanged, while capacity at 150 kV declines and spreads to MV substations. The stability at 380 kV reflects the nature of the national electricity profile: roughly two thirds of annual hours carry net surplus and lithium-ion batteries absorb that surplus through short-cyclic intra-day cycling. Unlike hydrogen-to-power, lithium-ion at 380 kV does not form a complementary capacity arrangement with 150 kV, because it responds to national surplus rather than to demand peaks that flow through the 150 kV layer. The introduction of MV topology therefore has little direct effect on its role at that level. The decline at 150 kV follows the same logic as hydrogen-to-power: the intra-day imbalances that lithium-ion resolved there were a product of demand aggregation and redistribute to the underlying substations once MV topology is introduced.

The vanadium redox flow battery disappears entirely in the HV–MV model (6 MW to 0 MW). In the HV model its marginal presence already indicated that it was barely competitive with lithium-ion. Once flexibility shifts deeper into the network, where shorter cycle lengths and lower investment costs favour lithium-ion, the vanadium redox flow battery cannot compete at any location in the network.

Hypothesis 4

Lithium-ion battery capacity at 150 kV declines when MV topology is included, because the intraday imbalances it resolved there were a product of demand aggregation rather than a structural property of the 150 kV network. Its role at 380 kV is unaffected, as that role is driven by the national electricity profile, which is identical in both model configurations.

Hypothesis 5

Hydrogen-to-power deployment shifts toward MV substations when MV topology is included, because it responds to local peak demand. In the HV model, it is cost-effective to distribute hydrogen-to-power capacity across both 380 kV and 150 kV, as demand peaks at these levels do not coincide exactly and shared capacity reduces total investment. Once MV topology is introduced, demand at 150 kV falls to its actual origin, this complementary arrangement dissolves, and hydrogen-to-power follows demand to the MV substations where it occurs.

Electrolyser

Electrolyser deployment shows the least spatial change but the largest installed capacity increase (20%) between the two model configurations. In both models, capacity is concentrated at the highest voltage levels, following stable and consistently large surplus availability.

Electrolyser deployment seems to be influenced by two complementary conditions that together determine whether local hydrogen production is more cost-effective than curtailment or battery storage.

The first condition is surplus volume. The placement of electrolyzers follows from a trade-off between curtailment and local hydrogen production. Battery storage also competes for the same surplus, but that trade-off depends on different parameters and is discussed separately below. For the electrolyser specifically, investment becomes viable in the model when the value of the produced hydrogen, in the form of avoided hydrogen import costs, exceeds its annualised investment costs. This break-even capacity factor is given by:

$$CF_{be} = \frac{CAPEX \times CRF + O\&M}{\eta_{el} \times P_{H_2} \times 8760} \quad (6.1)$$

where CF_{be} is the minimum required capacity factor, meaning the fraction of the year during which the turbine operates. $CAPEX$ the capital investment in kEUR/MW, $O\&M$ the annual operations and maintenance cost in kEUR/MW, η_{el} the electrolyser efficiency, and P_{H_2} the hydrogen import price. The capital recovery factor CRF converts the one-time capital investment into an equivalent annual cost [78]:

$$CRF = \frac{i(1+i)^N}{(1+i)^N - 1} \quad (6.2)$$

where i is the interest rate and N the technology lifetime in years. With the model parameters used in this study, this results in a minimum required capacity factor of 4.4%. Since the electrolyser can only operate when local

surplus is available, this translates to a minimum of 384 hours per year during which sufficient surplus must be present to justify investment. This is a necessary condition: substations below this threshold do not attract electrolyser investment regardless of other local characteristics. At the 380 kV level, where surplus is large and consistent, all substations exceed this threshold, with a minimum of 1,972 annual surplus hours. This holds in both model configurations, as the national surplus profile at 380 kV is identical and unaffected by the introduction of MV topology. The 380 kV level therefore remains the dominant electrolyser location in both configurations.

The second condition is surplus structure. A surplus block is defined as an uninterrupted period during which generation exceeds demand at a substation. Among substations that exceed the surplus volume threshold, electrolyser deployment is associated with longer such blocks. Short frequent blocks favour lithium-ion batteries because their higher round-trip efficiency and shorter cycle length allow surplus to be absorbed and returned within the same day. The empirical block duration threshold that best discriminates between the two technologies is approximately 12 hours, as shown in Table 6.6. This criterion is indicative rather than deterministic, meaning that block duration is one characteristic associated with electrolyser deployment, but final placement is determined by the optimisation across all technologies.

Table 6.6: Surplus block characteristics for substations with and without electrolyser deployment in the HV–MV model.

Metric	With electrolyser (n=41)	Without electrolyser (n=257)	<i>r</i>	p-value
Mean block duration (hrs)	11.7	8.2	+0.214	0.014*
Max block duration (hrs)	48.0	15.0	+0.410	<0.001*
Share of blocks > 24 hrs (%)	14.75	6.56	+0.401	<0.001*
Share of blocks < 6 hrs (%)	30.1	43.9	-0.354	0.999
Annual surplus hours (hrs)	2,871	1,758	+0.294	<0.001*

* Significant at the 5% level (one-sided Mann–Whitney U test).

In the HV model, a subset of 150 kV substations also attracts electrolyser capacity because they carry the aggregated surplus of all downstream MV substations, pushing 35 of the 47 150 kV substations above the 384-hour threshold. Once MV topology is introduced, that aggregated surplus redistributes to the individual substations where it originates. The average surplus available per 150 kV substation drops sharply once MV topology is introduced, and most substations fall back below the break-even threshold. The marginal electrolyser capacity that remains at a small number of 150 kV and MV substations in the HV–MV model is consistent with the two conditions described above: sufficient surplus hours and sustained surplus blocks.

A small number of 150 kV substations attracts electrolyser capacity despite having zero local surplus hours. All these five substations receive continuous surplus flow from connected nodes throughout the year. For four of the five, this surplus flows down from upstream 380 kV connections. For the other substation, it flows up from downstream MV substations that cannot absorb their surplus locally. When these flows are included, all five substations exceed the 384-hour threshold at every time step. This confirms that the surplus exposure criterion applies to total surplus availability at a node, including surplus flowing in from upstream connections, rather than to locally generated surplus alone.

The 20% capacity increase is not driven by more surplus, because the 380 kV surplus profile is identical in both models, but by the increase in hydrogen-to-power deployment discussed above. As hydrogen-to-power increases (+3.9%) and spreads across more MV substations, hydrogen demand rises, increasing the value of the electrolyser chain relative to curtailment. The model responds by expanding electrolyser capacity at 380 kV substations. Both local production and import increase to meet the additional demand, maintaining a roughly stable balance between the two, as shown in Table 6.7.

Table 6.7: Hydrogen balance in the HV and HV–MV model.

	HV	HV–MV	Δ
H ₂ import (GWh/yr)	14,300	15,116	+816 (+5.7%)
H ₂ production (GWh/yr)	18,921	21,659	+2,738 (+14.5%)
Total H ₂ (GWh/yr)	33,221	36,776	+3,555 (+10.7%)
Share domestic	57%	59%	(+2 pp)
Share import	43%	41%	(-2 pp)

These two conditions together determine whether electrolyser investment is cost-effective at a given substation. This is formalized in the following hypotheses:

Hypothesis 6

The minimum annual surplus exposure required to justify electrolyser investment over curtailment can be derived from technology costs and the hydrogen import price:

$CF_{be} = \frac{CAPEX \times CRF + O\&M}{\eta_{el} \times P_{H_2} \times 8760}$. *Within the model parameters used in this study, no substation below this threshold attracts electrolyser investment.*

This hypothesis holds under the assumption that the only benefit of converting surplus electricity to hydrogen is avoiding hydrogen import costs. Curtailment itself carries no cost in the model: it reduces network loading and requires no compensation from the DSO.

Hypothesis 7

Among substations that exceed the minimum surplus threshold, the temporal structure of the surplus profile influences which flexibility technology dominates. Substations with electrolysers show significantly longer uninterrupted surplus blocks and a higher share of blocks exceeding 24 hours than substations without (Mann-Whitney U, $p < 0.05$; Table 6.6). Where surplus occurs in short frequent blocks, lithium-ion batteries are more cost-effective. Both technologies may be deployed at the same substation when surplus blocks of varying duration are present.

6.3.4. Shift in network expansion patterns

Including MV topology does not only change where flexibility is deployed, it also changes where network expansion occurs and why. In the HV-model, a single link expands: the KIJ_380-LLN_150 connection, adding 414 MW. Once MV topology is introduced, expansion spreads across 33 links with a total of 797 MW, concentrated at the 150 kV ↔ MV interface (Table 6.8).

Table 6.8: Network expansion by voltage level in the HV and HV-MV models.

Voltage level	HV model		HV-MV model	
	Links	Expansion (MW)	Links	Expansion (MW)
380 kV	1	+414	1	+15
150 kV MV	0		19	+664
50 kV MV	0		4	+53
25/23 kV MV	0		9	+65
Total	1	+414	33	+797

The selection of KIJ_380-LLN_150 in the HV model is not driven by an actual overload on that link, but by a combination of properties that make it the least-cost pathway to the aggregated MV demand at the 150 kV substations. The link is among the shortest 380–150 kV connections in the network at 0.42 km, minimising distance-dependent cable costs. KIJ_380 is connected to two other 380 kV substations, providing sufficient supply from the national system, while LLN_150 connects to four other 150 kV substations. Once MV topology is introduced, that aggregated demand redistributes to the substations where it originates, and this gateway function dissolves.

Hypothesis 8

In an HV model, network expansion is selected on cost-effectiveness grounds rather than because a link is actually overloaded: the link that provides the cheapest connection to aggregated MV demand is expanded. When MV topology is included, demand redistributes to the substations where it actually originates, and expansion shifts to the transformer links where the flow of electricity exceeds what the link can handle. The location of network expansion is therefore determined by the network level represented in a HV model, not by the physical structure of the network alone.

In the HV–MV model a smaller set of expansions occurs deeper in the network, at the 50 kV, 25 kV, and 23 kV levels. These expansions are modest in absolute terms, ranging from 2 to 14 MW, and confirm that capacity constraints are not limited to the 150 kV interface. Of the 238 transformer links in the HV–MV model where expansion is technically feasible, only 33 are selected in the cost-optimal solution. The following section examines whether those decisions can be anticipated without running the full optimisation.

Network expansion screening index

Of the 238 transformer links in the HV–MV model where expansion is technically feasible, only 32 MV links and one HV link are selected for expansion in the cost-optimal solution. The question is: can those 32 MV expansion decisions be anticipated without running the full optimisation? In this section, a screening tool is discussed that answers that question by reducing the full set of 238 links to a smaller candidate set, based on an economic formula and one physical check. The screening does not replace the optimisation, it makes the optimisation's reasoning transparent and testable.

The tool consists of three parts. First, a measure of how much each link is overloaded on an annual basis. Second, a cost estimate for the alternative to expansion: absorbing that overload through flexibility. Third, a structural check that exclude links where expansion is not physically possible. A link becomes a candidate when the local overload is large enough that managing it through flexibility would cost more than expanding the link.

Aggregated overload

The starting point is the imbalance between electricity supply and demand in the network area served by a link. Each link connects an upstream substation to a downstream area. Everything that the downstream area cannot produce or absorb locally must flow through that link. The net flow at each time step t is therefore the total downstream demand minus the total downstream supply:

$$F_t = D_t^{\text{down}} - S_t^{\text{down}} \quad (6.3)$$

When F_t is positive, the downstream area has more demand than supply, and power flows downward through the link. When F_t is negative, supply exceeds demand, and the surplus flows upward to be used elsewhere in the system. The link is congested whenever the absolute net flow exceeds its existing capacity $C_{\min}$.

The aggregated overload O_{agg} is the total energy per year that cannot pass through the link without exceeding its capacity limit. It sums the overload across all time steps, in both directions:

$$O_{agg} = \underbrace{\sum_t \max(F_t - C_{\min}, 0) \cdot \Delta t}_{O_{agg}^{\text{demand}}} + \underbrace{\sum_t \max(-F_t - C_{\min}, 0) \cdot \Delta t}_{O_{agg}^{\text{surplus}}} \quad (6.4)$$

The first term captures overload in the demand direction: time steps where downstream demand exceeds what the link can deliver. The second term captures overload in the surplus direction: time steps where downstream generation exceeds what the link can transport upward. The two terms are never non-zero at the same time step, because the net flow F_t has a single sign at any given moment. Their sum gives the total annual energy that the link fails to transport. Since F_t and $C_{\min}$ are in MW and Δt is in hours, each term has units of MWh, and the sum over all time steps in a year gives O_{agg} in MWh/yr.

Because the model runs at three-hour temporal resolution, $\Delta t = 3$, meaning that short-duration overloads within a single time step are averaged with adjacent hours. O_{agg} therefore slightly underestimates the true annual energy overload for links where overloads are brief and intense.

This choice to measure energy rather than hours matters. Two links may both be overloaded during 200 hours per year, but one may carry a small overload of a few MW while the other carries hundreds of MW. Only the energy-based measure captures that difference, and it directly determines how costly it would be to handle the overload through flexibility instead.

Marginal flexibility cost

The next step is to place a price on handling the overload through flexibility rather than expanding the link. The relevant question is: if the link is not expanded, how much would it cost per MWh to provide or absorb the unserved energy locally?

This cost is expressed as a levelised cost of flexibility ($LCOE_{flex}$): the annualised investment and maintenance cost of a flexibility technology per MWh of energy it delivers or absorbs annually. For batteries, this cost depends on the storage capacity investment, the number of charge-discharge cycles per year, and the discharge efficiency.

For a hydrogen gas turbine it depends on the turbine investment cost, operational costs, the assumed utilisation rate, and the cost of the hydrogen fuel consumed.

For batteries:

$$LCOE_{flex}^{battery} = \frac{D \cdot P_{stor} \cdot CRF_{tech} + O\&M}{N_{cyc} \cdot D \cdot (1 - d) \cdot \eta_{out}} \quad (6.5)$$

where D is the storage duration (MWh per MW of installed power), P_{stor} is the storage investment cost in kEUR/MWh, CRF_{tech} is the capital recovery factor over the technology lifetime, $O\&M$ is the annual maintenance cost in kEUR/MW, N_{cyc} is the number of full charge-discharge cycles per year, d is the storage discharge depth, and η_{out} is the discharge efficiency.

For hydrogen-to-power:

$$LCOE_{flex}^{H2P} = \frac{P_{turb} \cdot CRF_{tech} + O\&M}{CF \cdot 8760} + \frac{P_{H_2}}{\eta_{out}} \quad (6.6)$$

where P_{turb} is the turbine investment cost in kEUR/MW, CF is the fraction of the year during which the turbine operates, P_{H_2} is the hydrogen import price in kEUR/MWh of fuel, and η_{out} is the conversion efficiency of the turbine. The first term covers the annualised capital and maintenance cost in kEUR/MWh; the second covers the fuel cost in kEUR per delivered MWh.

With the model parameters and assuming one full battery cycle per day, this gives 39.30 EUR/MWh for lithium-ion, 49.90 EUR/MWh for vanadium redox flow, and 332.40 EUR/MWh for hydrogen-to-power. The fuel term P_{H_2}/η_{out} values the hydrogen consumed at the import price, which represents the marginal cost of hydrogen in the model: it is the price at which the system can always obtain an additional unit, regardless of how much is produced locally.

A low capacity factor of $CF = 0.05$ is assumed, reflecting the gas turbine's role as a peaking technology with limited annual utilisation. This assumption results in a high $LCOE_{flex}^{H2P}$, which maximises the candidate set and ensures that all economically plausible expansion links are captured. After optimisation, the actual capacity factor can be derived from model results and used to refine the candidate set further. The initial screening therefore functions as an upper bound on the candidate set and the post-optimisation refinement narrows it towards a more precise subset.

Choice of threshold technology

The three flexibility technologies represent different cost levels. For the screening to be permissive, meaning it should include every link that the model might expand, the most expensive technology is used as the reference.

The reasoning is as follows. The optimisation expands a link when expansion is cheaper than the cheapest available flexibility alternative at that location. In most locations, the cheapest option is a battery. But at substations with chronic supply shortages, where there is no local surplus to charge a battery, the only dispatchable alternative is hydrogen-to-power, which draws on system-wide hydrogen reserves regardless of local supply conditions. A link that fails to meet the screening criterion even when compared against the most expensive option, is a link where any flexibility technology would be cheaper than expansion. Expansion is then very difficult to justify on economic grounds alone.

On the surplus side, the alternative to expansion is curtailment (which has no direct cost) or hydrogen production via an electrolyser, which is cheaper than hydrogen-to-power. Using hydrogen-to-power as the benchmark for surplus-driven overload therefore applies a conservative test: if expansion still passes against this high-cost benchmark, the link is a credible candidate in either direction. This is a simplification that prioritises not missing genuine candidates over avoiding false positives. Its trade-off is lower precision: some links in the candidate set will not ultimately be expanded by the optimisation.

Screening index

The index I' compares the annual cost of handling the overload through flexibility against the annualised cost of expanding the link:

$$I' = \frac{E_{agg} \cdot LCOE_{flex}}{(n \cdot C_{trafo}^{std} \cdot (P_{trafo} + L \cdot P_{cable})) \cdot CRF} \quad (6.7)$$

where n is the additional standard transformer units required to cover the peak load, calculated as:

$$n = \max\left(1, \left\lceil \frac{\max_t |F_t| - C_{min}}{C_{trafo}^{std}} \right\rceil\right) \quad (6.8)$$

with $\max_t |F_t|$ the maximum absolute net flow through the link over the year. The $\max(1, \dots)$ ensures that at least one transformer unit is always assumed in the cost calculation.

The numerator is the annual cost of managing the overload through flexibility: the total annual energy overload in MWh multiplied by the cost per MWh of the reference flexibility technology. The denominator is the annualised cost of expanding the link by n standard transformer units, including the associated cable works. The transformer cost P_{trafo} is expressed in kEUR/MW, and the cable cost P_{cable} in kEUR/MW/km, so that cable costs scale with the capacity of the added transformer unit. The capital recovery factor CRF , based on a 40-year infrastructure lifetime and a 1% interest rate, giving $CRF = 0.0305$.

A value $I' \geq 1$ means the annual flexibility cost equals or exceeds the annualised expansion cost: expanding the link is at least as cost-effective as managing the overload through flexibility, and the link is flagged as an economic candidate. A value $I' \leq 1$ means flexibility remains the cheaper option, and expansion is harder to justify on local economic grounds alone.

A link is excluded from the candidate set if no expansion slots are available, that is, if the maximum allowed capacity equals the existing capacity. Only links where $C_{max} > C_{min}$ are considered as candidates.

Candidate set

A link is included in the candidate set if it passes both structural filters and satisfies $I' \geq 1$. Because the threshold is derived from cost parameters and not calibrated on the model's expansion outcomes, the recall of the screening against the 32 model-expanded links is the performance measure. Recall is the share of the model-expanded links that the screening correctly identifies as candidates: a recall of 100% would mean no expanded link is missed.

Results

The screening identifies 91 candidate links out of 238, of which all 32 are also expanded in the cost-optimal model solution. This corresponds to a recall of 100% and a precision of 35.2%. Table 6.9 reports the performance per voltage level. The Matthews Correlation Coefficient is 0.501, with Fisher's exact $p < 0.001$, confirming that the screening discriminates between expanded and non-expanded links.

The MCC measures the overall quality of a binary classification by accounting for all four cells of the confusion matrix simultaneously, ranging from 1 (perfect inverse prediction) through 0 (no better than chance) to +1 (perfect prediction). A value of 0.501 therefore indicates a moderate to strong association between the screening and the model expansion decisions.

Table 6.9: Index screening performance per voltage level.

Voltage levels	n	Expanded	Candidates	True positives	Recall (%)	Precision (%)
150/10 kV	21	7	14	7	100	50
150/21 kV	5	2	2	2	100	100
150/23 kV	8	1	2	1	100	50
150/25 kV	18	4	8	4	100	50
150/50 kV	18	5	14	5	100	35.7
50/10 kV	49	2	18	2	100	11.1
50/13 kV	24	2	4	2	100	50
25/10 kV	68	8	25	8	100	32
23/10 kV	4	1	1	1	100	100
Total	238	32	91	32	100	35.2

MCC = 0.501; Fisher's exact $p < 0.0001$.

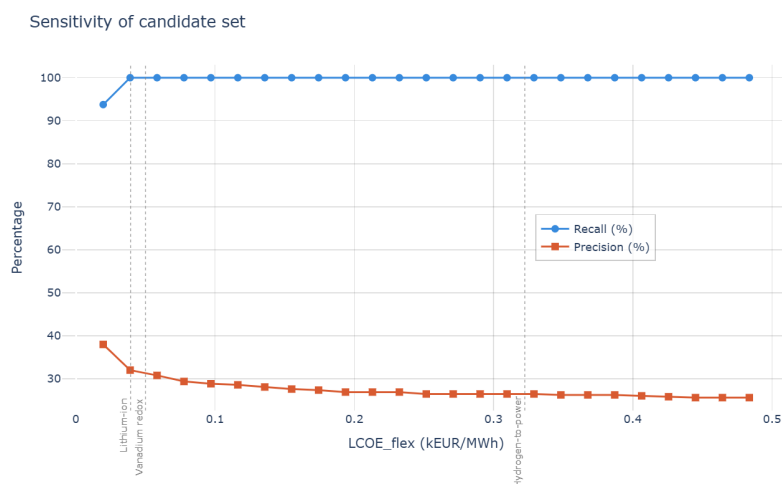
Source of false positives

A share of the false positives can be traced to a simplification in how the screening allocates overload to a link. The screening sums demand and supply across all downstream nodes and treats the net difference as flowing entirely through the link above. In a fully radial topology, where every downstream node has exactly one path to the rest of the network, this is exact. The MV network is radial, so the assumption holds in most cases.

Where it breaks down is when supply and demand are balanced locally within the downstream area, without any flow reaching the link above. For example, surplus generated at a 10 kV substation may be consumed by an adjacent 10 kV substation under the same 50 kV parent, never reaching the 150/50 kV link higher up. The screening nonetheless attributes that surplus to the 150/50 kV overload, overstating the overload at the upper link. The actual congestion occurs at the intermediate 50/10 kV link, where the screening computes the overload correctly. This overstates the candidate set at higher voltage levels and contributes to the false positives observed there. The links that are expanded carry imbalances large enough to flow through the full radial chain, which is why this simplification does not affect recall.

Robustness

A sensitivity analysis across the range of plausible $LCOE_{flex}$ values shows that recall stabilises at 100% once the LCOE exceeds approximately 39 EUR/MWh (Figure 6.6). Precision declines gradually as the LCOE rises, because a higher $LCOE_{flex}$ causes more links to pass the $I' \geq 1$ threshold, expanding the candidate set. The overall result is therefore stable across the full range and the choice of $LCOE_{flex}$ within this range does not meaningfully change the outcome.

**Figure 6.6:** Sensitivity of recall and precision to the value of $LCOE_{flex}$.

Interpretation

The screening reduces 238 technically expandable links to a candidate set of 91, capturing all 32 links expanded in the cost-optimal solution. Rather than assessing all 238 technically expandable links in detail, Stedin can focus their analysis on these 91 candidates. This supports two concrete follow-up steps. First, once the optimisation has been run, the actual capacity factor of hydrogen-to-power can be derived from the model results and used to refine the $LCOE_{flex}$, producing a smaller and more precise candidate set. Second, the candidate set defines a geographically focused subset of the network on which a more detailed approach can be applied, incorporating characteristics currently out of scope such as discrete transformer investments and switching field availability, without having to apply that additional detail to the full network simultaneously.

Hypothesis 9

Whether a transformer link is selected for expansion in the cost-optimal solution can be predicted by comparing the annualised cost of expanding the link to the cost of managing the equivalent annual energy imbalance through flexibility. The expansion cost accounts for the number of standard transformer units required to cover the peak load on the link. Links where expansion is cheaper than the most expensive available flexibility option are expected to be selected for expansion significantly more often than links where flexibility remains the cheaper response.

Appendix G describes the results of a sensitivity analysis in which all transformer expansion slots are doubled. The results confirm that 93.9% of the newly expanded links were already identified as economically motivated by the screening index, but were physically blocked by the slot constraint in the baseline. The candidate set therefore remains a reliable predictor of expansion pressure regardless of slot availability.

Answer to SQ2

Including MV network topology does not substantially change the total investment required, but fundamentally changes where that investment is placed. The HV model places investment at the voltage level where demand is visible in the model rather than where the underlying network constraints determine the response. Once MV topology is introduced, demand and supply imbalances redistribute to the substations where they actually originate, and both flexibility and network expansion follow.

The locations, technologies, and scale of investment that the HV model produces are therefore a consequence of the modelling choice, not of the physical network. For a DSO using an HV model to inform distribution-level planning, this means that planning signals reflect the model's aggregation level rather than the actual capacity needs of the MV network.

6.4. Scenario analysis

This section addresses SQ3A:

SQ3A How parametrically robust is the cost-optimal distribution of flexibility technologies in an HV–MV network under variations in key scenario assumptions?

Two alternative scenarios are tested against the baseline, a high hydrogen price and a low battery cost scenario, both evaluated on the Utrecht provincial model. Table 6.10 summarises the aggregate outcomes.

Table 6.10: Scenario outcomes relative to the baseline, cost-optimal solutions.

Metric	Baseline	High H ₂ price	Low battery cost
Total costs (M€/yr)	11.64	13.85 (+19%)	10.52 (-9.5%)
Network exp. (MW)	95	110 (+15.8%)	94 (-1.1%)
Total flex (MW)	35,606	41,601 (+15.8%)	34,231 (-3.9%)
Vanadium Redox Flow Battery (MW)	0	0	0
Lithium-ion Battery (MW)	14,699	14,759 (+0.4%)	15,424 (+4.9%)
Electrolyser (MW)	5,863	11,904 (+103%)	5,035 (-14.1%)
Hydrogen-to-Power (MW)	15,043	14,904 (-0.7%)	13,772 (-8.4%)

Network expansion is insensitive to the scenario assumptions tested here: in every configuration, only the ARK_150 to ARK_50 link expands, at approximately 100 MW. This matches the cost-optimal result for the Utrecht HV–MV model. Because only a single link expands across all scenarios, the screening index cannot be meaningfully validated against scenario outcomes. The candidate set sizes are nonetheless stable (baseline: 44, high H₂ price: 45, low battery cost: 44), and hydrogen-to-power remains the binding LCOE threshold in all configurations.

The following sections examine each scenario in turn.

High hydrogen price scenario

When hydrogen import prices are high, the break-even threshold for electrolyser investment drops from 384 to 161 surplus hours per year (Equation 6.1), directly confirming hypothesis 6: a higher hydrogen price lowers the threshold and makes electrolyser investment viable at a larger share of substations. This drives the observed expansion in electrolyser deployment: installed capacity more than doubles (+103%), and annual output rises by 73.1%, concentrated at substations with direct access to surplus. Despite this additional domestic production, hydrogen import declines only modestly by 15.8% (Table 6.11).

Table 6.11: Hydrogen balance under baseline and high import price scenario. All values in GWh unless stated otherwise.

	Baseline	High H ₂ price	Δ
<i>Supply</i>			
Electrolyser output	18,699	32,368	(+73.1%)
Hydrogen import	14,335	12,071	(-15.8%)
Total supply	33,034	44,439	(+34.5%)
<i>Demand</i>			
H2P dispatch	13,136	15,699	(+19.5%)
<i>Indicator</i>			
Import share (%)	43.4	27.2	(-16.2%)

To understand why extra electrolyser output does not translate directly into equivalent import reductions, the production of additional hydrogen is examined. Table 6.12 breaks this down by grouping all 2,920 time steps by

their net surplus level. Time steps are ranked from lowest to highest net surplus and divided into four equal groups: Q1 captures deficit periods where demand exceeds supply, Q4 captures peak surplus periods where generation far exceeds demand. The values shown are average flows per three-hour time step within each group.

In the baseline, electrolyser output is already high in Q3 and Q4 but cannot absorb all available surplus: substantial curtailment remains alongside near-maximum electrolyser operation, indicating that installed capacity is the binding constraint rather than surplus availability. Under high import prices, the lower investment threshold makes additional electrolyser capacity cost-effective, and this additional capacity absorbs the surplus that was previously curtailed. In Q3, average curtailment falls from 9.6 to 1.3 GWh per time step while electrolyser output rises from 10 to 18 GWh. The system therefore captures electricity surplus that was previously lost, rather than substituting for imported hydrogen on a one-to-one basis. This explains why a 73% increase in domestic electrolyser output translates into only a 15.8% reduction in hydrogen import.

Table 6.12: Average flows per time step (MWh) across net surplus quartiles. Values represent 3-hour time step averages.

Quartile	Electrolyser		Import		Curtailment	
	Base	High H ₂	Base	High H ₂	Base	High H ₂
Q1 (deficit)	352	112	15,736	13,170	45	104
Q2	3,999	4,528	3,868	3,340	266	270
Q3	10,090	18,193	33	26	9,582	1,362
Q4 (high surplus)	11,174	21,506	0	0	33,646	16,682

The additional hydrogen is stored rather than immediately consumed, building up a larger seasonal buffer: electrolyzers produce more during summer when surplus is abundant, this hydrogen is stored, and drawn down during winter when renewable generation is low and electricity demand peaks. Figure 6.7 shows that storage levels remain higher throughout the year compared to the baseline, reflecting this shift from real-time import to stored domestic production.

This buffer is what drives the import reduction. In the baseline, the system imports hydrogen and converts it to power in near real time: whenever the grid needs peak electricity capacity, hydrogen is imported and converted to power. Under high import prices, the system increasingly draws on stored domestically produced hydrogen instead. This weakens the direct link between import and dispatch: in the baseline, import and hydrogen-to-power dispatch move closely together (with a correlation of +0.837), meaning that almost every unit dispatched was recently imported. Under high import prices that coupling weakens (with a correlation of +0.694), meaning a growing share of dispatched hydrogen was produced and stored earlier in the year rather than imported on demand. The result is a reduction in import dependence from 43.4% to 27.2% of total hydrogen supply.

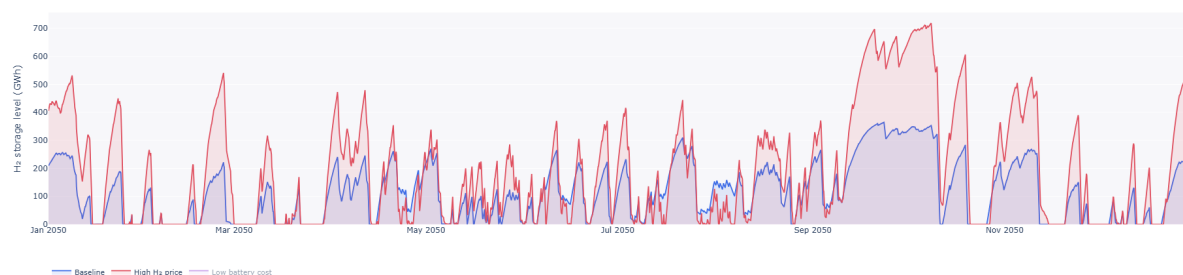


Figure 6.7: Hydrogen storage level at hub

On the demand side, hydrogen-to-power converts 19.5% more hydrogen into electricity compared to the baseline, while installed capacity remains nearly unchanged (-0.7%). This is a direct consequence of the larger seasonal buffer: more hydrogen is available for conversion during winter peak periods, so existing capacity operates more intensively without needing to grow.

System costs rise by 19%, driven by two factors: the higher unit price of imported hydrogen and the additional capital investment required to expand electrolyser capacity. Lithium-ion battery capacity remains stable (+0.4%),

confirming that the scenario triggers a targeted response within the hydrogen supply chain rather than a broader shift across flexibility technologies.

Low battery cost scenario

When battery investment costs fall by 50%, lithium-ion batteries become the preferred option for surplus absorption at 380 kV nodes, where both technologies compete for the same renewable surplus. Electrolyser capacity declines by 16.1% while lithium-ion capacity increases by 4.9%, but electrolyzers are not fully replaced. Batteries and electrolyzers do not compete for exactly the same surplus: batteries are more cost-effective during short surplus periods, absorbing and returning electricity within the same day, while electrolyzers remain the better option during prolonged surplus periods where the alternative is curtailment. The scenario therefore represents a partial rebalancing between the two technologies, not a full substitution.

This rebalancing flows through the hydrogen system. Because lithium-ion absorbs a share of the surplus previously converted to hydrogen, less hydrogen is produced domestically, less needs to be imported, and hydrogen-to-power converts less hydrogen to electricity. Electrolyser capacity falls by 14.1% and hydrogen-to-power capacity by 8.4%, while annual hydrogen import declines by 9.8%. These three quantities decline in proportion, confirming that the system requires less hydrogen overall rather than substituting domestic production for import. Total installed flexibility capacity falls modestly by 3.9% and system costs by 9.5%, reflecting that a cheaper technology now covers part of the flexibility function that previously required the more expensive hydrogen chain.

The spatial distribution of hydrogen-to-power capacity remains intact: all nodes that host hydrogen-to-power capacity in the baseline retain it under lower battery costs, with capacity declining modestly per node. The substitution therefore operates at the system level rather than as a spatial exchange: capacity reductions concentrate at 380 kV nodes where surplus competition between batteries and electrolyzers takes place, while MV substations where transformer constraints drive flexibility deployment are unaffected.

Robustness of spatial distribution

Despite these technology-level shifts, the dominant flexibility locations identified in the baseline remain dominant under both scenarios, as shown in Figure 6.8. This leads to the following hypothesis:



Figure 6.8: Top 10 substations by total installed flexibility capacity in the baseline. Bars show installed capacity per scenario. 380 kV and province-level nodes are excluded.

Hypothesis 10

The dominant flexibility locations are parametrically robust: when cost assumptions change, the same locations remain dominant while the technology mix at those locations changes. The technology mix is scenario-dependent, as the relative cost competitiveness of individual technologies shifts under different assumptions while the underlying congestion pattern does not.

This answers SQ3A: location decisions are more robust than technology decisions under parametric uncertainty. However, the scenario analysis cannot distinguish between locations that are dominant because the network demands it and locations that are dominant because the current cost assumptions favour them. The SPORIS analysis addresses this distinction.

6.5. Near-optimal solution space – SPORES

This section addresses SQ3B:

SQ3B How structurally robust is the cost-optimal distribution of flexibility technologies in an HV–MV network under near-optimal solutions?

This section tests the hypotheses formulated in Sections 6.3 and 6.4 against the near-optimal solution space, explored using 113 SPORES at a 15% cost slack. Where a hypothesis holds across statistical testing, it is elevated to a principle. Hypotheses that relate to the effect of including MV topology, specifically hypothesis 1, hypothesis 4 and hypothesis 5 cannot be tested here, as the SPORES exploration does not vary the network representation.

6.5.1. The near-optimal solution space

Figure 6.9 shows the total installed capacity per technology across all 113 SPORES, with the cost-optimal solution marked as SPORE 0 (indicated by the arrow). The variation is notable: across configurations that all remain within 15% of the optimal cost, the technology mix shifts fundamentally. Vanadium redox flow battery capacity ranges from zero to approximately 18 GW, while the cost-optimal solution installs none at all. The system can therefore achieve near-identical costs through fundamentally different technology choices, which means the cost-optimal solution is one valid configuration among many rather than the only viable outcome. The question for robust planning is not what the optimum selects, but which patterns persist across the full near-optimal solution space.

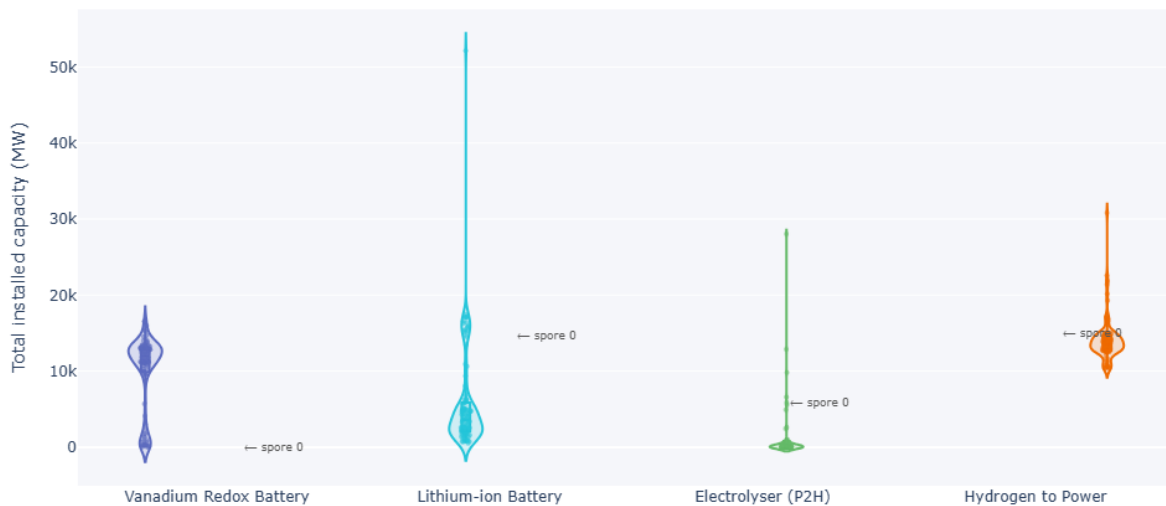


Figure 6.9: Total installed capacity per technology across all 113 SPORES, shown as violin plots. The width of each violin indicates the density of solutions at that capacity level. Spore 0 represents the cost-optimal solution.

6.5.2. Methodological validation of batch structure

Before drawing planning insights from these 113 configurations, a methodological question must be addressed. The set of 113 SPORES is not a homogeneous sample. Of the total, 25 originate from a broad exploration using random penalty weights, while the remaining 88 come from eight intensified batches that push the solver towards the maximum or minimum deployment of each flexibility technology. All 113 configurations remain within the 15% cost slack and are therefore equally plausible from a system-cost perspective. However, the intensified batches are designed to push the solver towards the extremes of the near-optimal solution space, meaning that the sample is not representative of the full distribution of plausible configurations. Drawing conclusions from the full set of 113 SPORES therefore risks overstating patterns driven by sampling bias rather than by properties of the network.

To assess the degree to which the batches differ statistically, a Kruskal-Wallis test is applied across six key metrics, as described in Section 5.7.3. The six metrics tested are total flexibility capacity, total network expansion, the share of power-to-hydrogen in total flexibility, the share of hydrogen-to-power in total flexibility, the share of lithium-ion in total flexibility, and the share of vanadium redox flow in total flexibility. Together these metrics capture both the scale and the technology composition of each SPORE.

Table 6.13 summarises the results. Five of the six metrics show a significant batch effect, with large effect sizes (η^2 ranging from 0.19 to 0.38). Only total network expansion does not, showing a negligible effect size ($\eta^2 = 0.01$).

The fact that steering the solver towards technology extremes measurably shifts the technology mix but leaves expansion decisions unchanged suggests that network expansion is determined by properties of the network itself rather than by how the flexibility portfolio is configured.

Table 6.13: Kruskal–Wallis test results for batch effects across metrics

Metric	H-statistic	p-value	η^2
Total flexibility capacity	47.2	< 0.001	0.377
Share of power-to-hydrogen	29.4	< 0.001	0.206
Share of hydrogen-to-power	36.9	< 0.001	0.278
Share of lithium-ion	28.1	< 0.001	0.193
Share of vanadium redox flow	40.8	< 0.001	0.315
Total network expansion	9.5	0.30	0.014

Figures 6.10, 6.11 and 6.12 illustrate this batch effect at the substation level. The technology-specific deployment frequencies shift between the broad and intensified batches, consistent with the significant Kruskal–Wallis results for all technology shares. At the same time, the figure reveals that substations which receive no flexibility in the broad batch largely remain without flexibility across the intensified batches as well, suggesting that location selection is less sensitive to intensification pressure than technology selection. This distinction between location robustness and technology variability is examined in detail in Section 6.5.3.

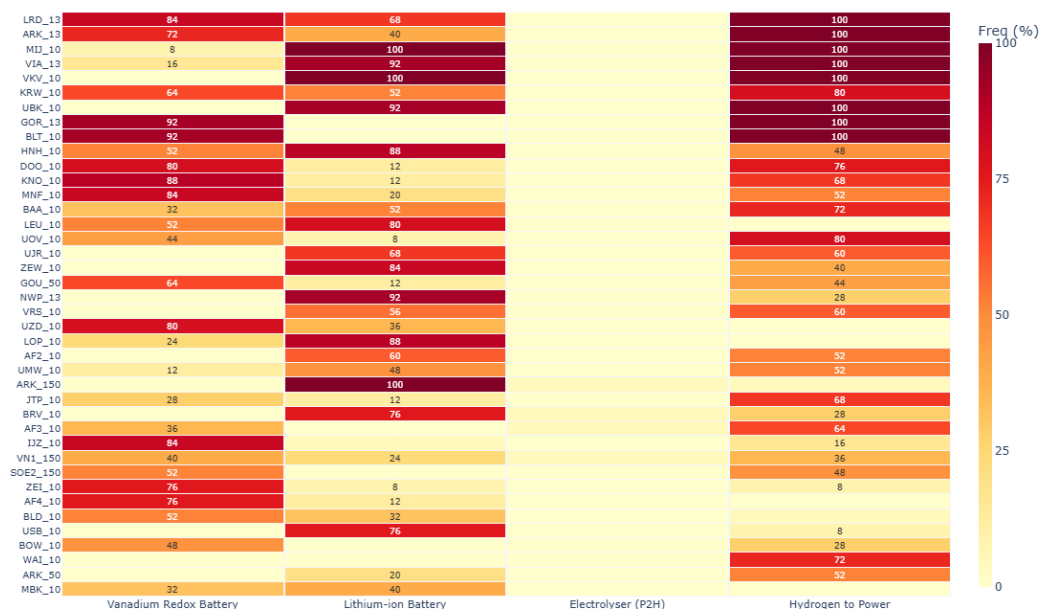


Figure 6.10: Deployment frequency across the 25 broad exploration SPORES.

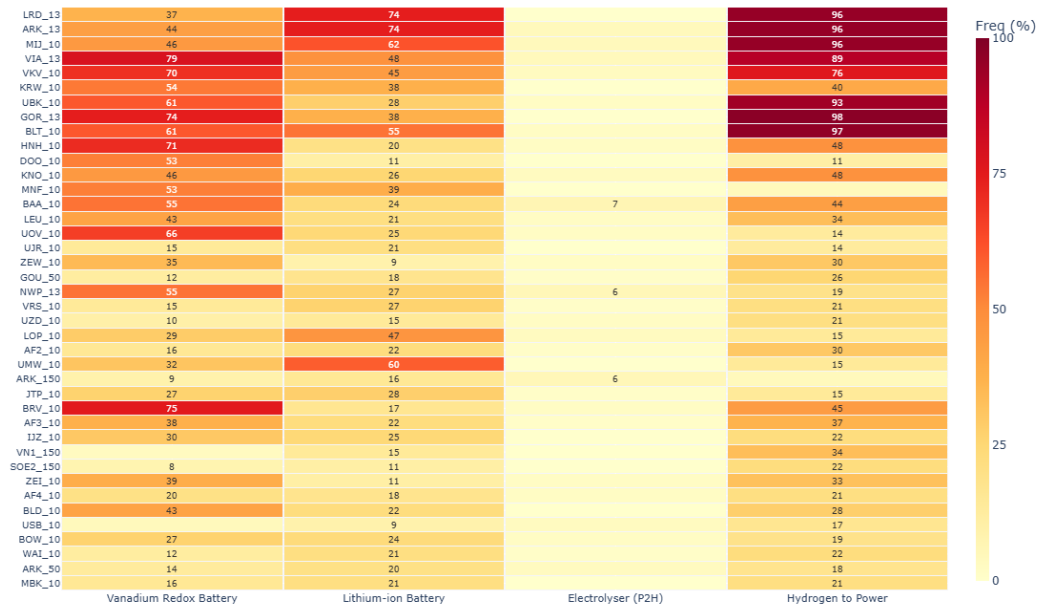


Figure 6.11: Deployment frequency across the 88 intensified SPORES.

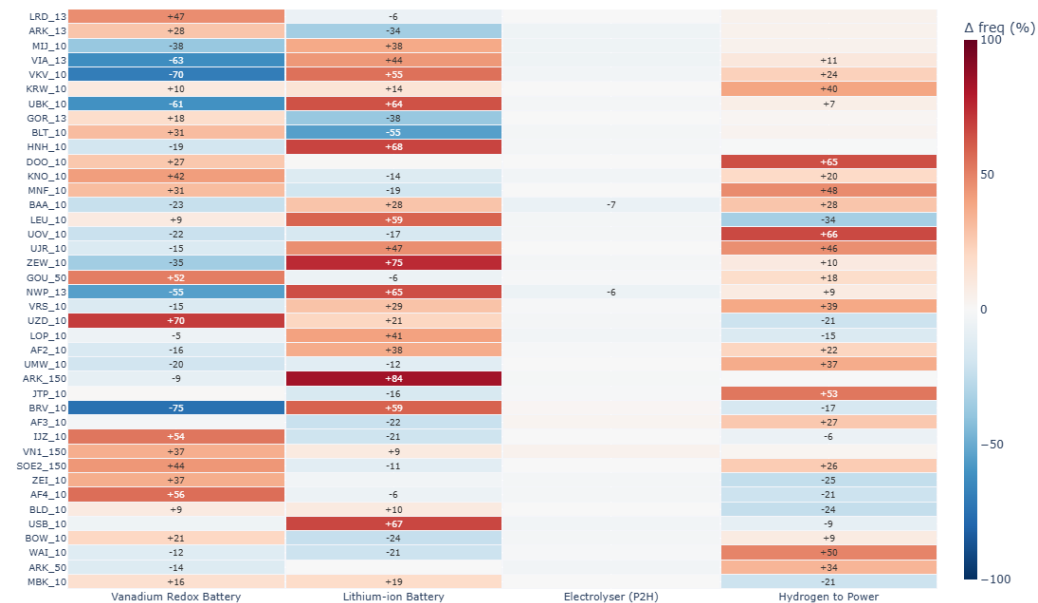


Figure 6.12: Difference in deployment frequency between batches. Positive = intensified batch, negative = broad exploration.

Because the intensified batches steer the technology mix rather than sampling the near-optimal space without bias, they cannot serve as the primary basis for hypothesis tests on technology deployment. The broad batch of 25 SPORES is therefore used as the primary analytical basis for all technology conclusions. The intensified batches are retained as a verification layer.

6.5.3. Robust locations and their network determinants

Figure 6.13 maps all MV substations along two dimensions: the frequency with which any flexibility technology is deployed, and the frequency with which the upstream transformer link is expanded across the 113 SPORES. The upstream link is the connection between a substation and its parent substation in the radial MV topology. Dashed lines at 60% and 90% divide the space into three levels, producing five planning categories summarised in Table 6.14. The following two sections examine what drives robustness along each dimension and derive

principles from the patterns that hold across the near-optimal solution space.

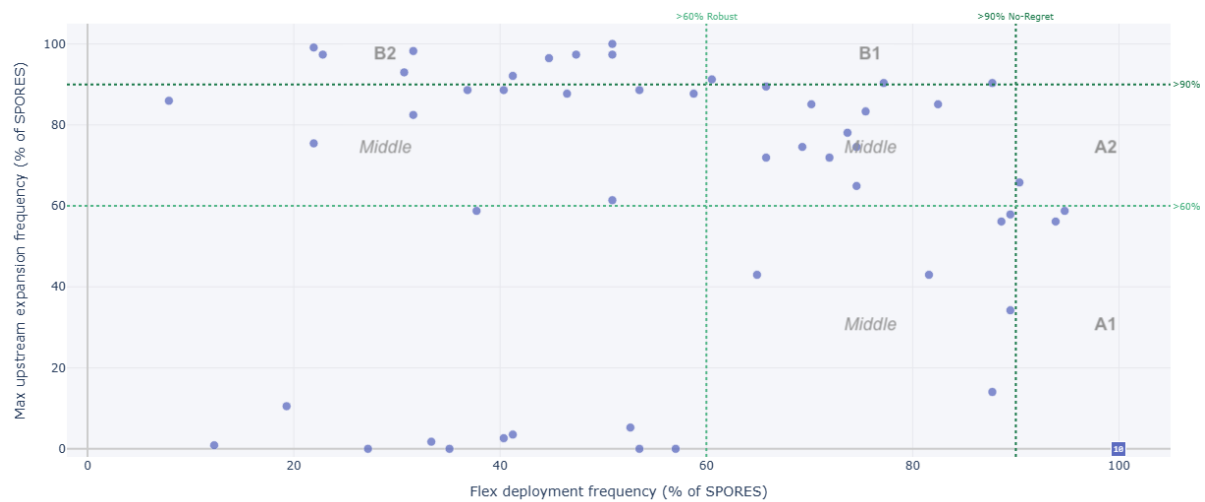


Figure 6.13: Planning categories for MV substations based on flexibility deployment and upstream link expansion frequency across 113 SPORES.

Spatial planning categories

The five categories are discussed below, ordered by flexibility deployment frequency and then by expansion frequency, moving from the most to the least structurally robust locations

Category A1 includes 10 substations with a flexibility deployment frequency of 100% and zero upstream expansion, as no expansion capacity is available. Two subgroups can be distinguished. The first eight have hydrogen-to-power deployment frequencies above 77%, meaning both location and technology are robust. The remaining two (UOV_10 and UMW_10) also reach 100% flex frequency but their technology mix varies: the location is no-regret but the technology choice is not.

Category A2 contains three substations, each reaching a flex frequency above 90% while receiving upstream expansion in roughly half to two thirds of all SPORES. Flexibility is almost always present at these substations, but in many configurations the system adds network expansion on top. The location is no-regret for flexibility but technology choices vary across configurations.

Category B1 includes three substations, with upstream expansion frequencies of 90% and flex deployment frequencies between 61% and 88%. Expansion is no-regret at these locations. Flexibility is consistently present alongside expansion.

Category B2 contains nine substations with upstream expansion frequencies at or above 92% and flex deployment frequencies below 51%. The expansion decision is no-regret at these locations; the flexibility response is not.

The middle category contains 25 substations that fall between the 60% and 90% boundaries on one or both axes. At these substations, neither dimension is consistent enough to be treated as a no-regret planning signal. The system resolves local constraints through flexibility, expansion, or a combination of both depending on the wider system conditions and configuration.

Across all categories, installed flexibility capacity is not structurally robust, meaning the scale of deployment varies across configurations regardless of whether the location itself is determined.

Table 6.14: MV substations by planning category. Flex freq = share of SPORES with any flexibility deployed. Exp freq = share of SPORES with upstream link expanded.

Station	Cat.	Flex freq	Exp freq	Flex med (P10–P90)	Exp med (P10–P90)	Dem. press.
A1 — No-regret flex, no expansion						
ARK_13	A1	100%	0%	62 (57–118)	0 (0–0)	30.4%
BLT_10	A1	100%	0%	88 (80–143)	0 (0–0)	46.5%
VKV_10	A1	100%	0%	21 (19–106)	0 (0–0)	14.0%
MIJ_10	A1	100%	0%	49 (47–72)	0 (0–0)	30.9%
UBK_10	A1	100%	0%	26 (25–56)	0 (0–0)	20.6%
UOV_10	A1	100%	0%	8 (7–109)	0 (0–0)	3.4%
UMW_10	A1	100%	0%	18 (17–136)	0 (0–0)	4.5%
GOR_13	A1	100%	0%	56 (53–150)	0 (0–0)	36.0%
LRD_13	A1	100%	0%	33 (31–113)	0 (0–0)	27.9%
VIA_13	A1	100%	0%	50 (46–101)	0 (0–0)	19.6%
A2 — No-regret flex, expansion present						
HNH_10	A2	94.7%	58.8%	44 (24–98)	12 (9–36)	30.7%
UJR_10	A2	93.9%	56.1%	52 (27–120)	12 (10–54)	28.0%
BRV_10	A2	90.3%	65.8%	46 (24–116)	11 (7–38)	23.0%
B1 — No-regret expansion, flex robust						
SDZ_10	B1	87.7%	90.3%	32 (16–116)	12 (10–37)	31.2%
BLD_10	B1	77.2%	90.3%	28 (15–135)	29 (18–45)	48.4%
HOU_10	B1	60.5%	91.2%	53 (17–168)	29 (8–72)	17.4%
B2 — No-regret expansion, flex limited						
ARK_50	B2	50.9%	100%	429 (20–912)	118 (105–238)	0.0%
VN1_10	B2	50.9%	97.4%	116 (20–306)	71 (38–73)	32.3%
WAI_10	B2	47.4%	97.4%	108 (24–262)	45 (18–76)	36.0%
BUN_10	B2	44.7%	96.5%	46 (17–252)	46 (27–73)	40.1%
UKW_10	B2	41.2%	92.1%	176 (46–396)	63 (23–76)	22.0%
VN2_10	B2	31.6%	98.2%	48 (15–231)	23 (9–23)	12.1%
OUR_50	B2	30.7%	93.0%	156 (24–447)	27 (7–87)	0.0%
DRB_10	B2	22.8%	97.4%	149 (15–404)	34 (32–42)	21.9%
OUR_10	B2	21.9%	99.1%	99 (14–257)	46 (33–46)	30.8%
Middle — Robust on one or both axes, no No-regret conclusion						
<i>See Table H.1 in Appendix H.</i>						

The flexibility dimension

This section examines which network properties explain the flexibility deployment patterns observed across the near-optimal solution space.

What determines whether a location is no-regret for flexibility

Hypothesis 3 states that substations with no upstream expansion capacity and high demand pressure consistently attract flexibility. To test this statistically, Fisher's exact test first establishes whether substations that simultaneously lack upstream expansion capacity and experience high demand pressure are significantly overrepresented among no-regret nodes ($p = 0.003$), confirming that this concentration is not a coincidence.

A logistic regression then estimates how much each condition independently contributes to the probability of no-regret classification. The absence of upstream expansion capacity emerges as the dominant predictor: substations without expansion room are approximately 131 times more likely to be classified as no-regret than substations with expansion room, when demand pressure is held constant ($OR = 130.9$, 95% CI [9.9, 1726.3], $p < 0.001$). The wide confidence interval reflects the small number of no-regret nodes ($n = 10$) rather than a weak effect: the interval does not include 1, confirming a strong and significant association. Demand pressure contributes in the expected direction but does not reach statistical significance on its own ($p = 0.067$). With only 10 positive cases, the model cannot reliably separate the contributions of two correlated predictors, and the estimate for demand pressure should be interpreted with caution.

It should be noted that the model does not include the option to build a new substation or install transformers beyond the available slots. In practice, a DSO may resolve transmission constraints at a saturated upstream link by constructing new substation rather than deploying flexibility. The no-regret classification of Category A1 substations therefore holds within the modelling assumptions but may not translate to all real-world situations where new

infrastructure is feasible. Appendix G confirms this: when slots are doubled, the cost-optimal solution for Utrecht is unchanged, but the upstream links of A1 substations carry high I-values and would become expansion candidates. The near-optimal solution space under doubled slots is therefore likely broader. Once upstream expansion becomes feasible at A1 substations, some configurations can resolve the same transmission constraints through expansion rather than flexibility at near-equal cost, increasing the number of valid configurations within the cost slack. The no-regret classification should be interpreted as conditional on the baseline slot assumption.

Demand pressure explains which technology is selected at that location. The eight A1 substations with demand pressure above 14% show hydrogen-to-power deployment frequencies above 77%, meaning both the location and the technology are determined for almost every spore. At UOV_10 and UMW_10, where demand pressure is below 5%, the location is no-regret but the technology choice varies across configurations. Without sustained demand pressure, the system must place flexibility at these substations but has no structural reason to prefer one technology over another. Which technology fulfils the role depends on wider system conditions rather than local network properties. This adds a layer of nuance to hypothesis 3, translated into:

Principle A

A substation with no downstream connection and no upstream expansion capacity is a no-regret flexibility location: the network leaves no alternative response regardless of cost assumptions or system configuration. Where demand pressure is sufficiently high, the technology choice is equally determined: hydrogen-to-power is deployed in the large majority of configurations. Where demand pressure is low, the location remains no-regret but the technology varies with wider system conditions.

Why not all dominant scenario substations are structurally robust

In the scenario analysis in Section 6.4, the top 10 substations dominating the flexibility distribution were parametrically robust. The SPORES analysis shows this does not extend equally to structural robustness, as shown in Table 6.15.

Table 6.15: Robustness classification of top scenario substations based on frequency across near-optimal solutions.

Station	Frequency	Category
ARK_150	46.5%	Moderate
GOU_150	46.5%	Moderate
BRK_150	44.7%	Moderate
ARK_50	50.9%	Moderate
VN1_10	50.9%	Moderate
BLT_10	100%	No-regret
GOR_13	100%	No-regret
LRD_13	100%	No-regret
UKW_10	41.2%	Moderate
BLD_10	77.2%	Robust

Three of the 10 substations score no-regret, and one scores robust. For these substations, both analyses agree: they attract flexibility consistently, whether cost assumptions change or the system explores alternative configurations of near-equal cost.

The remaining substations tell a different story. The 150 kV substations and ARK_50 and VN1_10 all fall in the moderate range, meaning they attract flexibility in roughly half of all near-optimal configurations. Once the system explores alternatives, it can achieve near-identical costs while placing flexibility elsewhere. Their dominance in the scenario analysis reflects cost-effectiveness under specific assumptions, not a structural property of the network. This does not mean these substations are unimportant. As shown in Figure 6.14, large volumes of flexibility are still placed on the parametrically dominant substations across many configurations, but the system alternates between them.

The difference between the two analyses is not a contradiction, it reflects what each analysis tests. The scenario analysis tests parametric uncertainty by varying cost assumptions and always identifies one new cost-optimal solution; across all scenarios the same substations remain dominant. The SPORES analysis tests structural uncertainty by keeping assumptions fixed and exploring configurations of near-equal cost, revealing that some of that dominance is structural while the rest is not. This challenges hypothesis 10 and leads to its revision into Principle B.



Figure 6.14: Spatial deployment of flexibility capacity per substation, normalised to $[0, 1]$ within each technology relative to its maximum deployment across all substations and SPORES. Each row = one substation, each dot = one SPORE.

Principle B

The spatial distribution of flexibility is parametrically robust: the same locations remain dominant when cost assumptions vary. However, this robustness does not extend equally to all locations under structural robustness analysis. Locations that are determined by network constraints are structurally robust across near-optimal configurations. Locations that are cost-effective under specific assumptions are not: once the system explores alternatives, different locations emerge as dominant.

This is consistent with hypothesis 2. The near-optimal solution space confirms that flexibility shifts to the substations where imbalances physically occur, not only in the cost-optimal solution but across all configurations of near-equal cost. At the same time, the contrast between the 150 kV and MV substations reveals why robustness differs with network depth. The 150 kV substations attract flexibility because it is cost-effective to place it there, once the model is steered towards alternative configurations, this preference does alternate between these stations. The deep MV substations attract flexibility because the network structure leaves no alternative, and their classification holds regardless of wider system conditions. Both observations are formalised as a principle:

Principle C

In an optimisation model that excludes MV network topology, flexibility concentrates at the highest modelled voltage level because MV demand is aggregated there by design. Once MV topology is included, flexibility shifts to the substations where capacity constraints actually bind. This redistribution holds across all 113 near-optimal configurations, confirming that it is a consequence of which network level the model represents rather than of specific cost assumptions.

The expansion dimension

The batch validation in Section 6.5.2 shows that expansion decisions are insensitive to how the flexibility portfolio is configured across batches. This section examines whether that insensitivity holds across the full near-optimal solution space, and whether the screening index developed in Section 6.3.4 provides a reliable candidate set not only in the cost-optimal solution but across all 113 SPORES.

To test this, the screening index is applied to all 113 SPORES to test whether the candidate set remains reliable beyond the cost-optimal solution. Recall equals 100% in 110 of 113 SPORES, with an average of 99.9%, with no significant batch effect (shown in Table 6.13). This confirms that steering the solver towards technology extremes does not alter which links are expanded. Table 6.16 summarises the recall per batch.

Table 6.16: Screening index recall per SPORES batch.

Batch	Mean recall (%)
Broad exploration	100%
Intensify MAX battery_flow	100%
Intensify MIN battery_flow	100%
Intensify MAX battery_liion	100%
Intensify MIN battery_liion	100%
Intensify MAX power_2_h2	99.3%
Intensify MIN power_2_h2	100%
Intensify MAX h2_2_power	100%
Intensify MIN h2_2_power	100%

The three cases missed by the index involve the same link, DRB_50_to_WBD_10, with $I' = 0.84$. Further analysis does not reveal a specific local driver for the expansion in these three SPORES: local flexibility capacity and surplus profiles are comparable across all max_p2h2 configurations. The most likely explanation is that these SPORES represent near-optimal system configurations in which expansion of this link is cost-equivalent to the alternative flexibility response.

The value of the candidate set becomes even more clear when viewed alongside the scenario analysis results. In every cost-optimal scenario solution, only a single link is expanded (the ARK_150 to ARK_50 link) at roughly the same capacity across all configurations.

The near-optimal solution space shows that this single expansion in the cost-optimal scenario solution understates the pressure on the network: 12 links reach expansion frequencies above 90% across the 113 SPORES, spread across different parts of the Utrecht network (Figure 6.15). The screening index captures all of them within its candidate set of 35.

These no-regret links have substantially higher index values than other links (median 123.8 versus 3.5). The Spearman correlation between I' and SPORES deployment frequency is $\rho = 0.687$ ($p < 0.001$), indicating that links with higher index values are expanded more consistently across near-optimal configurations. The magnitude of I' therefore reflects the degree to which expansion is favoured over flexibility, not only whether a link crosses the screening threshold.

Together, the screening index and the SPORES analysis provide a three-step basis for structurally robust expansion decisions. First, the index identifies which links have an economic case for expansion before running the optimisation. Second, the magnitude of I' ranks those candidates by the strength of that case. In the Utrecht model, all links with $I' > 115$ are classified as no-regret or robust, and above $I' > 5.5$ only one moderate link appears alongside no-regret and robust links. Links below this range are more configuration-dependent. Third, the SPORES analysis verifies this ranking and identifies the links within the candidate set that are structurally robust despite moderate index values, which the magnitude alone would not distinguish. The resulting classification provides a prioritised set of expansion candidates for more detailed follow-up analysis.

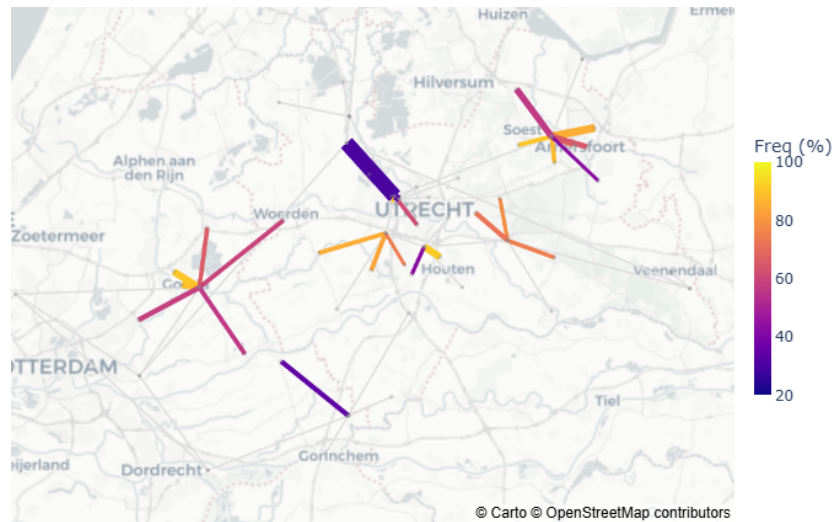


Figure 6.15: Expansion frequency per link across all 113 SPORES in the Utrecht model. Line colour indicates the share of SPORES in which the link is expanded.

Together, the stable recall across all batches and the broader expansion patterns visible in the near-optimal solution space confirm that the screening index provides a reliable and meaningful candidate set beyond the cost-optimal solution alone. This leads to the following principle:

Principle D

Before running a full optimisation, a candidate set of links justifying expansion can be identified by comparing the annualised cost of expansion to the cost of handling the equivalent local energy imbalance through flexibility. This candidate set reliably captures all links expanded in the cost-optimal solution and across near-optimal configurations, reducing the full set of technically expandable links to a structurally robust subset.

Is there a trade off between expansion and flex?

The spatial categories show that substations vary in how often they receive flexibility, expansion, both, or neither across the near-optimal solution space. The spatial categories show how often each substation receives flexibility or expansion, but not whether the two responses substitute for each other at the same location, appearing as alternatives in different SPORES, or complement each other, appearing together in the same SPORE. This section tests that relationship.

Two analyses are applied. At the system level, the Spearman correlation between total installed flexibility capacity and total network expansion is calculated across all 113 SPORES and separately for the broad batch. At the node level, the phi coefficient is calculated for each MV substation between two binary variables: whether any flexibility is deployed and whether the upstream link is expanded, both assessed per SPORE. A Wilcoxon signed-rank test then assesses whether the median phi across all substations differs significantly from zero.

At the system level, no significant pattern emerges. Configurations with more total flexibility do not have less total network expansion, and vice versa. The Spearman correlation between the two is weak and insignificant across both the full set of 113 SPORES ($\rho = -0.171$, $p = 0.071$) and the broad batch ($\rho = 0.097$, $p = 0.645$). The overall volume of the two responses therefore varies independently across near-optimal configurations.

At the node level, however, there is a consistent and significant pattern. The mean ϕ coefficient is -0.238 across all SPORES and -0.263 in the broad batch, with 85% of substations showing a negative ϕ . A negative phi means that at a given substation, flexibility and expansion tend not to appear together in the same SPORE. When expansion is selected, flexibility is typically absent, and vice versa. The Wilcoxon signed-rank test confirms that the median ϕ differs significantly from zero in both the full set ($p < 0.001$) and the broad batch ($p = 0.0003$), confirming that substitution is a structural robust pattern at the node level rather than an incidental finding.

Principle E

At the substation level, flexibility and network expansion act as substitutes: when a substation receives expansion in a given configuration, it is significantly less likely to also receive flexibility in that same configuration, and vice versa. This substitution is a structurally robust pattern across near-optimal configurations of equal cost. It does not translate into a system-wide trade-off: the total volume of flexibility investment and the total volume of network expansion vary independently across configurations. The choice between flexibility and expansion is therefore a local decision driven by conditions at the individual substation, not a system-wide one.

6.5.4. Technology stability and substitution

The previous section showed that location robustness and technology robustness are independent properties. This section addresses two follow-up questions: which technologies substitute for each other, what cost logic drives that substitution, and whether the surplus volume threshold for electrolyser placement established in Section 6.3.3 holds as a necessary condition across near-optimal configurations.

Technology substitution

Figure 6.16 shows the correlation between technology pairs across all SPORES. The dominant pattern is a strong negative correlation between vanadium redox flow batteries and hydrogen-to-power across almost all substations. When vanadium redox flow is placed at a substation, hydrogen-to-power largely disappears there, and vice versa. A weaker but consistent negative correlation also exists between redox and lithium-ion batteries. Lithium-ion and hydrogen-to-power also compete but less strongly.

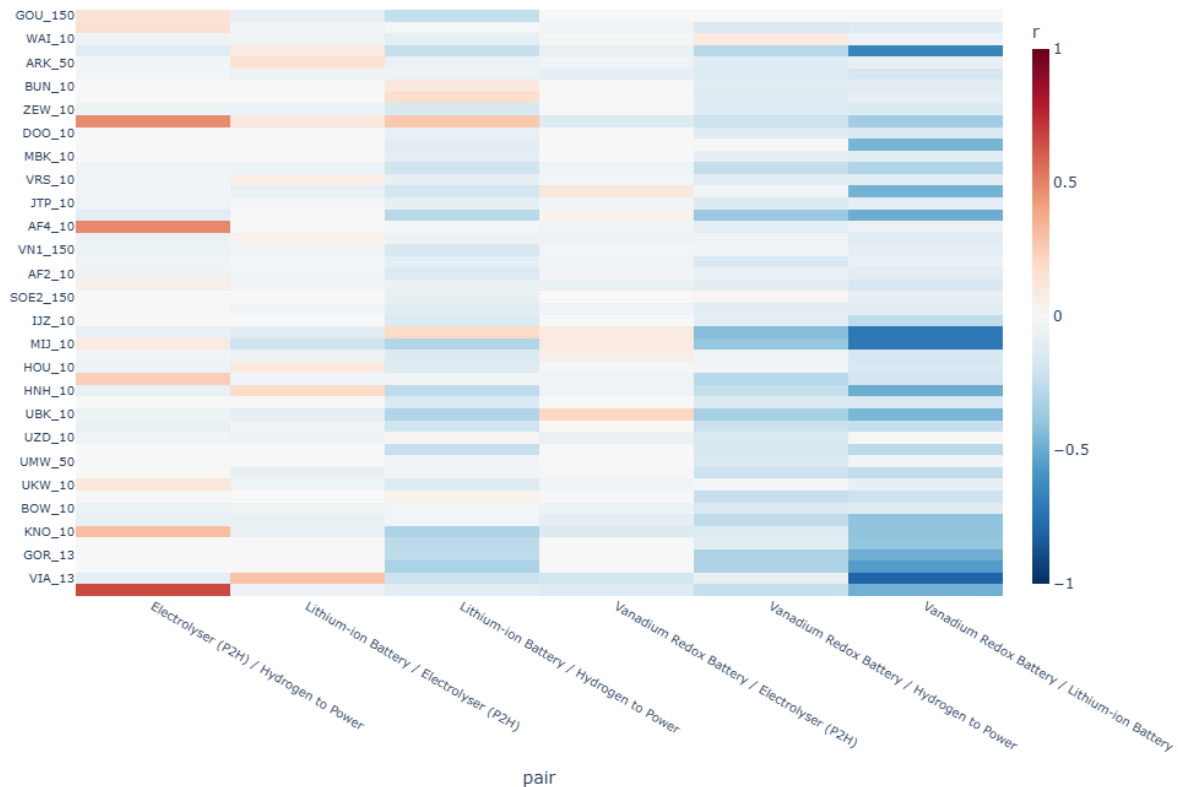


Figure 6.16: Correlation heatmap of technology deployment across substations in the near-optimal solution space. Values represent pairwise correlations in installed capacity across SPORES.

In the cost-optimal solution, vanadium redox batteries are absent while lithium-ion and hydrogen-to-power together fulfil the balancing and dispatchable peak roles. Once the system explores alternative configurations, redox emerges as a substitute for both simultaneously. It covers the short-cyclic surplus absorption role of lithium-ion and the dispatchable response to local peak demand of hydrogen-to-power within a single technology. The system therefore treats vanadium redox flow batteries as an alternative to the combination of the other two, not as an addition to them.

This substitution has a cost logic that explains the wide range of redox capacity in Figure 6.9. In the cost-optimal solution, lithium-ion outcompetes redox for the balancing role (162 versus 320 kEUR/MWh), leaving no cost-effective role for vanadium redox flow. Once penalty weights discourage lithium-ion deployment, vanadium redox flow becomes competitive for surplus absorption. Because vanadium redox flow also covers longer discharge durations, it simultaneously displaces hydrogen-to-power at locations where dispatchable peak response is needed. Vanadium redox flow therefore absorbs the capacity of two technologies at once, which explains why its installed capacity can grow very large in alternative configurations.

Electrolyser placement

Hypothesis 6 states that a minimum annual surplus exposure is a necessary condition for electrolyser deployment. To test this across the near-optimal solution space, a per-SPORE check counts the number of configurations in which any node below the 384-hour threshold receives an electrolyser. The threshold is confirmed as a necessary condition in 109 of the 113 SPORES (96.5%), and in all 25 broad SPORES without exception. The four exceptions come from the min_power-to-hydrogen and min_lithium-ion intensified batches and can be explained as boundary effects of intensification. In the min_power-to-hydrogen batch, the solver is directly steered away from electrolyser deployment. In the min_lithium-ion batch, removing the cheapest surplus absorption option makes the electrolyser competitive at nodes that would not cross the threshold under non-intensified conditions. Both violating nodes sit close to the analytical threshold, with surplus hours of 108 and 327 against a threshold of 384, which quantifies the marginality of the exceptions. The Mann-Whitney test reported in Section 6.3.3 is not repeated here: the SPORES cover the Utrecht model, and the number of MV-level electrolyser deployments per SPORE is too small for a reliable statistical comparison.

Hypothesis 7 states that substations with electrolyser deployment show significantly longer uninterrupted surplus blocks than substations without, among nodes exceeding the surplus threshold. This association cannot be meaningfully tested across the near-optimal solution space of the Utrecht model. Electrolyser deployment is concentrated at 380 kV substations, which function as a black-box interface and fall outside the scope of the SPORES analysis, while the Utrecht network itself attracts almost no electrolyser deployments across the optimal and near-optimal configurations. Whether block duration is a structurally robust discriminator therefore remains an open question. This does not contradict the confirmation of hypothesis 7 in Section 6.3.3, which establishes the association in the cost-optimal solution for the full HV–MV model.

Principle F

The minimum annual surplus exposure required to justify electrolyser investment over curtailment is a necessary condition that holds across near-optimal configurations: no substation below this threshold receives an electrolyser regardless of how the rest of the system is configured. The threshold can be calculated from technology cost parameters and hydrogen prices, and shifts predictably when those parameters change. Whether the temporal structure of surplus is an equally structural robust condition cannot be assessed from the Utrecht model alone, as electrolyser deployment there is too limited across near-optimal configurations to test reliably.

Answer to SQ3B

The cost-optimal distribution of flexibility is only partially structurally robust, and the degree of robustness depends on whether a location or technology choice is determined by network properties or by cost assumptions.

At the location level, substations where no upstream expansion is possible are structurally robust: the network leaves no alternative response, so flexibility is placed there across all 113 near-optimal configurations regardless of how the rest of the system is configured. The 10 Category A1 substations reach a deployment frequency of 100%. Where demand pressure is high, the technology choice is equally determined: hydrogen-to-power is deployed in above 77% of configurations. Where demand pressure is low, the location is fixed but the technology varies with wider system conditions.

At the technology level, no single technology choice is structurally robust beyond these constrained locations. The cost-optimal solution installs no vanadium redox capacity, yet across the near-optimal space it emerges as a substitute for the combination of lithium-ion and hydrogen-to-power, with capacity ranging up to approximately 18 GW. Technology choices at locations that are not network-constrained therefore reflect cost assumptions rather than structural necessity.

Network expansion is more structurally robust than flexibility deployment. Expansion decisions are insensitive to how the flexibility portfolio is configured across all 113 SPORES, and the screening index captures this stability with an average recall of 99.9%.

6.6. Key Takeaways

This chapter addressed four sub-questions that together build towards the main research question. The findings are summarised below.

Model development (SQ1A & SQ1B). A computationally tractable HV–MV optimisation model of the Stedin service area is constructed, divided into three provincial sub-models and run at three-hour temporal resolution. The model satisfies all seven methodological requirements defined in Section 3.2.

Impact of MV topology (SQ2). Including MV topology does not substantially change the total investment required, but fundamentally changes where it is placed. Flexibility shifts from 150 kV substations, where demand aggregation creates an artificial local imbalance, to the MV substations where congestion actually occurs. The trade-off between expansion and flexibility follows a predictable economic logic: the screening index identifies expansion candidates by comparing annualised expansion costs to the cost of managing the equivalent imbalance through flexibility, reducing 238 technically expandable links to 91 candidates while capturing all 32 MV links expanded in the cost-optimal solution.

Parametric robustness (SQ3A). When cost assumptions change, the locations where flexibility is needed remain stable. What changes is the technology that fills that role. Location decisions are more robust than technology decisions.

Structural robustness (SQ3B). Structural robustness of substations depends on whether a location is constrained by the network or only cost-effective under specific assumptions. The 10 Category A1 substations, where no upstream expansion is possible, reach a flexibility deployment frequency of 100% across all 113 SPORES; where demand pressure is high, the technology choice is equally determined. All other locations can be substituted at near-equal cost. At the technology level, no choice is structurally robust beyond these constrained locations: vanadium redox emerges as a substitute for the combination of lithium-ion and hydrogen-to-power across the near-optimal space, despite being absent from the cost-optimal solution. Network expansion is more structurally robust, with the screening index achieving an average recall of 99.9% across all SPORES.

7

Discussion

This chapter interprets the results of the four sub-questions in relation to the main research question and places them in the broader context of the literature reviewed in Chapter 2. The chapter is structured in four sections. Section 7.1 reflects on the modelling process and argues that the planning purpose of a model should drive every abstraction decision. Section 7.2 interprets the findings across the four sub-questions. Section 7.3 defines the boundaries of those insights by distinguishing between design choices and limitations. Section 7.4 identifies the implications for DSO and Stedin specific. Section 7.5 presents possible directions for future research.

7.1. The modelling goal as the primary criterion for model scope

The development of the HV–MV model in SQ1A and SQ1B illustrates a methodological point that extends beyond this study. The literature reviewed in Chapter 2 frames the central challenge of modelling flexibility in distribution networks as a tension between model detail and computational tractability: the more network detail is included, the harder the model becomes to solve. This framing captures only part of the challenge. Equally important is the question of which detail is decision-relevant given the purpose of the model.

In this study the modelling purpose was to determine the cost-effective spatial distribution of flexibility technologies and network expansion across an HV–MV network in a way that is both computationally tractable and decision-relevant for a DSO planning towards 2050. This purpose, rather than technical representativeness or data availability, served as the primary criterion for every modelling decision. The seven methodological requirements defined in Section 3.2 operationalised this purpose into concrete design criteria, providing a reference against which each abstraction decision could be evaluated.

The central trade-off in the modelling process was between representing MV network capacity constraints (R2) and maintaining computational tractability (R5). Including the full Stedin service area at MV resolution produced a model too large to solve within reasonable computation time. Dividing the network into three provincial sub-models and applying three-hour temporal resampling preserved the network detail that makes the outcomes decision-relevant while keeping each model solvable.

This perspective also clarifies how to interpret the model's abstractions. Not all excluded constraints or details carry the same weight. Some were intentionally excluded because they fall outside the scope of a 2050 strategic planning horizon. Others were excluded due to data unavailability or time constraints, and these define the conditions under which the planning insights hold. That distinction is developed further in Section 7.3.

A third element that shaped the modelling process was the integration of domain knowledge. The literature on structural uncertainty in energy system models notes that modelling choices cannot be evaluated from data alone [40]: they require practical knowledge of how the system operates and how planning decisions are made. In this study, informal consultations with Stedin experts allowed that knowledge to inform abstraction decisions. The expert interviews afterwards served as a verification step, assessing whether the model assumptions, structure and results produce insights that are meaningful in planning practice.

Taken together, these three elements suggest a modelling approach in which model quality is measured by planning relevance, rather than only physical comprehensiveness. That reframing has direct consequences for how models at the HV–MV interface should be scoped, validated, and communicated to the DSO.

7.2. What the models reveal about the network

The results of SQ2, SQ3A, and SQ3B together produce four insights about the spatial planning of flexibility in HV–MV networks, captured across six principles. Table 7.1 summarises each principle before it is developed in the subsections below.

Principle	Summary
Principle A	A substation with no downstream connection and no upstream expansion capacity is a no-regret flexibility location. High demand pressure also fixes the technology to hydrogen-to-power; low demand pressure fixes the location but leaves the technology open.
Principle B	Flexibility locations are parametrically robust, but not all are structurally robust. Only network-constrained locations hold consistently across near-optimal configurations; system-condition-dependent ones do not.
Principle C	Excluding MV topology pushes flexibility to the highest modelled voltage level by design. Including it shifts flexibility to where imbalances and capacity constraints originate.
Principle D	The screening index reliably identifies expansion candidates before running a full optimisation, capturing all expanded links across both the cost-optimal solution and the near-optimal space.
Principle E	Across near-optimal configurations, flexibility and expansion substitute for each other at the substation level. At the system level, their total volumes vary independently.
Principle F	A minimum annual surplus exposure is a necessary condition for electrolyser deployment across near-optimal configurations. The threshold is analytically derivable and shifts predictably with changing cost parameters.

Table 7.1: Overview of principles.

7.2.1. MV topology determines the specificity of planning signals

The comparison between the HV and HV–MV model addresses the limitation identified in Sections 2.5.1 and 2.6.1. Transmission-level models represent MV demand as aggregated loads at higher-voltage substations, without capturing the capacity constraints of the underlying network, and may therefore misplace flexibility. The results show what that misplacement looks like in practice. In the HV model, flexibility concentrates at 150 kV substations because aggregated MV demand appears there. Once MV topology is introduced, demand distributes across individual substations with their own capacity constraints, and flexibility follows. The HV model is not internally inconsistent. It produces correct results for a network representation that does not reflect where congestion actually occurs. The mismatch identified in Chapter 2 between top-down and bottom-up models is therefore not simply a matter of one approach being better than the other. It is a consequence of modelling a different network level for the planning question being asked (Principle C).

This finding relates to but also extends the work of Jacquier et al. (2025), who show that including MV distribution grids in national long-term planning models has little effect on capacity investment plans but significantly increases system costs through operational constraints [9]. That study uses 14 generic grid types to represent the full range of French MV networks, which is sufficient to capture system-level cost effects but does not preserve the substation-specific topology that determines where congestion occurs. The HV–MV model in this study uses the real network topology of the Stedin service area, with substation-level capacity constraints, and it is this topological accuracy that makes the spatial redistribution of flexibility visible. The level of MV detail therefore determines what the model can say: an aggregated representation is sufficient for system-level cost analysis, while a topologically accurate representation produces the location-specific planning signals. The electrotechnical expert confirmed this distinction, noting that substation-level network detail is a must for DSO planning decisions [B.1.7T].

The choice of MV representation has different consequences depending on the technology, but in all cases the HV model produces signals that reflect network aggregation rather than actual congestion locations. For electrolyser deployment, HV models provide a more reasonable approximation, because the surplus volumes required to operate electrolysers economically are typically concentrated at higher voltage levels, which are already represented in the HV model. For hydrogen-to-power and battery storage, the misrepresentation is more fundamental: these technologies respond to local supply-demand imbalances that are invisible without MV topology. Planning decisions for these technologies based on HV outcomes risk placing flexibility where it appears cost-effective but cannot serve the imbalances that exist in the MV network.

This finding also reframes an earlier result from the national HV model by Bordignon (2025), on which this study builds [8]. In that model, flexibility concentrates at 150 kV substations, where the TenneT transmission network connects to the Stedin distribution network. The HV–MV model clarifies what that concentration reflects: not where flexibility is needed, but where aggregated MV demand appears in a model without MV topology. The 150 kV signal is therefore not a planning recommendation but an indication that flexibility is needed somewhere in the downstream MV network, a location that only becomes visible once MV topology is represented.

7.2.2. The trade-off between expansion and flexibility is locally determined and predictable

The cost-optimal results show that network expansion concentrates at links where the annualised investment cost is lower than the cost of managing the equivalent annual energy imbalance through flexibility. This relationship is not a post-hoc observation about model outputs: it is a predictable consequence of the cost structure, and it can be evaluated before running a full optimisation. The screening index developed in Section 6.3.4 formalises this logic by comparing the annualised expansion cost to the levelised cost of the reference flexibility technology multiplied by the annual energy overload on a given link. A link becomes an expansion candidate when flexibility is the more expensive response.

Applied to the 238 transformer links in the full HV–MV model, the index identifies 91 candidates and captures all 32 links expanded in the cost-optimal solution, a recall of 100%. Across all 113 near-optimal configurations of the Utrecht model, the average recall is 99.9% (Principle D). The magnitude of I' further predicts how consistently a link is expanded across those configurations, confirming that the index reflects the degree to which expansion is favoured over flexibility. Steering the solver towards technology extremes does not change which links are expanded, directly confirming that expansion decisions are determined by network structure rather than by the broader flexibility portfolio configuration.

This finding connects to but also operationalises the decision framework described by Netbeheer Nederland [79]. The 'Verzwaren tenzij' framework provides the qualitative logic: congestion that is infrequent and short in duration is more efficiently managed through flexibility, while long-duration congestion favours reinforcement or expansion. It identifies congestion duration as a key screening indicator but explicitly notes that reference values remain to be developed. The ENTSO-E TSO-DSO report describes the same logic at European level [80]. The screening index closes that gap by comparing annualised expansion costs to the levelised cost of the reference flexibility technology multiplied by annual energy overload, producing a calculable break-even threshold from load forecasting data and topology, without requiring a full network optimisation.

Across all 113 SPORES, the flexibility technologies and expansion consistently substitute at the individual substation level. When a substation receives expansion in a given configuration, it is significantly less likely to also receive flexibility in that same configuration, and vice versa. At the system level, however, no such pattern emerges. Total flexibility and total expansion vary independently across configurations. The choice between the two is therefore a local decision driven by conditions at the individual substation, not inferable from system-wide investment totals (Principle E). This extends the finding of Holweger et al. (2023), who demonstrate that distributed flexibility can substitute for grid expansion at specific congestion points, to a structurally robust pattern across DSO service area and the near-optimal solution space [32].

7.2.3. Parametric and structural robustness test different dimensions of planning uncertainty

This study applies two complementary robustness analyses that test fundamentally different dimensions of planning uncertainty. Scenario analysis varies cost assumptions and identifies a new cost-optimal solution under each: the same locations remain dominant while the technology mix shifts. SPORES analysis holds assumptions fixed and explores configurations within a 15% cost slack: some of those dominant locations disappear once the system can achieve near-identical costs differently. The near-optimal space also reveals patterns invisible in the cost-optimal solution: vanadium redox capacity can reach approximately 18 GW across configurations, as the system treats it as a substitute for the combination of hydrogen-to-power and lithium-ion.

Only by combining both analyses does the full picture emerge. Scenario analysis confirms parametric robustness but cannot distinguish whether that robustness is structural or assumption-dependent. SPORES analysis identifies structural robustness but cannot confirm stability across the full range of cost assumptions. Principle B formalises this distinction. This study further extends near-optimal analysis by introducing attributed structural robustness: the goal is not only to establish whether a planning decision is robust, but to explain why in terms of a specific network property. This study extends both the frequency-based stability analysis of Bordignon and the argument of Lombardi et al. (2025) and de Tomás-Pascual et al. (2025) that near-optimal exploration is necessary for robust planning decisions [10, 8, 11]. By grounding planning insights in specific network properties, the analysis moves beyond identifying which decisions are stable towards explaining why they are stable, and under what conditions

that robustness holds.

7.2.4. Network structure determines location robustness; demand pressure determines technology robustness

The conditions that make locations and technologies robust can be traced to specific network properties. Technologies that respond to local supply-demand imbalance, hydrogen-to-power and lithium-ion batteries, are subject to the local flexibility-expansion trade-off described above. Technologies driven by structural surplus conditions operate under a different logic: the minimum annual surplus exposure threshold for electrolyser investment holds as a necessary condition across near-optimal configurations and is calculable from cost parameters alone (Principle F). Block duration predicts electrolyser placement in the cost-optimal solution but is not a structural condition.

The same distinction applies to location robustness. The absence of upstream expansion capacity is the dominant predictor of no-regret flexibility deployment, confirmed by logistic regression, while demand pressure determines whether the technology choice is equally constrained. Where both conditions are met, the network leaves no alternative for either the location or the technology. Where demand pressure is low, the location remains structurally robust but the technology varies with wider system conditions (Principle A).

This classification holds within the modelling assumptions. The model does not include new substation construction as an alternative response, which is technically feasible at some locations in practice. The no-regret classification should therefore be read as conditional: given existing infrastructure, these are the locations where local flexibility deployment is the only available response. The underlying principle generalises regardless, the more severely constrained the upstream capacity, the fewer the alternatives. Hennig et al. (2023) and Stawska et al. (2021) establish that the value of flexibility for congestion management is strongly location-dependent [19, 16]. The contribution here is to identify which network properties make a location not just valuable for flexibility but structurally robust, and to show that those same properties determine whether the technology choice is equally constrained.

7.3. Boundaries of the planning insights: limitations

As discussed in Section 7.1, not all excluded constraints carry the same weight. Some were excluded by design because they fall outside the scope of a 2050 planning horizon. Others were excluded due to data unavailability or time constraints. The first category does not affect the planning-relevant outcomes of the model; the second defines the conditions under which the insights hold.

Methodological limitations affect the generalisability of the principles. The SPORES analysis was conducted on the Utrecht provincial model only, so the no-regret classifications apply directly to Utrecht and should be treated as hypotheses about Zeeland and Zuid-Holland until the same methodology is applied there. Three-hour temporal resampling underestimates the operational value of short-cyclic battery storage, as the electrotechnical expert noted [B.1.2], though this affects absolute battery capacity rather than spatial distribution or network expansion outcomes, making it an acceptable compromise for long-term planning.

In addition, the hydrogen network is represented as a centralised hub with unconstrained transport capacity, which may overstate the attractiveness of hydrogen-based flexibility at locations far from actual hydrogen infrastructure. The analysis is further limited to the four flexibility technologies included in the model. Other options such as demand response, vehicle-to-grid, or large-scale heat storage are not represented, meaning the substitution patterns identified in the near-optimal solution space reflect the competition between these four technologies only. Technologies not included in the model cannot be distributed, which may affect both the technology robustness conclusions and the identification of no-regret technology choices at Category A1 substations.

Technical limitations affect the precision of specific model outcomes and define the conditions under which the planning signals can be acted upon directly. The model uses continuous rather than discrete capacity expansion, as including binary or integer variables would make the model computationally intractable at this scale. This underestimates actual investment costs where only small fractional expansions occur, and the actual expansion volumes and associated costs at the 380150 kV interface are therefore likely to be higher than the model suggests, as real investments occur in discrete steps [B.1.1C, B.3.7L].

Short-circuit current limits are not represented, meaning hydrogen-to-power placements deep in the MV network require additional technical screening before they can inform operational decisions [B.1.5M, B.3.4F, B.3.4G]. Connection category rules are also absent, so some flexibility placements at 10 kV substations may not be directly realisable without additional network adjustments [B.3.3E]. Switching field availability is not represented either: substations where connection points are fully occupied would need to be rebuilt before new assets can be connected, and rebuilding an existing substation is more expensive than constructing a new one because all equipment must be temporarily relocated. The model assigns zero cost to this, meaning implementation costs are

underestimated at capacity-constrained substations [B.1.4J, B.1.4K, B.2.6P]. The model enforces energy balance at each node but does not represent power flow physics: power can be freely directed through the network as long as link capacities are respected. In reality, electricity does not flow where it is told, it distributes across all available paths according to the physical properties of the network, which can cause some links to become more heavily loaded than the model anticipates. This matters most in the meshed 150 kV network, where multiple parallel paths exist. In the radial MV network, where each substation has exactly one upstream connection, this is less of a concern. In addition, voltage levels and reactive power are not captured, so solutions that are feasible in the model may require additional adjustments in practice.

Social and institutional constraints such as permitting, spatial planning, and local acceptance are also absent, meaning model outcomes should be understood as technically optimal rather than fully implementable without further screening [B.3.5H, B.3.5I]. Several further abstractions are unlikely to affect the main planning insights but are relevant for substation-level interpretation: a uniform power factor of 0.95 across all voltage levels, capacity assigned only to the secondary winding of three-winding transformers, the absence of low-voltage network constraints, and the spatial footprint parameter set to infinity due to unavailable substation-level data.

Data limitations affect the accuracy of model inputs at specific locations. Generic demand profiles for large industrial customers introduce uncertainty in the timing and magnitude of peak loads, particularly at substations in the Botlek and Europoort areas [B.2.1C]. Flexibility volumes placed at substations such as BOT_25 and EUR_25 should be interpreted with this in mind. Several large industrial consumers expected to connect directly to the TenneT transmission network by 2050 are still modelled as Stedin network demand, potentially overstating the required response at those substations [B.2.6O]. The network is represented as static based on current topology, excluding planned changes such as the separation of the dual 380 kV connection at BRK_150, which partly explains the disproportionate flexibility concentration observed at that substation in the high hydrogen price scenario [B.1.3I]. New planned substations are excluded due to unavailable demand forecasts, meaning the model places flexibility and expansion on existing substations to cover demand that could be served by new infrastructure in 2050. Existing battery installations are modelled as regular demand rather than flexible assets, which may slightly overstate the need for additional flexibility at substations where batteries are already present. Finally, the interest rate of 1% applied to annualise capital costs may favour capital-intensive investments such as network expansion over operational flexibility technologies as expansions have longer lifetimes, potentially affecting the trade-off between the two across all model configurations.

Computational limitations determined several key modelling choices in this study. Three problems arise: memory shortage, computation time, and numerical instability in the Gurobi solver. No single measure resolved all three. Instead, a combination of interventions was applied, several of which addressed multiple problems simultaneously. *Memory shortage* is managed through access to the Delft Blue HPC cluster and the provincial subdivision of the model.

Computation time is reduced through the same provincial subdivision, three-hour temporal resampling, and the distribution of national load across multiple 380 kV nodes rather than concentrating it at a single point. Time clustering was explored as a more aggressive temporal reduction strategy but proves unsuitable: the non-chronological ordering of representative periods breaks the temporal continuity required for seasonal hydrogen storage dispatch, and the required reduction factor remains insufficient to bring the full model within tractable bounds. Three-hour temporal resampling is therefore adopted for the full HV–MV model, reducing the number of time steps from 8,760 to 2,920 while preserving chronological structure. The effect of this choice on model outcomes is assessed in Section 6.2. The spatial distribution of flexibility investments remains stable across all tested resolutions, but absolute capacity estimates for electrolyzers and hydrogen-to-power should be interpreted with caution, as three-hour resampling underestimates the installed capacity of these technologies by up to 13%. The provincial subdivision introduces two limitations. First, substations outside the focus province are represented as a single aggregated node, removing their MV topology from the optimisation. As the HV–MV comparison in Section 6.3 shows, this leads to an underestimation of flexibility in those provinces and of the full system. Second, substations directly connected to an aggregated provincial node (GDU_150 and ARK_150 in the Utrecht model) have access to a larger surplus than their physical position suggests, which may contribute to their dominance as flexibility locations in the scenario analysis. This effect is partially constrained by the link capacities connecting these substations to the aggregated node, which are preserved from the original network. The relative ordering across scenarios is not distorted, as the topology and imbalance profiles are held constant across scenarios.

Numerical instability arises from decision variables at very different orders of magnitude across voltage levels and from the volume of time-indexed variables. The most effective measures are rescaling cost parameters to reduce the coefficient range, distributing national load across multiple nodes, temporal resampling, and the provincial subdivision. The distribution of national load is, however, limited to the 380 kV nodes directly connected to the Stedin network. In reality, the residual imbalance of the Netherlands enters the modelled area through a much larger set of nodes across the TenneT transmission network, and those imbalances would partially offset one

another through existing transmission capacity before reaching the Stedin service area. Assigning an identical profile to each directly connected node removes this inter-nodal compensation and concentrates the national residual on a small number of interface points. This does not distort the relative ordering of planning insights across scenarios and configurations, since all model runs share the same interface representation, but it affects the absolute magnitude and timing of the energy exchanges at the 380 kV interface nodes.

Adjusting solver settings including `NumericFocus` and tolerances is also explored but worsens computation time without sufficiently resolving the instability. Together, these measures substantially reduced but did not fully eliminate numerical instability: isolated solver failures during the SPORES intensified batches, where no output is produced, are managed by rerunning affected configurations with adjusted settings. Whether alternative solvers would handle the coefficient range of HV–MV models more reliably remains an open question for future work.

Taken together, these limitations do not invalidate the planning insights this study produces. They define the conditions under which the principles are valid and point directly to the refinements needed to sharpen and extend them further, the subject of the following sections.

7.4. Implications for DSOs

The insights and principles derived in this study extend beyond the specific case of Stedin. Three methodological lessons translate into planning practice for DSOs operating under similar conditions.

For DSOs seeking substation-level guidance on flexibility placement, MV topology must be explicitly represented in the planning model (Principle C). National or HV-level outputs can serve as a signal that a response is needed somewhere in the downstream network, but cannot identify where. The appropriate model scope depends on the planning question being asked, not on what is computationally convenient.

When interpreting model outputs, DSOs should distinguish between location signals and technology signals (Principle B). Location signals derived from a combined scenario and near-optimal analysis are sufficiently stable to inform spatial prioritisation and market engagement. Technology signals are not: they should always be reported with explicit bandwidths and should not be treated as point recommendations unless confirmed across the near-optimal solution space. Acting on a technology signal without that confirmation risks locking in investments that a near-identical-cost alternative would not have made.

Before running a full optimisation, the screening index provides a transferable instrument to identify which transformer links are economically justified expansion candidates and ranks them by structural robustness (Principle D). Its underlying logic applies to any DSO with load forecasting data and network topology, though threshold values are derived from local cost parameters and must be recalculated for different network contexts.

7.4.1. Implications for Stedin

The most robust outputs concern network expansion. The screening index identifies which transformer links have an economic case for expansion before any optimisation run, and this candidate set captures expansion decisions reliably across all near-optimal configurations. The Category B links with expansion frequencies above 90% across all 113 SPORES are structurally robust expansion priorities and can be treated as such in follow-up analysis such as optimal power flow calculations or discrete investment assessments. The screening index has been applied to the full Stedin service area, providing a preliminary ranking of expansion pressure across Zeeland and Zuid-Holland without further model runs.

For flexibility locations, the Category A substations in Utrecht are no-regret locations within the modelling assumptions (Principle A) and represent the highest-priority candidates for spatial assessment and market engagement. This classification is conditional on the assumption that new substation construction is not available as an alternative response; where slot saturation is the binding constraint, constructing a new substation may reopen the expansion dimension. Stedin can communicate viable flexibility locations to market parties at the A substations without first resolving the technology question, which remains open for two of them [B.3.1B]. At eight of A1 substations, where demand pressure exceeds approximately 14% of annual hours, hydrogen-to-power is the dominant technology choice. For all other locations, technology signals should be reported with explicit bandwidths rather than as point recommendations. Category A2 substations are no-regret flexibility locations where expansion may additionally be justified; Category B substations are no-regret expansion locations where flexibility deployment is inconsistent across configurations and cannot be recommended without further analysis. For substations in the middle category, neither signal is consistent enough to act on without further analysis. For electrolyser placement, the minimum annual surplus exposure threshold can be applied immediately to Zeeland and Zuid-Holland from existing load forecasting data as a pre-screening step (Principle F).

Strengthening and extending these signals

Two steps can be taken without additional model runs. Short-circuit current limits should be verified at A1 substations before hydrogen-to-power designations inform operational decisions [B.1.5M, B.3.4F]. Extending the screening index to incorporate the cost of new substation construction would further sharpen the expansion versus flexibility comparison at locations where slot saturation is the binding constraint.

Extending the SPORES analysis to Zeeland and Zuid-Holland requires new model runs but no changes to the modelling approach. This would produce no-regret flexibility classifications outside Utrecht and identify which expansion candidates from the screening index are structurally robust across near-optimal configurations the same step that elevated the Utrecht candidates to planning priorities. Increasing the cost slack from 15% to 30% is a closely related step. Stedin's own planning estimates carry a bandwidth of approximately 30% [B.1.6R, B.3.6J], and a wider slack would test whether the Utrecht classifications hold across a solution space that better reflects that uncertainty. A SPORES analysis of Zuid-Holland would additionally provide the basis to test whether block duration constitutes a structurally robust screening criterion for electrolyser placement, which could not be confirmed in the Utrecht model (Hypothesis 7).

An improvement to the national residual representation would be to disaggregate the ETM imbalance profile by province, introducing a representative 380 kV node per Dutch province and assigning each node its provincial ETM imbalance profile. This would better approximate the spatial heterogeneity of renewable generation and demand across the Netherlands, and would allow imbalances originating in different parts of the country to partially resolve one another through inter-provincial connections within the model. Nodes connected to regions with high offshore wind exposure would carry correspondingly larger and more volatile imbalance profiles, while provinces with more flexible generation would impose lower residual loads on the network. This refinement preserves the computational benefit of distributing national load across multiple nodes while moving the representation closer to physical reality.

Further model development would bring the planning signals closer to decision-relevant outputs. Replacing continuous capacity expansion with discrete investment steps would align cost comparisons with real investment decisions at the 380–150 kV interface [B.1.1, B.3.7]. Implementing the model in PyPSA would retain the current modelling structure while adding support for optimal power flow, allowing voltage and reactive power constraints to be included without rebuilding the model from scratch. Incorporating an explicit hydrogen network representation would constrain hydrogen-to-power placements by transport availability, which the current hub representation does not. Expanding the technology portfolio, particularly through multi-day storage options, may reveal substitution patterns that the current four technologies cannot produce. The no-regret classifications have not been tested against structural demand uncertainty; flexibility volumes at substations with high industrial peak loads should be interpreted with caution until alternative demand scenarios are explored, including the expected TenneT connection of large industrial customers currently modelled as Stedin demand [B.2.1C, B.2.6O]. Finally, developing demand approximations for new planned substations would allow them to be incorporated into the model, reducing the overestimation of required response at existing substations in areas where new infrastructure is anticipated.

Each of these directions builds on the current results rather than replacing them, treating this study as a first iteration in an ongoing planning process for DSOs.

7.5. Future research

The practical next steps outlined for Stedin in Section 7.4.1 are not only relevant for planning practice, but they are also meaningful directions for future academic research. The model developed in this study is, to the author's knowledge, the first to combine substation-level HVMV network topology with near-optimal solution space exploration including statistical tests for DSO investment planning. Because the model itself is new, every extension brings academic value alongside practical value. Applying the methodology to larger or different network areas, exploring a wider cost slack, or incorporating discrete investment steps would each deepen the understanding of how flexibility and network expansion interact in distribution networks under long-term uncertainty. Larger sample sets and broader geographic coverage may additionally reveal new principles or refine existing ones, strengthening the concept of the attributed structural robustness beyond what a single DSO service area can support.

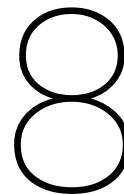
Beyond those steps, three more academically specific directions follow from the methodological choices and limitations of this study.

Firstly, combining near-optimal exploration with scenario variation. In this study, scenario analysis and SPORES are applied sequentially: scenarios vary cost assumptions, SPORES explores alternative configurations under fixed assumptions. Combining both, generating near-optimal solution sets under each scenario and pooling them, would allow the attributed structural robustness analysis to identify decisions that remain stable for the same structural reasons across both dimensions of uncertainty. This would produce a stronger subset of no-regret planning decisions than either method can reveal independently.

Secondly, strengthening the statistical basis for technology conclusions. The broad exploration batch of 25 SPORES is the primary basis for hypothesis testing on technology deployment. A larger unbiased sample would reduce the sensitivity of those conclusions to the specific configurations generated and strengthen the statistical power of the tests applied in Section 6.5. Expanding the broad batch is computationally manageable and does not require methodological changes to the existing analysis.

Thirdly, improving computational tractability. Several limitations in this study are direct consequences of computational constraints rather than modelling decisions. Addressing those constraints would expand what is analytically possible in subsequent iterations. The most direct step is testing alternative solvers such as HiGHS or CPLEX. The numerical instability encountered in this study arises from decision variables at different orders of magnitude combined with the volume of time-indexed variables. These were partially managed through cost rescaling and temporal resampling, but isolated solver failures persisted during the SPORES intensified batches. Whether the instability is specific to Gurobi's barrier implementation or inherent to the model structure at this resolution is an open question that a solver comparison would answer. Improved tractability would have concrete consequences for both preceding directions. Running the Utrecht model at full hourly resolution would reduce the underestimation of flexibility capacity introduced by three-hour resampling. Extending the SPORES analysis to Zeeland and Zuid-Holland would allow the no-regret classifications to be verified across the full Stedin service area. And combining near-optimal solution sets across multiple parametric scenarios, as described under the first direction, would be substantially more feasible.

Each of these directions moves the modelling approach closer to bridging the gap between top-down transmission and bottom-up distribution planning, towards a model that is both spatially precise enough to guide local investment decisions and structurally robust enough to inform long-term policy.



Conclusion

As flexibility transitions from a tool for balancing supply and demand at the national level to an instrument for managing scarce network capacity at the distribution level [5], the spatial deployment of flexibility technologies becomes a central planning challenge for DSOs. This requires three things simultaneously: knowing where congestion originates in the physical network, optimising deployment across the broader electricity system, and ensuring that the resulting insights are robust under the uncertainty inherent to long-term decision-making. Existing modelling approaches do not satisfy all three demands simultaneously. National models have the system-level scope but aggregate distribution network demand onto higher voltage nodes, losing the topological detail needed to identify where congestion occurs. Local models resolve individual congestion points but cannot optimise flexibility deployment across the wider MV network, leaving interactions between substations unresolved. Even models that bridge both levels typically identify a single cost-optimal solution, which may not be robust under the parametric and structural uncertainty a DSO faces when planning decades ahead.

This thesis addresses these limitations for Stedin's HV–MV network, and investigates the following research question:

How can flexibility technologies be spatially distributed across an HV–MV network in a way that combines decision-relevant detail with computational tractability in order to generate robust planning insights for DSOs?

This thesis answers that question through three interconnected elements: developing a spatial linear optimisation model that covers both the HV and MV network, keeping that model computationally tractable, and assessing the resulting planning insights along three dimensions of robustness: parametric, structural, and attributed structural.

Decision-relevant detail requires modelling the network level where congestion actually occurs. When MV topology is absent, demand is aggregated onto higher voltage substations and flexibility follows, not because that is where it is needed, but because the model has no network structure below that level to assign imbalances to their actual origin. The HV model is not internally inconsistent; it produces correct results for the network it represents. What it cannot do is distinguish where within the downstream MV network the capacity constraints bind. Once MV topology is included, that distinction becomes visible and flexibility shifts accordingly. But capturing this detail is only useful if the model remains solvable.

Computational tractability is achieved by simplifying with purpose and identifying which detail is planning-relevant for a DSO. Provincial subdivision and three-hour temporal resampling keep the model solvable while preserving the network structure that makes the outcomes meaningful. Time clustering was rejected because non-chronological ordering breaks the temporal continuity that seasonal hydrogen storage dispatch requires. Together, these choices produce a model that is both spatially detailed enough to generate meaningful planning insights and computationally tractable enough to solve them.

Robust planning insights require going beyond the cost-optimal solution. Three layers of robustness each reveal something the previous layer cannot.

Parametric robustness is tested through scenario analysis: location signals are more stable than technology signals under varying cost assumptions. The dominant flexibility locations identified in the cost-optimal solution remain dominant when hydrogen prices rise or battery costs fall; what changes is the technology mix at those locations. The where is more certain than the what.

Structural robustness, tested through near-optimal solution space exploration using SPORES, refines this finding.

Not all parametrically robust locations prove equally structurally robust. Locations that are dominant under specific system conditions can be displaced once the system explores configurations of near-equal cost. Locations that are dominant because the network leaves no alternative cannot. Substations with no upstream expansion capacity attract flexibility across all 113 near-optimal configurations regardless of how the rest of the system is configured: these are the no-regret locations. Where demand pressure at such a substation is sufficiently high, the technology choice is equally constrained, with hydrogen-to-power deployed in the large majority of configurations. Where demand pressure is low, the location remains no-regret but the technology varies with wider system conditions. A minimum annual surplus exposure threshold, derivable from technology costs and the hydrogen import price, holds as a necessary condition for electrolyser placement across near-optimal configurations. At the substation level, flexibility and network expansion consistently substitute for each other; at the system level, their total volumes vary independently, confirming that the choice between the two is locally determined. For network expansion, the near-optimal analysis extends the reach of a screening index. This index identifies which transformer links have an economic case for expansion before any optimisation run, and the SPORES analysis reveals which of those candidates are expanded consistently across configurations and which are configuration-dependent. The magnitude of the index further predicts that consistency, translating the candidate set from a planning focus into a robustness-ranked instrument.

Attributed structural robustness goes one step further by linking each frequency pattern to a specific network property through statistical testing, identifying not only which decisions are structurally robust but why they persist across the solution space. This makes it possible to separate decisions enforced by network topology from those that depend on wider system conditions, and to communicate that distinction to planning practice.

Together, these three elements form an integrated answer to the research question. The spatial answer that emerges is that flexibility is required at substations where no upstream expansion is possible, that location is more certain than technology choice, and that the trade-off between expansion and flexibility at any given link follows from a derivable economic index. This answer is only reachable by combining decision-relevant detail with computational tractability, which are balanced by letting planning purpose govern every modelling choice. Robust planning insights can be formulated because that detail is preserved, and the principles they rest on make explicit where this thesis approach ends and what a next iteration would require.

These findings rest on five academic contributions. First, it demonstrates that the tension between decision-relevant network detail and computational tractability can be balanced by a design rule: planning purpose as the primary criterion for every abstraction decision, determining which detail is worth including rather than which detail is technically possible to include. Second, it provides the first demonstration, at this scale and network level, of how real MV network topology changes the spatial distribution of flexibility in a model that simultaneously optimises across system balance and network capacity constraints. Third, it translates a qualitative planning rule into a quantitative, derivable index for the trade-off between flexibility and grid expansion, calculable from standard cost parameters and load forecasting data. Fourth, it demonstrates that parametric and structural robustness are distinct properties that require different analytical methods, and that only their combination separates network-determined decisions from cost-dependent ones. Finally, it introduces attributed structural robustness as a planning concept by combining near-optimal solution space exploration with statistical hypothesis testing of network properties, identifying not only which decisions are structurally robust but which specific network property makes them so.

For DSOs navigating long-term uncertainty, this thesis demonstrates that robust spatial insight into flexibility deployment is within reach, not by eliminating uncertainty, but by identifying which decisions the network has already made.

References

- [1] *Power Line Grid - Free photo on Pixabay*. URL: <https://pixabay.com/photos/power-line-grid-electricity-energy-7101420/>.
- [2] Netbeheer Nederland. *Netbeheer Nederland Scenario's Editie 2025*. Tech. rep. Netbeheer Nederland, May 2025. URL: <https://www.netbeheernederland.nl/publicatie/netbeheer-nederland-scenarios-editie-2025>.
- [3] Tennet. "20250515 TenneT Monitor Leveringszekerheid 2025 final". In: (May 2025).
- [4] Netbeheer Nederland. *Integrale infrastructuur-verkenning 2030-2050*. Tech. rep. June 2023. URL: <https://www.netbeheernederland.nl/publicatie/rapport-ii3050-scenarios>.
- [5] W Terlouw and T Alders. "TOEKOMSTBESTENDIGE FLEXIBILITEIT IN HET ELEKTRICITEITSSYSTEEM Naar inhoudsopgave". Feb. 2025.
- [6] Energy Storage NL. *Energieopslag maakt energie betaalbaar en beschikbaar*. Tech. rep. 2025.
- [7] Stedin. *Stedin Investeringsplan 2026-2028*. Tech. rep. Oct. 2025. URL: <https://www.bing.com/ck/a?!&p=656b80cc3e64ba86cbbd8263489a77b322cc255f20e124f256af15105c53e539JmltdHM9MTc2NDg5MjgwMA&ptn=3&ver=2&hsh=4&fclid=0c2708ca-4a73-69c6-1690-1e6d4b336807&psq=stedin+ip+2026+2028&u=a1aHR0cHM6Ly93d3cuc3RlZGluLm5ldC8tL21lZGhlL3Byb2plY3Qvb25saW5lL2ZpbGVzL2phYXJ2ZXJzbGFuZW4tZW4tcHVibGljYXRpZXMvc3RlZGluLWludmVzdGVyaW5nc3BsYW4tMjAyNi0yMDI4LS0tY29uc3VsdGF0aWV2ZXJzaWUucGRmP3Jldj1iMGZiYzNmNjlmMTIOZDBiYmM2YWE2ZjZjYTg2YTZiMSZoYXNoPTgwRTMzMjg0ODNENzAyMkQzNT1FMdY1QUZERDk1QTQ0>.
- [8] Brando Bordignon. *Optimising Spatial Deployment of Flexibility Assets in the Power Grid MSc Sustainable Energy Technology*. Tech. rep. TU Delft, Nov. 2025.
- [9] Corentin Jacquier et al. "National energy system modeling for decarbonization pathways considering distribution grids". In: *Energy Strategy Reviews* 58 (Mar. 2025). ISSN: 2211467X. DOI: 10.1016/j.esr.2025.101688.
- [10] Francesco Lombardi et al. "Near-optimal energy planning strategies with modeling to generate alternatives to flexibly explore practically desirable options". In: *Joule* (Nov. 2025), p. 102144. ISSN: 25424351. DOI: 10.1016/j.joule.2025.102144.
- [11] Alexander de Tomás-Pascual et al. "The optimal is not always the best: Life cycle impacts of near-optimal energy systems". In: *Applied Energy* 399 (Dec. 2025), p. 126487. ISSN: 0306-2619. DOI: 10.1016/J.APENERGY.2025.126487.
- [12] *Positions infrastructure - Energie Nederland*. URL: <https://www.energie-nederland.nl/en/topics/infrastructure/positions/>.
- [13] *Phase to Phase Netten voor distributie van elektriciteit, hoofdstuk 2*. URL: https://www.phasetophase.nl/boek/boek_1_2.html#_2.2.
- [14] *Netbeheerders Nederland in 2026 (+ kaart)*. URL: <https://www.energievergelijk.nl/onderwerpen/netbeheerders>.
- [15] Maximilian Bernecker et al. "Quantifying the impact of load forecasting accuracy on congestion management in distribution grids". In: *International Journal of Electrical Power & Energy Systems* 168 (July 2025), p. 110713. ISSN: 0142-0615. DOI: 10.1016/J.IJEPES.2025.110713.
- [16] Anna Stawska et al. "Demand response: For congestion management or for grid balancing?" In: *Energy Policy* 148 (Jan. 2021). ISSN: 03014215. DOI: 10.1016/j.enpol.2020.111920.
- [17] M Thijsen et al. *Maatschappelijke kostprijs van netcongestie*. Tech. rep. Apr. 2024.
- [18] *Basisdocument over energie-infrastructuur (oktober 2019) | Netbeheer Nederland*. URL: <https://www.netbeheernederland.nl/publication/basisdocument-over-energie-infrastructuur-oktober-2019>.

- [19] Roman J. Hennig, Laurens J. de Vries, and Simon H. Tindemans. "Congestion management in electricity distribution networks: Smart tariffs, local markets and direct control". In: *Utilities Policy* 85 (Dec. 2023). ISSN: 09571787. DOI: 10.1016/j.jup.2023.101660.
- [20] Alice Patig et al. "Fast Mapping of Flexibility Regions at TSO-DSO Interfaces under Uncertainty". In: (May 2022). URL: <http://arxiv.org/abs/2205.09163>.
- [21] J. F. DeCarolis et al. "Modelling to generate alternatives with an energy system optimization model". In: *Environmental Modelling and Software* 79 (May 2016), pp. 300–310. ISSN: 18736726. DOI: 10.1016/j.envsoft.2015.11.019.
- [22] Cheng Yang et al. *Optimal Power Flow in Distribution Network: A Review on Problem Formulation and Optimization Methods*. Aug. 2023. DOI: 10.3390/en16165974.
- [23] *PowerFactory - DlgSILENT*. URL: <https://www.digsilent.de/en/powerfactory.html>.
- [24] *Introduction to OpenDSS*. URL: <https://opendss.epri.com/IntroductiontoOpenDSS.html>.
- [25] Martha Maria Frysztacki, Veit Hagenmeyer, and Tom Brown. "Inverse methods: How feasible are spatially low-resolved capacity expansion modelling results when disaggregated at high spatial resolution?" In: *Energy* 281 (Oct. 2023). ISSN: 03605442. DOI: 10.1016/j.energy.2023.128133.
- [26] Jonas Hörsch et al. "PyPSA-Eur: An open optimisation model of the European transmission system". In: *Energy Strategy Reviews* 22 (Nov. 2018), pp. 207–215. ISSN: 2211-467X. DOI: 10.1016/J.ESR.2018.08.012.
- [27] Kyuil Kwak et al. "PyPSA-Korea: An open-source energy system model for planning Korea's sustainable energy transition". In: *Energy Reports* 13 (June 2025), pp. 5677–5691. ISSN: 2352-4847. DOI: 10.1016/J.EGYR.2025.05.018.
- [28] Cristobal Gallego-Castillo and Marta Victoria. "PyPSA-Spain: An extension of PyPSA-Eur to model the Spanish energy system". In: *Energy Strategy Reviews* 60 (July 2025), p. 101764. ISSN: 2211-467X. DOI: 10.1016/J.ESR.2025.101764.
- [29] G Thomassen et al. "REDISPATCH AND CONGESTION MANAGEMENT". In: Publications Of-
fice of the European Union, May 2024. ISBN: 978-92-68-15413-7. DOI: 10.2760/853898. URL: <https://data.europa.eu/doi/10.2760/853898>,.
- [30] Sergey Klyapovskiy et al. "Incorporating flexibility options into distribution grid reinforcement planning: A techno-economic framework approach". In: *Applied Energy* 254 (Nov. 2019), p. 113662. ISSN: 0306-2619. DOI: 10.1016/J.APENERGY.2019.113662.
- [31] Rubi Rana et al. "Economic assessment of integrating fast-charging stations and energy communities in grid planning". In: *Sustainable Energy, Grids and Networks* 35 (Sept. 2023), p. 101083. ISSN: 2352-4677. DOI: 10.1016/J.SEGAN.2023.101083.
- [32] Jordan Holweger et al. "Distributed flexibility as a cost-effective alternative to grid reinforcement". In: *Sustainable Energy, Grids and Networks* 34 (June 2023), p. 101041. ISSN: 2352-4677. DOI: 10.1016/J.SEGAN.2023.101041.
- [33] Víctor Taltavull-Villalonga et al. "Enhancing Distribution Grid Efficiency and Congestion Management through Optimal Battery Storage and Power Flow Modeling". In: *Electricity* 2024, Vol. 5, Pages 351-369 5.2 (June 2024), pp. 351–369. ISSN: 2673-4826. DOI: 10.3390/ELECTRICITY5020018. URL: <https://www.mdpi.com/2673-4826/5/2/18/htm%20https://www.mdpi.com/2673-4826/5/2/18>.
- [34] Jairo Yumbla et al. "Optimal operational planning of distribution systems: A neighborhood search-based matheuristic approach". In: *Sustainable Energy, Grids and Networks* 38 (June 2024), p. 101330. ISSN: 2352-4677. DOI: 10.1016/J.SEGAN.2024.101330.
- [35] Yanlin Jiang et al. "Enhanced Flexibility Aggregation Using LinDistFlow Model with Loss Compensation". In: (May 2025). URL: <http://arxiv.org/abs/2505.01715>.
- [36] Xin Li et al. "Hybrid Heat Pump Flexibility Allocation: Quantified Thermal Comfort-Based Congestion Management". In: *Conference Proceedings - 2025 IEEE International Conference on Environment and Electrical Engineering and 2025 IEEE Industrial and Commercial Power Systems Europe, IEEEIC / I and CPS Europe 2025* (Sept. 2025), p. 11169153. DOI: 10.1109/IEEEIC/ICPSEUROPE64998.2025.11169153. URL: <https://research.tue.nl/nl/publications/hybrid-heat-pump-flexibility-allocation-quantified-thermal-comfor/>.

- [37] Robert Gaugl, Kelvin Walenta, and Sonja Wogrin. “A comparative analysis of energy system modeling frameworks”. In: *Elektrotechnik und Informationstechnik* (Oct. 2025), pp. 1–19. ISSN: 0932383X. DOI: 10.1007/S00502-025-01345-X/TABLES/5. URL: <https://link.springer.com/article/10.1007/s00502-025-01345-x>.
- [38] Sander Claeys et al. “Applications of optimization models for electricity distribution networks”. In: *Wiley Interdisciplinary Reviews: Energy and Environment* 10.5 (Sept. 2021), e401. ISSN: 2041-840X. DOI: 10.1002/WENE.401. URL: <https://onlinelibrary.wiley.com/doi/full/10.1002/wene.401> <https://onlinelibrary.wiley.com/doi/abs/10.1002/wene.401> <https://wires.onlinelibrary.wiley.com/doi/10.1002/wene.401>.
- [39] Ajla Mehinovic, Nermin Suljanovic, and Matej Zajc. “Quantifying the impact of flexibility asset location on services in the distribution grid: Power system and local flexibility market co-simulation”. In: *Electric Power Systems Research* 238 (Jan. 2025). ISSN: 03787796. DOI: 10.1016/j.epsr.2024.111037.
- [40] Katharina Esser et al. “Participatory modelling to generate alternatives to support decision-makers with near-optimal decarbonisation options”. In: *Applied Energy* 395 (Oct. 2025), p. 126184. ISSN: 0306-2619. DOI: 10.1016/J.APENERGY.2025.126184.
- [41] Evren M. Turan, Stefano Moret, and André Bardow. “ORACLE: A rigorous metric and method to explore all near-optimal designs for energy systems”. In: *Computers & Chemical Engineering* 210 (July 2026), p. 109630. ISSN: 0098-1354. DOI: 10.1016/J.COMPCHENG.2026.109630. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0098135426000839>.
- [42] Koen van Greevenbroek et al. “Little to lose: The case for a robust European green hydrogen strategy”. In: *Joule* 9.7 (July 2025). ISSN: 25424351. DOI: 10.1016/j.joule.2025.101974.
- [43] Francesco Lombardi, Bryn Pickering, and Stefan Pfenninger. “What is redundant and what is not? Computational trade-offs in modelling to generate alternatives for energy infrastructure deployment”. In: *Applied Energy* 339 (June 2023), p. 121002. ISSN: 0306-2619. DOI: 10.1016/J.APENERGY.2023.121002.
- [44] Stefan Pfenninger and Bryn Pickering. “Calliope: a multi-scale energy systems modelling framework”. In: *Journal of Open Source Software* 3.29 (Sept. 2018), p. 825. DOI: 10.21105/JOSS.00825.
- [45] *2. Economic dispatch as a linear optimisation problem Modelling energy systems*. URL: <https://www.modelling-energy-systems.org/stable/basics/dispatch-lp.html>.
- [46] Manuel Bröchin et al. “Harder, better, faster, stronger: understanding and improving the tractability of large energy system models”. In: *Energy, Sustainability and Society* 14.1 (Dec. 2024). ISSN: 21920567. DOI: 10.1186/s13705-024-00458-z.
- [47] *Congestie provincie Utrecht | Stedin*. URL: <https://www.stedin.net/zakelijk/energietransitie/beschikbare-netcapaciteit/congestie-en-congestiemanagement/provincie-utrecht>.
- [48] *Basic concepts - Calliope*. URL: https://calliope.readthedocs.io/en/v0.7.0.dev7/getting_started/concepts/.
- [49] *HoogspanningsNet Netkaart*. URL: <https://webkaart.hoogspanningsnet.com/index2.php#8/52.154/5.295>.
- [50] *Energietransitiemodel*. URL: <https://energytransitionmodel.com/about>.
- [51] *Uurlijkse profielen voor elektriciteit - Data-export - Energietransitiemodel*. URL: https://2025-01.energytransitionmodel.com/scenario/data/data_export/hourly-curves-for-electricity.
- [52] *Uurlijkse profielen voor elektriciteit - Data-export - Energietransitiemodel*. URL: https://energytransitionmodel.com/scenario/data/data_export/hourly-curves-for-electricity.
- [53] *Uurlijkse profielen voor elektriciteit - Data-export - Energietransitiemodel*. URL: https://energytransitionmodel.com/scenario/data/data_export/hourly-curves-for-electricity.
- [54] Danish Energy Agency. “Technology Data for Renewable Fuels”. In: (Feb. 2026). URL: <https://ens.dk/en/analyses-and-statistics/technology-data-renewable-fuels>.

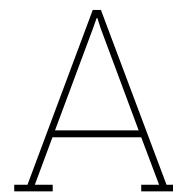
- [55] *Technology Data-Energy storagetechnologydata Design and production: Danish Energy Agency* Front cover photo: Adobe Stock. ISBN: 978-87-94447-11-9.
- [56] *Generation of Electricity and District heating Technology descriptions and projections for long-term energy system planning. TECHNOLOGY DATA.* ISBN: 9788794447089. URL: <https://ens.dk/technologydata>.
- [57] David Reber, Sam R. Jarvis, and Michael P. Marshak. "Beyond energy density: flow battery design driven by safety and location". In: *Energy Advances* 2.9 (July 2023), pp. 1357–1365. ISSN: 27531457. DOI: 10.1039/d3ya00208j.
- [58] Wesley Cole, Vignesh Ramasamy, and Merve Turan. "Cost Projections for Utility-Scale Battery Storage: 2025 Update". In: (2035). URL: www.nrel.gov/publications.
- [59] *Capex Rates | Electrolysis Techno-Economic Analysis.* URL: <https://apps.epri.com/lcri-electrolysis-tea/en/capex-rates.html>.
- [60] Institute for Sustainable Process Technology (ISPT). *Hydrohub Innovation Program Public report A One-GigaWatt Green-Hydrogen Plant Advanced Design and Total Installed-Capital Costs.* Tech. rep. ISPT, 2022.
- [61] *Geïmporteerde waterstofdragers en ammoniak - Waterstofdragers en ammoniak - Energietransitiemodel.* URL: https://2025-01.energytransitionmodel.com/scenario/costs/costs_hydrogen/imported-hydrogen-carriers-and-ammonia.
- [62] Bjarne Steffen. "A comparative analysis of green financial policy output in OECD countries". In: *Environmental Research Letters* 16.7 (July 2021). ISSN: 17489326. DOI: 10.1088/1748-9326/ac0c43.
- [63] *GitHub - FLomb/Calliope-NL: A lightweight model of the Dutch power system* u GitHub. URL: <https://github.com/FLomb/Calliope-NL>.
- [64] Nathan Johnson et al. "Realistic roles for hydrogen in the future energy transition". In: *Nature Reviews Clean Technology* 1.5 (Apr. 2025), pp. 351–371. DOI: 10.1038/s44359-025-00050-4.
- [65] Het Resterende Koolstofbudget. "WERELDWIJDE CO2-EMISSIONS EN". In: (2024).
- [66] L Eblé and M Weeda. "Evaluation of the levelised cost of hydrogen based on proposed electrolyser projects in the Netherlands". In: (May 2024).
- [67] *Market Data Hub.* URL: <https://www.eex.com/en/market-data/market-data-hub>.
- [68] *Lithium-Ion Battery Pack Prices See Largest Drop Since 2017, Falling to \$115 per Kilowatt-Hour: BloombergNEF | BloombergNEF.* URL: <https://about.bnef.com/insights/commodities/lithium-ion-battery-pack-prices-see-largest-drop-since-2017-falling-to-115-per-kilowatt-hour-bloombergnef/>.
- [69] *Executive summary Batteries and Secure Energy Transitions Analysis - IEA.* URL: <https://www.iea.org/reports/batteries-and-secure-energy-transitions/executive-summary>.
- [70] William H Kruskal and W Allen Wallis. *Use of Ranks in One-Criterion Variance Analysis.* Tech. rep. 260. 1952, pp. 583–621.
- [71] BY A Sir RONALD FISHER, frs DSc Ames, and LLD Calcutta. *Statistical Methods for Research Workers THIRTEENTH EDITION-REVISED.* Tech. rep.
- [72] "Applied_Logistic_Regression". In: ().
- [73] H B Mann and D R Whitney. *On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other.* Tech. rep. 1. 1947, pp. 50–60.
- [74] C Spearman. *The Proof and Measurement of Association between Two Things.* Tech. rep. 4. 1987, pp. 441–471.
- [75] Alan. Agresti. *Categorical data analysis.* Wiley-Interscience, 2002, p. 710. ISBN: 0471360937.
- [76] Frank Wilcoxon. *Individual Comparisons by Ranking Methods.* Tech. rep. 6. 1945, pp. 80–83.
- [77] Karl Pearson. *Note on Regression and Inheritance in the Case of Two Parents.* Tech. rep. 1895, pp. 240–242. URL: <https://about.jstor.org/terms>.

- [78] Anurag Chauhan and R. P. Saini. *Techno-economic feasibility study on Integrated Renewable Energy System for an isolated community of India*. June 2016. DOI: 10.1016/j.rser.2015.12.290.
- [79] Netbeheer Nederland. “Afwegingskader verzwaren tenzij”. In: (2018).
- [80] Cedec et al. *TSO-DSO REPORT AN INTEGRATED APPROACH TO ACTIVE SYSTEM MANAGEMENT WITH THE FOCUS ON TSO-DSO COORDINATION IN CONGESTION MANAGEMENT AND BALANCING CONTENT*. Tech. rep.
- [81] *Index - ETHOS.TSAM Documentation*. URL: <https://tsam.readthedocs.io/en/latest/>.
- [82] Bryn Pickering, Francesco Lombardi, and Stefan Pfenninger. “Diversity of options to eliminate fossil fuels and reach carbon neutrality across the entire European energy system”. In: *Joule* 6.6 (June 2022), pp. 1253–1276. ISSN: 2542-4351. DOI: 10.1016/J.JOULE.2022.05.009.

AI Statement

In the process of writing this thesis, several AI-assisted were used. Grammarly was used to improve the clarity and academic style of the written text. Specifically, it was applied to rephrase and refine sentences, and to enhance grammar, readability, and consistency of tone throughout the report. Google NotebookLM was used as a digital workspace to support the organisation and coding of the literature reviewed. Claude was consulted as a source of inspiration during the development of post-processing codes for the research data.

All outputs generated by these tools were critically reviewed and evaluated. I take full responsibility for the content presented in this thesis.



Model choices & abstractions

Table A.1: Overview of modelling choices and abstractions

Modelling choice	Description of abstraction	Req(s)	Rationale	Limitation / trade-off
Group 1: Network representation				
Planning-based substation definition	Physical sites with multiple voltage levels are split into separate nodes, one per voltage level per site	R1	Enables voltage-level-specific capacity assignment and substation-level flexibility deployment; consistent with Stedin's planning dataset	Physical co-location of equipment at the same site is not captured; switching interactions between voltage levels at a site are not modelled
Stub substation topology (<i>steeltje</i>)	Stub substations are stations that lack a switching installation on the primary side; assets can only be connected on the secondary side	R1, R2	Under the planning-based substation definition, each voltage level within a physical site is represented as a separate node. The secondary side of a stub substation is therefore its own node, to which flexibility technologies can be allocated directly. The absence of a switching installation on the primary side is irrelevant for the model: every node has a primary and secondary side.	Not a limitation; the planning-based substation definition ensures that stub substations are correctly handled without requiring additional abstraction
Path length correction factor (1.2)	A uniform tortuosity factor of 1.2 is applied to all link distances to approximate actual cable routing	R2	Exact cable routing data are not available; the factor is a standard planning approximation	The factor is uniform across all links regardless of urban density or terrain; individual link cost estimates may deviate from actual routing costs
Exclusion of topologically isolated substations	Two categories of substations are excluded: newly planned substations for which no demand or generation forecasts are available, and externally fed substations that are not part of the internal Stedin HV–MV topology and cannot contribute to congestion relief elsewhere in the network (Appendix D, Table D.1)	R1, R2	Newly planned stations lack demand forecasts; externally fed substations cannot contribute to congestion relief within the Stedin network	Flexibility demand in areas served by planned future substations is assigned to existing upstream substations, potentially overstating the required response at those locations
Exclusion of LV network	The low-voltage network (400 V) below the modelled MV substations is not represented	R5	The LV network adds very large numbers of nodes and edges; it is not decision-relevant at the 2050 HV–MV strategic planning horizon	Aggregated LV demand and generation are assigned to the lowest-level MV substations in the model; LV-level congestion is not visible
Three-winding transformer representation	The shared capacity limit of a three-winding transformer is assigned to the link at the secondary voltage level; the tertiary winding is not independently constrained	R2, R5	Calliope's link structure does not support shared capacity constraints across two downstream links from a single transformer; incorporating it would require additional data processing	Available expansion capacity at substations with three-winding transformers may be underestimated; as Stedin moves towards replacing these with two separate two-winding transformers, the abstraction becomes less representative [B.2.1C]
Group 2: Capacity constraints and expansion				
Transformer capacity as primary constraint	Cable thermal limits within voltage levels are not treated as binding; only transformer capacity at substations is enforced as the primary congestion constraint	R2	Consistent with Stedin's internal planning practice, where load forecasts are assessed against transformer capacity; confirmed by electrotechnical expert [B.1.1A]	Cable thermal limits may bind in specific configurations not captured by the model; the model may underestimate congestion on inter-substation cables

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Modelling choice	Description of abstraction	Req(s)	Rationale	Limitation / trade-off
N-1 safe transformer capacities	All substation capacities are expressed as N-1 safe values, representing the maximum load the substation can carry while one component fails	R2	Consistent with the capacity standard Stedin applies internally; confirmed by data expert [B.2.1B]	Emergency headroom above the N-1 safe value is not captured; the model does not assess N-1 contingency behaviour
Capacity constraints via upstream links	Node-level capacity limits are not directly supported in Calliope; constraints are assigned to the upstream link connecting a substation to its parent node	R2	Required by the modelling framework; feasible because the radial topology ensures all power passing through a substation traverses exactly one upstream link	For 150 kV substations with two 380 kV connections, both links are assigned the same transformer capacity, potentially relaxing the local constraint
150 kV cable capacity based on thermal limit	For 150–150 kV transmission links between substations, flow capacity is set equal to the thermal limit of a single 150 kV circuit: $\sqrt{3} \cdot U \cdot I \cdot \cos \varphi$, with $U = 150 \text{ kV}$, $I = 800 \text{ A}$, and $\cos \varphi = 0.95$	R2	The 150 kV network is meshed; a single upstream transformer capacity cannot be assigned because multiple upstream connections exist; the thermal limit is the physically correct binding constraint for cable connections	The model assumes a single-circuit rating; double-circuit configurations on the same route would have higher effective capacity; the assumed current rating of 800 A may not apply to all 150 kV conductors in the Stedin network
380 kV transmission links unbounded	Transmission links between 380 kV substations are assigned no flow capacity limit	R3, R5	The national TenneT transmission network is not the focus of this study; imposing capacity limits would require detailed TenneT network data beyond the scope of the DSO planning problem	The model cannot signal transmission congestion at the 380 kV level; flexibility allocated to 380 kV nodes is unconstrained by the national grid and may be physically unrealisable under specific TenneT network conditions
Continuous capacity expansion	Transformer investments are treated as a continuous variable; fractional capacity additions are permitted	R5	Necessary for linear optimisation; binary or integer variables would make the problem computationally intractable at this network scale	Deviates from the discrete nature of real transformer investments; expansion volumes should be interpreted as lower bounds rather than precise investment recommendations [B.1.1C, B.3.4G]
Expansion bounded by transformer slots	Maximum expansion per substation is determined by the number of available transformer slots, derived from the difference between installed and maximum transformers per substation type	R2	Ensures all network investments remain physically realisable within existing substation infrastructure	Switching field availability is not checked; a substation may have available transformer slots but insufficient cable connection points for new assets [B.1.2D]; rebuilding costs when switching fields are full are not captured
Spatial footprint constraint set to infinity	The parameter <code>area_use_max</code> , which limits the total installed capacity footprint per substation, is set to infinity for all nodes	R1	No substation-level data on available physical space were available at the time of modelling; the constraint can be activated in future analyses when spatial data become available	Physical space within the fenced perimeter of existing substations is a real constraint, particularly at dense urban locations; the model may place more capacity at a substation than can physically fit [B.3.3E]
Group 3: System coupling and demand representation				
380 kV nodes as national interface	The national electricity system is represented through 380 kV nodes that absorb and supply electricity according to a predetermined profile; internal national dynamics are not simulated	R3, R5	Reflects the DSO perspective, for whom cross-border flows and national market dynamics are external conditions; limits computational complexity	The interaction between regional congestion management and national system balancing is only partially captured; TSO–DSO coordination conflicts (e.g. TenneT dispatch requests conflicting with local network conditions) are not modelled [B.3.1B]

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Modelling choice	Description of abstraction	Req(s)	Rationale	Limitation / trade-off
Equal distribution of national profile	The national residual demand and supply profile is distributed equally across all included 380 kV nodes	R3, R5	Concentrating the full national load in a single node causes numerical instability in the Gurobi solver; equal distribution preserves system-level balance	All 380 kV nodes are assumed to have equivalent access to national surplus and demand; this is not physically accurate and may amplify flexibility allocation at nodes with structural advantages such as dual 380 kV connection
Subtraction of provincial ETM profiles	Electricity demand and generation already modelled through Stedin substations are removed from the national ETM profile by subtracting the ETM profiles for Zuid-Holland, Utrecht, and Zeeland	R3	Avoids double-counting of demand and generation in the model	Provincial ETM profiles are assumed to correspond exactly to the Stedin service area; in practice, part of Zuid-Holland is served by Liander, resulting in slight over-subtraction
Net node profile method	For each substation in the HV–MV model, the aggregated demand and generation of all directly connected downstream substations is subtracted from the substation's own aggregated profile, yielding a net profile representing only the local load at that substation	R1, R2	The only workable approach given the structure of Stedin's planning dataset; confirmed as internally consistent by the data expert [B.2.1A]	Numerical inconsistencies between upstream and downstream profiles may introduce small residual errors; the method assumes that local generation first serves local demand before exchange with the network
Generic demand profiles for large industrial customers	Stedin's planning dataset applies generic load profiles to large industrial customers for which customer-specific measurement data are unavailable	R1	Data constraint; customer-specific profiles are not available for all large consumers	Introduces uncertainty in peak load timing and magnitude at substations in heavy-industrial areas such as Botlek and Europoort [B.2.1C]; flexibility volumes at BOT_25 and EUR_25 should be interpreted with this in mind
Large industrial customers expected to connect to TenneT by 2050	Several large industrial consumers expected to connect directly to the TenneT transmission network by 2050 are still modelled as Stedin network demand	R1	Future connection arrangements were not available at the time of modelling	May overstate the required flexibility and expansion response at substations serving the Botlek and Europoort areas; the high flexibility volumes at BOT_25 should be read with this in mind [B.2.2F]
Group 4: Technology and cost representation				
Technology portfolio selection	Four flexibility technologies are included: lithium-ion batteries, vanadium redox flow batteries, power-to-hydrogen electrolyzers, and hydrogen-to-power gas turbines. Demand-side flexibility, vehicle-to-grid, and pumped hydro are excluded	R4	The four selected technologies represent the three key flexibility functions identified in the Netbeheer Nederland scenarios: short-term balancing, energy carrier conversion, and dispatchable peak capacity; including additional technologies would increase model complexity without adding decision-relevant diversity for DSO planning at this horizon	Technologies not included cannot substitute for the selected portfolio in the optimisation; the substitution pattern identified in the near-optimal space is bounded by the modelled technology set
Centralised hydrogen hub	All nodes are connected to a single centralised hydrogen node; hydrogen transport infrastructure is not explicitly modelled	R4, R5	Modelling the hydrogen network would require assumptions about a future infrastructure whose spatial layout is highly uncertain; a hub abstraction avoids introducing a separate planning problem beyond the scope of this study	Hydrogen-based flexibility can be placed at any substation without transport cost or availability constraints; the attractiveness of hydrogen technologies may be overstated at locations far from actual future hydrogen infrastructure

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Modelling choice	Description of abstraction	Req(s)	Rationale	Limitation / trade-off
Infinite hydrogen transmission capacity	Links between all nodes and the hydrogen hub have unconstrained flow capacity	R5	Consistent with the hub abstraction; ensures hydrogen transport is never the binding constraint in the optimisation	The model cannot signal where hydrogen network limitations would affect the viability of power-to-hydrogen or hydrogen-to-power deployment
Hydrogen storage capacity unbounded	The maximum installed energy capacity of hydrogen storage is set to infinity	R5	Avoids imposing a capacity constraint that cannot be justified from available data and that would distort the optimisation	May overestimate system flexibility during periods of high renewable surplus if actual hydrogen storage infrastructure is limited
Hydrogen storage initial state of charge (50%)	The hydrogen storage is initialised at 50% of installed capacity at the start of the modelled year	R5	Prevents boundary effects at the start and end of the modelled period; consistent with standard practice in energy system modelling	The chosen initialisation affects seasonal storage dynamics; the sensitivity of results to this parameter has not been explicitly tested
Hydrogen export cap (50,000 MWh/year)	The maximum annual export volume for hydrogen is capped at 50,000 MWh	R4, R5	Prevents hydrogen export from becoming a dominant driver of the optimisation; ensures hydrogen production serves system balancing rather than commodity export	The cap is a modelling choice without direct empirical basis; a different cap value would alter the incentive to deploy electrolyser
Interest rate (1%)	A discount rate of 1% is applied globally to annualise all capital costs	R4	Follows from the average wind onshore WACC for OECD countries [62], adopted to maintain consistency with the technology cost data used in the model. This rate is applied uniformly across all flexibility technologies and network expansion, whereas in practice these asset classes would carry different capital costs. The direction and magnitude of the resulting bias depend on the actual WACC applicable to Stedin, which has not been determined.	A lower interest rate relatively favours capital-intensive investments with longer asset lifetimes, such as network expansion (40 years), over shorter-lived flexibility technologies (1725 years). The current rate of 1% may therefore modestly favour expansion in the flexibility-expansion trade-off. Sensitivity to this assumption has not been tested
Fixed power factor (0.95)	A uniform power factor of 0.95 is applied across all voltage levels to convert MVA capacities to MW	R5	Consistent with the DC approximation; reactive power is not modelled; a single factor simplifies the conversion across all transformer types	Stedin internally uses voltage-level-specific and component-specific power factors; the uniform assumption introduces a systematic deviation from actual capacities, though the direction and magnitude vary by location [B.2.2E]
Lost load penalty (10,000,000 kEUR/MWh)	An extremely high cost is assigned to any unmet electricity demand, making demand curtailment a last resort	R3	Ensures model feasibility under all conditions; prevents unmet demand from distorting the optimisation results	Does not represent a real economic cost; if the penalty were lower, the model could select demand curtailment as a cost-efficient response in some configurations
Curtailment unbounded	Excess generation can be curtailed without limit and at zero cost	R5	Avoids infeasibility in periods of surplus renewable generation; renewable curtailment reflects a real operational option	The model does not penalise curtailment; the social and economic cost of wasted renewable energy is not captured
Group 5: Temporal and computational structure				

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Modelling choice	Description of abstraction	Req(s)	Rationale	Limitation / trade-off
Single modelling year (2050)	The model represents the system state in 2050 as a single planning horizon; no intermediate years or investment pathways are modelled	R1, R5	Consistent with Stedin's long-term planning practice and the KM scenario horizon; a pathway model would require substantially more data and computational resources	The model does not capture path dependency in investment decisions; assets installed before 2050 that affect available network capacity or technology competition are not represented; near-term investment decisions cannot be derived directly from the results
Three-hour temporal resampling (HV–MV and HV model comparison, scenario and spores)	The hourly time series is aggregated into three-hour blocks by averaging; consecutive time steps are preserved	R5, R7	The full HV–MV model cannot be solved at hourly resolution within available computational resources; time clustering is unsuitable because it disrupts the seasonal patterns required for hydrogen storage	Short-cyclic battery dynamics are underestimated; installed battery and electrolyser capacity is 2–13% lower than in the hourly reference model; dispatch patterns of short-duration technologies are smoothed
Provincial subdivision into three sub-models	The full HV–MV service area is divided into three separate provincial models covering Zuid-Holland, Utrecht, and Zeeland	R5, R6	The full HV–MV model covering the entire Stedin service area is too large to solve reliably within available resources; provincial subdivision preserves full network detail within each model while keeping each optimisation problem solvable	Cross-provincial energy flows are partially aggregated; substations outside the focus province are represented as a single aggregated node; inter-provincial network interactions are not fully captured
Scenario parameters limited to technology costs	The scenario analysis varies two parameters only: hydrogen import price and battery investment cost; demand growth rates, electrification trajectories, renewable penetration, and policy conditions are held constant at KM scenario values	R6	Technology cost uncertainty is the most directly actionable parametric uncertainty for DSO investment planning; demand-side uncertainty is partially addressed through Stedin's internally validated load forecasts	Parametric robustness is confirmed only for technology cost variation; the no-regret classifications are not tested against structural demand uncertainty, different electrification scenarios, or alternative renewable generation mixes
SPORES cost slack of 15%	Near-optimal solutions are defined as all configurations whose total system cost remains within 15% of the cost-optimal solution	R6	Sensitivity analysis shows that a 10% slack is too narrow to reveal meaningful alternative configurations; the scenario analysis reveals cost differences of approximately 19% under the high hydrogen price scenario, providing an empirical upper reference; expert-validated as an acceptable planning bandwidth [B.1.2F, B.3.4F]	A 15% slack does not cover the full 30% bandwidth that Stedin's internal planning estimates use; some structurally relevant configurations may lie outside the explored space
SPORES analysis restricted to Utrecht provincial model	Near-optimal solution space exploration is conducted on the Utrecht model only; Zeeland and Zuid-Holland are not explored	R6	Applying the full SPORES analysis to all three provincial models is computationally infeasible within the available time and resources; Utrecht is selected because it currently experiences some of the most severe congestion within the Stedin service area	No-regret classifications apply directly to Utrecht only; their generalisation to Zeeland and Zuid-Holland requires replication of the same methodology in those provinces
Gurobi barrier method without crossover	The Gurobi solver uses the barrier algorithm (Method: 2) with crossover disabled (Crossover: 0)	R5	Improves numerical stability for large-scale linear optimisation problems; crossover is disabled to avoid additional numerical adjustments after the barrier solution converges	Solutions may lie on the interior of the feasible region rather than at a vertex; this can affect the reproducibility of exact optimal solutions across solver versions or settings
Group 6: Excluded physical and institutional constraints				

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Modelling choice	Description of abstraction	Req(s)	Rationale	Limitation / trade-off
Absence of short-circuit current limits	The fault current contribution of flexibility assets connected to a substation is not modelled; switching installations are not checked against their design limits	R5	Short-circuit current calculations require detailed fault analysis beyond the scope of this long-term planning study	Hydrogen-to-power via rotating generators adds fault current from below; batteries via inverters dampen it; at Category A1 substations where hydrogen-to-power is no-regret, the technology choice requires additional technical screening before operational implementation [B.1.2E, B.3.2D]
Absence of switching field availability	The number of available cable connection points at each substation is not modelled; every technology placement is assumed to have a physically available connection point	R5	Switching field data are not systematically available in a format compatible with the model	Substations where connection points are fully occupied would require costly rebuilding before new assets can be connected; the model assigns zero cost to this, systematically underestimating implementation costs at capacity-constrained substations [B.1.2D]
Absence of connection category rules	Assets of any power rating can be placed at any voltage level; the Dutch regulatory requirement that assets above 10 MVA connect at transport voltage is not enforced	R5	Implementing connection category rules requires substation-level regulatory mapping not available for all substations	Flexibility placements at 10 kV substations that exceed 10 MVA per customer may not be directly realisable without additional network adjustments [B.3.2C]
Absence of voltage and reactive power constraints	The model uses a DC approximation; voltage levels and reactive power flows are not represented	R5	AC power flow formulations would make the optimisation computationally intractable at this network scale; DC approximation is standard practice in long-term investment planning	Solutions that are feasible in the model may require voltage management measures in practice; voltage violations at the end of long MV feeders are not visible
Absence of ramp rate constraints at MV level	No limits are imposed on the rate of change of output from flexibility assets between time steps	R5	Ramp rate constraints are primarily relevant at operational timescales shorter than the model's temporal resolution	Rapid power changes at lower voltage levels can cause transformer tap-changer switching and voltage fluctuations; operational ramp limits (e.g. 1 MW per 3 seconds at MV level) are not captured [B.1.2E]
Absence of spatial and social constraints	Permitting requirements, spatial planning restrictions, noise regulations, and local acceptance barriers are not represented	R5	These constraints are not quantifiable at the level of individual substations from available data	Model outcomes should be understood as technically cost-optimal rather than fully implementable without further screening; gas-to-power assets in particular are subject to noise regulations that introduce hidden costs [B.3.3E]
Static network topology	The model is based on the current network topology; planned changes such as the separation of the dual 380 kV connection at BRK_150 are not incorporated	R1	Future network changes are not yet finalised in a form compatible with the model	BRK_150 is modelled with a dual 380 kV connection that TenneT plans to split; the disproportionate flexibility concentration at this substation in the high hydrogen price scenario is partly an artefact of the current topology [B.1.1C]



Summaries Expert Interviews

B.1. Elektrotechnical Expert

B.1.1. Capaciteitsrepresentatie en radiale modelstructuur

1A. De keuze om capaciteitsbegrenzings via links te representeren en transformatorcapaciteit als primaire bottleneck te behandelen sluit aan bij hoe Stedin intern werkt. De expert omschreef dit als 'boekhoudkundig': een station heeft capaciteit, en de onderliggende stations moeten daarbinnen kloppen.

1B. De radiale MS-topologie is een terechte vereenvoudiging voor langetermijnplanning, omdat Stedin's planingsdataset deze structuur al hanteert.

1C. Op 380-150 kV niveau heeft het TenneT-net een sterk discreet investeringskarakter. Het bijplaatsen van een verbinding betekent een stap van 300450 MW, of zelfs 1 GW bij een nieuw 380 kV-blok. De continue optimalisatie in het model onderschat daarmee de werkelijke investeringssprongen op transmissieniveau: "Als je bij 380 kV een verbinding bijlegt, is dat een bouwblok van één gigawatt. Dat is helemaal discreet, en dan hang je gelijk voor ontzettend veel geld."

B.1.2. Temporele resolutie en batterijgedrag

1D. Een tijdstap van 3 uur is te grof voor het modelleren van kortetermijnopslag. In congestieanalyses werkt Stedin liever met kwartier- of 5-minutenwaarden voor de meest kritieke dagen: "Ik vrees dat 3 uur te grof is voor korte termijnopslag. Dan willen we liever kwartier of 5-minuten waarden, voor de meest spannende dag in de zomer en de meest spannende dag in de winter."

1E. Het modelleren van een volledig jaar is gerechtvaardigd omdat waterstof als seizoensopslagmedium meegaat in de optimalisatie. Een beperkte tijdshorizon zou de seizoensdynamiek elimineren. De expert erkende dit als een geldige afweging.

1F. De autonomieduur van de lithium-ion batterij (4 uur) en de vanadium redox flow batterij (12 uur) liggen mogelijk te dicht bij elkaar om duidelijk te differentiëren, zeker in combinatie met een 3-uurs tijdstap: "Die 4 en 12 uur liggen misschien ook wel te dicht bij elkaar. Als je gewoon na een dag kijkt, dan denk ik dat je niet zo'n lange periode hebt waarbij je heel tekort of een overschot hebt."

B.1.3. Continue versus discrete investeringen en toekomstige netuitbreiding

1G. De continue investeringsoptimalisatie werkt redelijk als benadering voor MS-niveau: bij prognoses klopt het gemiddeld over alle stations, ook al wijkt het per individueel station af.

1H. Het model kan geen nieuwe stations toevoegen als investeringsoptie, terwijl Stedin's masterplannen toekomstige stations al bevatten met bekende voedingsgebieden: "Wij hebben masterplannen en allerlei investeringsplannen. We weten welke toekomstige stations komen en ook al welke voedingsgebieden we daaronder willen hebben. Dat mis ik eigenlijk nog wel in zo'n model."

1I. Station X is momenteel gekoppeld aan twee 380 kV-bronnen, waardoor het extra belasting trekt en het model er veel flexibiliteit plaatst. TenneT heeft plannen om in dit gebied een knip te zetten in het 150 kV-net, zodat parallelstromen via de juiste 380 kV-koppelingen worden gestuurd. Dit verklaart het afwijkende gedrag van station X in het model en suggereert dat de huidige netconfiguratie, waarop de modeluitkomsten zijn gebaseerd, in 2050 mogelijk niet meer representatief is.

B.1.4. Schakelveldenbeperking

1J. Het model houdt geen rekening met de beschikbaarheid van schakelruimte op bestaande stations. Elke technologieaansluiting vereist doorgaans twee kabelvelden, waardoor meerdere assets op één station de fysieke aansluitruimte kunnen overstijgen: "Die stations hadden dan vaak niet voldoende schakelvelden, dus plekken waar je kabels kan aansluiten voor die technologieën."

1K. Dit leidt tot verborgen investeringskosten die in het model op nul worden gesteld, terwijl verbouwen van een bestaand station in de praktijk duurder is dan nieuwbouw: "Die werden gewoon op nul afgeschat. Terwijl verbouwen is veel duurder dan nieuwbouw. Want je moet alles tijdelijk overnemen, uitbreiden, dan weer terug."

1L. Voor vervolgonderzoek is de aanbeveling om het aantal beschikbare schakelvelden per station als additionele beperking mee te nemen, inclusief een kostencomponent voor verbouwingsinvesteringen.

B.1.5. Technische aspecten buiten beschouwing: kortsluitvermogen en regelsnelheid

1M. Kortsluitvermogen is een toenemend praktisch probleem. Flexibiliteitsassets op lager spanningsniveau dragen ook kortsluitstroom bij van onderaf, waardoor de totale kortsluitstroom groter wordt dan waarvoor bestaande schakelinstallaties zijn ontworpen. Dit speelt al actueel in het Utrechtse gebied: "Kortsluitvermogen dat ze toevoegen aan het net. Als een kortsluiting optreedt, kan dat nu ook een kortsluitsel vanaf de onderkant komen. Ik denk dat kortsluitvermogen nu al in de praktijk steeds vaker problemen geeft."

1N. Regelsnelheid speelt een rol bij assets op lager spanningsniveau. Snelle vermogenswisselingen veroorzaken stap-schakelingen in transformatortapposities en spanningsvariaties. Klanten krijgen daarvoor rampcurves opgelegd, zoals maximaal 1 MW per 3 seconden. Hoe lager in het net, hoe gevoeliger dit effect: "Hoe lager je in het net zit, hoe gevoeliger dat wordt. Daarvoor zeggen we tegen klanten: je mag opschakelen, maar maximaal 1 megawatt per 3 seconden."

1O. Blindvermogen is een minder groot probleem: klanten hebben een financiële prikkel om de vermogensfactor dicht bij 1 te houden, waardoor de aanname van een vaste vermogensfactor van 0,95 in de praktijk redelijk opgaat.

B.1.6. Kostennauwkeurigheid en de 15% kostenslack

1P. Stedin's masterplannenramingen hanteren traditioneel een bandbreedte van ±30%; na externe druk is dit teruggebracht naar ±15%, maar de onderliggende methodiek is onveranderd: "Bij de masterplannen maken we ook altijd ramingen. Plus of min 30% nauwkeurig. Toen hebben we het maar plus of min 15% gemaakt, maar het is nog steeds dezelfde methodiek."

1Q. Een kostenslack van 15% voor de SPORES-analyse is acceptabel en verdedigbaar. Een oplossing die iets duurder is maar meer flexibiliteit biedt voor toekomstige ontwikkelingen is in planningspraktijk prima te rechtvaardigen: "Als jij iets hebt wat een klein beetje duurder is, zeg 10%, maar wat veel meer flexibiliteit geeft om allerlei ontwikkelingen aan te kunnen, dan kan het toch gewoon een hele goede keuze zijn."

1R. Zelfs 25% slack is inhoudelijk verdedigbaar gezien de onzekerheid van langetermijnprognoses: "Ik vind 25% echt niet gek. Ik denk dat het in dezelfde nauwkeurigheid zou moeten hangen als hoe nauwkeurig kun je kosten berekenen en dat is zeker in deze fase plus of min 30%."

B.1.7. Bredere bruikbaarheid van het model en DSO-perspectief

1S. De expert stelde dat de methodologische bijdrage van dit onderzoek, inzicht bieden in wat HV-only modellen missen ten opzichte van HV–MV modellen, relevanter is dan de specifieke technologieaanbevelingen per locatie. Locatiespecifieke aanbevelingen zijn afhankelijk van aannames die onzeker zijn, terwijl de conclusie dat MV-topologie de ruimtelijke verdeling van flexibiliteit fundamenteel verandert, robuuster is en bredere planningswaarde heeft.

B.2. Data Expert

B.2.1. Netto-belastingsprofielen per station

2A. De methode waarbij de geaggregeerde profielen van direct onderhangende stations worden afgetrokken van het bovenliggende stationsprofiel werd bevestigd als de enige werkbare aanpak gegeven de beschikbare planningsdata van Stedin. De expert gaf aan dat de data geen alternatieve opties bieden. De berekening $P_{node,t} = P_{station,t} - P_{child,t}$ is daarmee intern consistent.

2B. De expert bevestigde tevens dat alle stationscapaciteiten in Stedin's planningsdataset zijn uitgedrukt als N-1 veilige waarden. Dit betekent dat de capaciteiten de maximale belasting vertegenwoordigen die een station kan dragen terwijl nog één component uitvalt. Het gebruik van deze waarden als bindende bovengrens in het model

is daarmee consistent met de capaciteitsstandaard die Stedin intern hanteert.

2C. De expert gaf aan dat voor grootverbruikers in Stedin's planningsdataset een generiek belastingsprofiel wordt gebruikt, omdat er voor veel grote klanten geen klantspecifieke meetdata beschikbaar zijn. Batterij-installaties worden in de dataset gemodelleerd als gewone afnemers. Daarnaast zijn voor nieuwe grote klanten nog geen betrouwbare profielen beschikbaar. Dit introduceert een onzekerheid in de vraagprofielen voor stations met een hoge industriële piekvraag, zoals de stations in het Botlek- en Europoortgebied. Bakkers en industriële klanten hebben nu dezelfde profielen.

2D. De dataset sluit flexibiliteitsopties expliciet uit bij de regionalisering vanuit het ETM.

B.2.2. Radiale MS-topologie en flexibiliteit op 10 kV-niveau

2E. De radiale MS-topologie die in het model is overgenomen uit Stedins planningsdataset werd als realistisch beoordeeld voor langetermijnplanning. Het reflecteert de dominante vermogensstroom onder normale bedrijfsomstandigheden. De expert bevestigde dat de planningsdataset deze structuur al hanteert en dat de modellering daarmee consistent is met interne planningspraktijk.

2F. De bevinding dat flexibiliteit dieper in het net terechtkomt (tot op 10 kV-niveau) werd als realistisch beoordeeld. De expert wees op de groeiende rol van energiehubbs op laag- en middenspanningsniveau. Flexibiliteit op 10 kV is technisch haalbaar en sluit aan bij verwachte ontwikkelingen in 2050.

2G. De expert merkte op dat laagspanning in de praktijk makkelijker uit te breiden is dan middenspanning, onder meer omdat de doorlooptijd voor aanpassingen korter is en minder vergunningentrajecten vereist zijn. Dit versterkt de gedachte dat capaciteitsproblemen diep in het net relatief eenvoudiger op te lossen zijn dan op middenspanningsniveau.

B.2.3. Driewindingstransformatoren en capaciteitsrepresentatie

2H. De keuze om de capaciteit van driewindingstransformatoren toe te wijzen aan de secundaire winding en de tertiaire winding niet als aparte capaciteitsbeperking mee te nemen, werd besproken. De expert gaf aan dat Stedin in haar masterplannen streeft naar het vervangen van driewindingstransformatoren door twee aparte tweewindingstransformatoren, zodat de 10 kV- en 50 kV-netten los van elkaar kunnen worden aangestuurd. De huidige modelkeuze kan daarmee in de toekomst minder representatief worden.

2I. De transitie weg van driewindingstransformatoren impliceert dat de uitbreidingsruimte per station in het model mogelijk te conservatief is geschat, omdat de tertiaire winding in de huidige opzet geen eigen uitbreidingslots krijgt. Dit zou kunnen leiden tot een onderschatting van de beschikbare netuitbreidingscapaciteit op stations met dergelijke transformatoren.

B.2.4. Uitbreidingsruimte en nieuwe stations

2J. De expert bevestigde dat uitbreidingsruimte op bestaande stations in de praktijk een relevante beperking vormt. Als het maximale aantal transformatorslots op een station bereikt is, is de enige optie een volledig nieuw station. Dit onderscheid tussen het bijplaatsen van een transformator en het bouwen van een nieuw station, is in het model niet expliciet gemodelleerd, wat leidt tot een onderschatting van de werkelijke investeringskosten bij grootschalige uitbreiding.

2K. Toekomstige stations zijn niet opgenomen in het model, mede omdat er geen prognoses beschikbaar zijn voor stations die nog niet bestaan. De expert gaf aan dat Stedin intern ook werkt aan het opstellen van prognoses voor nieuwe stations, maar dat dit nog in ontwikkeling is. Het ontbreken van nieuwe stations als uitbreidingsoptie is een bekende modelbeperking die ook intern wordt erkend.

B.2.5. Vermogensfactor

2L. De uniforme vermogensfactor van 0,95 die in het model is toegepast werd in de praktijk genuanceerder beschreven: Stedin hanteert intern per spanningsniveau en per type netonderdeel een eigen gemiddelde vermogensfactor. De expert gaf aan dat er voor sommige stations voldoende data aanwezig zijn om een stationsspecifieke factor te bepalen, maar dat dit niet voor alle stations geldt. De aanname van 0,95 als globale benadering is verdedigbaar, maar introduceert een stelselmatige marge ten opzichte van de werkelijke situatie.

B.2.6. Plausibiliteit van de modelresultaten

2M. De bevinding dat flexibiliteit bij stations met een hoge industriële piekvraag en geen uitbreidingsruimte, zoals het Botlekstation (BOT_25), disproportioneel veel flexibiliteitscapaciteit trekt, werd herkend. De expert bevestigde dat dergelijke stations met grote aangesloten klanten structureel veel vraag kennen en dat het logisch is dat het model daar flexibiliteit plaatst als netuitbreiding niet mogelijk is.

2N. Ten aanzien van de technologiemix uitte de expert twijfel bij de realistische inzetbaarheid van waterstof-naar-stroom op MV-niveau in 2050. De verwachting is dat batterijen op stationsniveau de dominante flexibiliteitstechnologie zullen zijn voor lokaal congestiebeheer.

2O. De expert wees daarnaast op een structurele onzekerheid in de vraagprofielen: zeer grote industriële klanten die momenteel op het middenspanningsnet zijn aangesloten, zoals in het Botlek- en Europoortgebied, zullen naar verwachting in 2050 rechtstreeks op het hoogspanningsnet (TenneT) worden aangesloten. Dit betekent dat de hoge piekvraag die in het model op stations zoals BOT_25 wordt gemodelleerd, in de werkelijke situatie van 2050 mogelijk niet meer aan het Stedin-net toebehoort. De stations die in het model als prioriteitslocaties voor flexibiliteit naar voren komen vanwege hun hoge industriële vraag, kunnen daardoor op een vraagprofiel zijn gebaseerd dat in 2050 niet langer representatief is.

2P. De expert merkte op dat het model geen rekening houdt met de beschikbare schakelveldruimte op bestaande stations. Elke aansluiting van een flexibiliteitsasset vereist in de praktijk beschikbare kabelaansluitpunten. Dit vormt een verborgen kostenpost en fysieke beperking die in het model niet is meegenomen. De expert wees erop dat het ombouwen van een bestaand station voor meerdere assets soms duurder uitvalt dan het bouwen van een volledig nieuw station.

B.2.7. Bredere opmerkingen

2Q. Op de vraag of er modelkeuzes zijn die significant van invloed kunnen zijn op de betrouwbaarheid van de resultaten maar nog niet besproken waren, kon de expert geen aanvullende blinde vlekken benoemen. De gepresenteerde aanpak werd als intern consistent beschouwd gegeven de beschikbare data.

2R. Op de vraag welke kritische vraag een planningsteam als eerste zou stellen bij presentatie van de resultaten, gaf de expert aan dat de twijfel vooral zou liggen bij de technologiemix: of waterstof-naar-stroom in 2050 daadwerkelijk de rol zou spelen die het model eraan toekent, en of de modellering voldoende rekening houdt met de praktische aansluitbeperkingen

B.3. Systeem strategie

B.3.1. Bevestiging kernbevinding: locatierobustheid als bruikbaar planningssignaal

3A. De expert bevestigde dat locatiegebonden inzichten bruikbaar zijn voor Stedin, ook als de technologiemix onzeker blijft. De bevinding dat locaties robuust zijn onder scenarioonzekerheid terwijl de technologiemix gevoelig is, sluit aan bij de manier waarop Stedin haar planningsvragen formuleert.

3B. De expert nuanceerde de DSO-rol: Stedin kan niet voorschrijven welke technologie op een station moet komen, maar kan wel ruimtelijke signalen afgeven aan marktpartijen. De concrete formulering was dat Stedin richting batterijpartijen of andere flexibiliteitsaanbieders kan zeggen: 'als je een business case wil hebben voor ons net, dan zit die in station XYZ'.

B.3.2. Spanning tussen systeembalans en congestiebeheer

3C. De expert bevestigde het fundamentele onderscheid tussen de twee functies van flexibiliteit. Voor systeembalans maakt locatie niet uit; voor congestiebeheer is locatie allesbepalend. Hij voegde een praktisch spanningspunt toe: als flexibiliteit lokaal is geoptimaliseerd voor congestiebeheer, maar TenneT die asset wil afroepen voor nationale balanshandhaving, kunnen die doelen conflicteren. Stedin kan dan niet zonder meer voldoen aan het afroepverzoek als het netwerk dat op dat moment niet toestaat.

3D. Dit betekent dat het model, dat optimaliseert vanuit DSO-perspectief, geen rekening houdt met de interactie tussen lokale congestieoplossingen en nationale balansdiensten. Dit is een structurele beperking die in de discussie benoemd moet worden.

B.3.3. Aansluitcategorieën als praktische beperking

3E. De expert wees op de aansluitcategorieën die in Nederland van kracht zijn voor het aansluiten van assets op het elektriciteitsnet. Assets met een vermogen boven 10 MVA zijn verplicht aan te sluiten op de aanwezige transportspanning, in de praktijk 25 kV, 50 kV of hoger, afhankelijk van de beschikbaarheid in het betreffende gebied. Dit betekent dat flexibiliteitsassets van substantiële omvang niet vrijelijk op elk spanningsniveau kunnen worden aangesloten. Het model kent deze beperking niet: het kan in principe op elk station elk vermogen plaatsen, ongeacht de aansluitcategorie. Voor stations waar het model grote vermogens op 10 kV plaatst, is de fysieke haalbaarheid daarvan afhankelijk van de vraag of het betreffende vermogen verdeeld is over meerdere kleinere klanten of geconcentreerd bij één grote afnemer.

B.3.4. Kortsluitvermogen als ontbrekende beperking

3F. De expert gaf een uitvoerige toelichting op kortsluitvermogen als technische beperking die niet in het model is opgenomen. De kernlogica: transformatoren dempen de kortsluitstroom die van boven het net instroomt. Zodra lokale assets op dezelfde rail worden aangesloten, voeden die ook de kortsluitstroom, waardoor schakelinstallaties die zijn ontworpen voor de originele stroomlimiet overbelast kunnen raken.

3G. Er is een relevant verschil tussen technologieën. Batterijen werken via omvormers (wisselspanning), die een dempend effect hebben op kortsluitstroom. Gas-to-power via een draaiende generator heeft juist een versterkend effect: de kinetische energie van de draaiende machine wordt bij een kortsluitgebeurtenis omgezet in enorme kortsluitstroom. Dit maakt gas-to-power via generatoren op MV-niveau technisch problematischer dan batterijen bij toenemende decentrale opwekking.

B.3.5. Ruimtelijke en sociale beperkingen

3H. Het model beschikt over een parameter voor ruimtegebruik per asset (`area_use_max`), maar omdat er geen data beschikbaar zijn over de beschikbare ruimte per station, is deze beperking op oneindig gezet. De expert bevestigde dat fysieke ruimte binnen het hekwerk van bestaande stations een reële beperking is die in de praktijk relevant is, met name op volgebouwde stedelijke stations.

3I. Geluidsnormen vormen een aanvullende sociale beperking die niet in het model zit. Met name gas-to-power assets produceren geluid en vereisen extra bouwkundige maatregelen om aan normen te voldoen. Dit zijn verborgen kosten die het model onderschat.

B.3.6. Kostenslack en planningsnauwkeurigheid

3J. De expert gaf aan dat een kostenslack van 15% acceptabel is voor het model. Hij voegde toe dat Stedin intern bij masterplanramingen rekening houdt met een bandbreedte van circa 30%, mede vanwege geopolitieke onzekerheden zoals inflatie en grondstoffenprijzen. Voor vervolgonderzoek zou een slack van 30% een realistischere afspiegeling geven van de planningsnauwkeurigheid die Stedin intern hanteert.

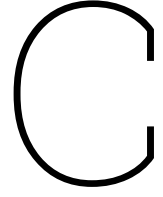
B.3.7. Positie in een iteratief onderzoeksprogramma

3K. De expert schetste de bredere onderzoekscontext: het onderzoek bouwt voort op een eerdere nationale studie uitgevoerd onder begeleiding van Netbeheer Nederland, waarbij de eerste grove aannames over flexibiliteitsplaatsing zijn getoetst. Deze thesis is de volgende stap: dezelfde vraag voor het Stedin-verzorgingsgebied met expliciet MS-detail. De expert gaf aan dat dit stap voor stap richting de werkelijkheid gaat en dat het model als methodologische bouwsteen gezien moet worden, niet als volledig operationeel planningsinstrument.

3L. De expert bevestigde dat op basis van de huidige modelresultaten al uitspraken gedaan kunnen worden richting marktpartijen over kansrijke locaties, maar dat er meer onderzoek nodig is voordat operationele investeringsbeslissingen volledig hierop kunnen worden gebaseerd.

3M. De expert bevestigde dat de continue behandeling van transformatorinvesteringen in het model verder van de werkelijkheid afraakt naarmate de gemodelleerde uitbreidingsvolumes kleiner worden. Bij kleine uitbreidingen, bijvoorbeeld 40 tot 60 MW op een link met een transformatorcapaciteit van 125 MVA, is het verschil met een discrete investering in een volledige transformator groot, zowel qua fysieke realiseerbaarheid als qua kosten. Hij adviseerde dit als limitatie te benoemen en voor vervolgonderzoek te verkennen of de vaste projectkosten van een transformatorinvestering op een slimme manier in de kostenstructuur kunnen worden verwerkt.

3N. De expert schetste de bredere onderzoekscontext en positioneerde dit onderzoek als een volgende stap in een iteratief programma. Hij gaf aan: "Als je gesimuleerd hebt en dan met experts praat, zie je limitaties. Die moeten verwerkt worden, en er komt steeds meer naar de werkelijkheid." De verwachting is dat de modelresultaten, ook met de huidige beperkingen, al voldoende richting bieden om uitspraken te doen richting marktpartijen over kansrijke locaties voor flexibiliteitsassets. Operationele investeringsbeslissingen vereisen verdere verfijning, maar de locatiesignalen die het model genereert, zijn bruikbaar als startpunt.



Consistency check: Stedin's dataset and ETM demand profiles

To verify that Stedin's internal load forecasts and the ETM provincial profiles are sufficiently consistent to be used alongside each other in the model, their temporal patterns are compared. Since the two datasets differ in absolute magnitude (the internal dataset covers only the Stedin service area while the ETM represents the full provinces) both time series are z-score normalised before comparison:

$$z_t = \frac{x_t - \mu}{\sigma} \quad (\text{C.1})$$

where x_t is the value at time step t , μ is the mean, and σ is the standard deviation of the time series. The z-score allows the shape of the profiles to be compared independently of their scale.

The net load of all 150 kV substations from the internal dataset is compared against a subset of ETM output categories for the combined Zuid-Holland, Utrecht, and Zeeland provinces. To identify which ETM categories best represent the internal dataset, a greedy selection algorithm is applied. Starting from the full set of ETM categories, the algorithm iteratively removes the category whose removal most improves the correlation with the internal net load profile, until no further improvement is achieved. Categories related to flexibility technologies and curtailment are excluded from the selection before the algorithm is applied, as their deployment is determined by the optimisation model and should not be prescribed as a fixed input. An overview of the excluded categories is provided in Tables C.1 and C.2.

Figure C.1 shows the year-level comparison for demand. Both profiles follow similar seasonal patterns, though differences in peak timing and magnitude are visible, particularly in winter. These differences reflect localised adjustments made by Stedin's area managers to the national ETM assumptions, covering heat pump penetration rates, new-build utility demand, and electric vehicle charging profiles.

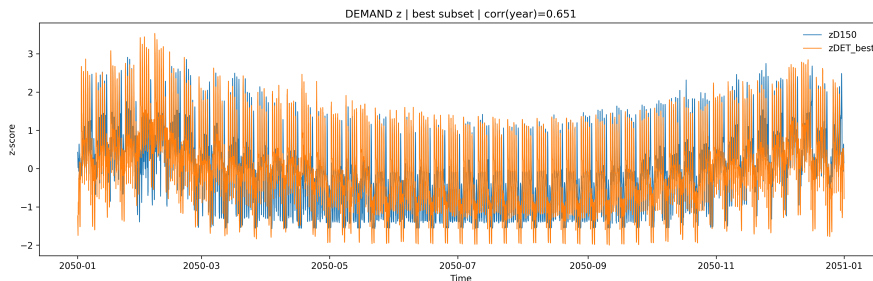


Figure C.1: Z-score comparison of aggregated demand: Stedin's 150 kV substations vs. best-matching ETM subset

Figure C.2 shows the supply comparison. The seasonal pattern is well captured in both datasets, though hour-to-hour variation differs due to differences in assumed installed capacity and generation profiles.

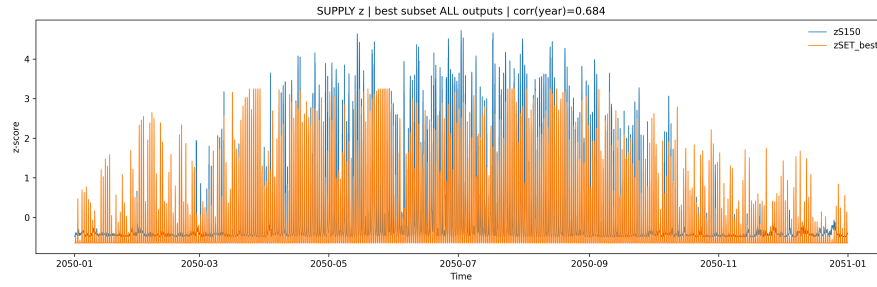


Figure C.2: Z-score comparison of aggregated supply: Stedin's 150 kV substations vs. best-matching ETM subset (year, corr = 0.68)

Figures C.3, C.4, and C.5 show the net load comparison at year, winter week, and summer week level respectively. The year-level correlation of 0.77 indicates sufficient alignment for combined use in the model. The lower winter correlation of 0.37 reflects the greater sensitivity of winter net load to heating technology assumptions, which differ between the two datasets. The summer correlation of 0.84 is stronger, driven by consistent daily demand patterns that are well captured in both datasets regardless of supply-side differences.

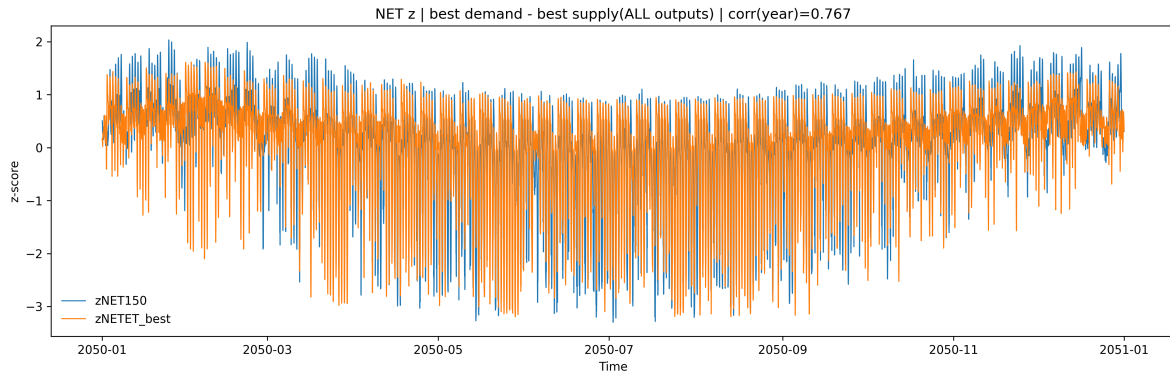


Figure C.3: Z-score comparison of net load: Stedin's dataset vs. ETM (year, corr = 0.77)

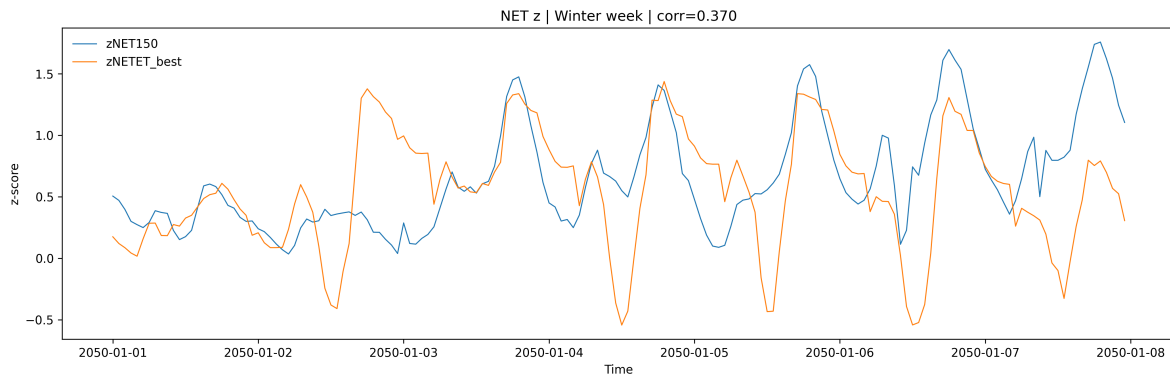


Figure C.4: Z-score comparison of net load: Stedin's dataset vs. ETM (winter week, corr = 0.37)

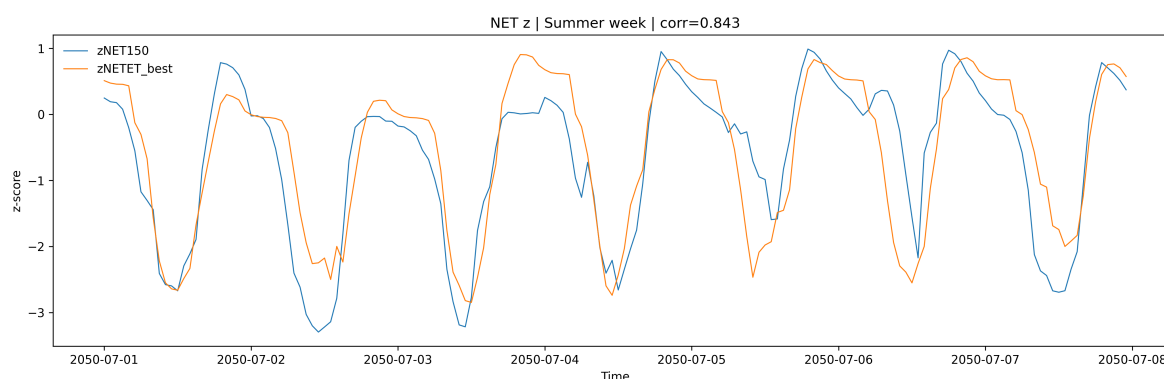


Figure C.5: Z-score comparison of net load: Stedin's dataset vs. ETM (summer week, corr = 0.84)

The main sources of divergence between the two datasets are:

- **Localised expertise in the internal dataset:** Stedin's internal forecasts incorporate feedback from area managers, resulting in adjustments to electrification rates for heat pumps, electric vehicle charging, and industrial demand that are not reflected in the ETM provincial profiles.
- **Scope differences:** The internal dataset includes specific long-term electrification projects in innovation areas, such as circular economy, ammonia, and biofuels in the Rotterdam port area, that are not captured in the ETM. Conversely, the ETM includes new-build utility demand in more detail than Stedin's dataset.
- **Profile differences:** Assumptions around hybrid heat pump behaviour, electric vehicle charging profiles, and demand-side response differ between the two datasets, causing shifts in peak timing and magnitude.

Table C.1: ETM demand and supply categories removed by greedy selection

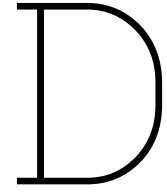
Category	ETM category	Reason for removal
Agriculture	agriculture useful demand electricity	Scope differences between Stedin's dataset and ETM
	agriculture heatpump water electricity	
Commercial buildings	buildings appliances electricity	New-build utility demand underrepresented in Stedin's dataset
	buildings cooling airconditioning electricity	
	buildings lighting led electricity	
	buildings cooling collective heatpump water ts electricity	
District heating	energy heat heatpump waste water water ts mt electricity	Profile differences in heat network assumptions
	energy heat heatpump surface water water ts mt electricity	
Industry	industry final demand for other non specified electricity	Scope differences (ICT, food, paper sectors)
	industry final demand for other ict electricity	
	industry useful demand for other food electricity	

Category	ETM category	Reason for removal
	industry other food heater electricity	
	industry useful demand for other paper electricity	
Other	buildings space heater hybrid heatpump air water electricity	
Personal road transport	transport car using electricity	Not connected to Stedin MV grid (private charging not modelled separately)
	transport van using electricity	
	transport bicycle using electricity	
	transport motorcycle using electricity	
Public transport	transport passenger train using electricity	NS/ProRail/shipping not included in Stedin's dataset
	transport ship using electricity	
	transport tram using electricity	
Residential cooling	households cooling airconditioning electricity	Limited representation in Stedin's dataset
	households cooling heatpump air water electricity	
	households cooling heatpump ground water electricity	
Residential heating	households space heater electricity	Different heat pump assumptions / profile differences between Stedin's dataset and ETM
	households space heater heatpump air water electricity	
	households space heater hybrid heatpump air water electricity	
	households space heater heatpump ground water electricity	

Table C.2: ETM supply categories removed by greedy selection

Category	ETM category	Reason for removal
Agriculture CHP	agriculture chp wood pellets	Profile mismatch with Stedin's dataset
Interconnector	energy interconnector imported electricity	Cross-border flows treated as exogenous
Nuclear	energy power nuclear gen2 uranium oxide	Not present in Stedin service area

Category	ETM category	Reason for removal
	energy power nuclear gen3 uranium oxide	
Offshore wind	energy power hybrid wind turbine offshore energy power wind turbine offshore	Not connected to Stedin service area
Onshore wind	energy power wind turbine inland	Profile mismatch with Stedin's dataset
Solar PV	buildings solar pv solar radiation energy battery solar electricity energy power solar pv solar radiation	Profile or capacity assumptions differ between datasets
Vehicle-to-grid / peer-to-peer	households flexibility p2p electricity transport car flexibility p2p electricity	Explicitly optimised in model
Waste incineration CHP	energy power supercritical ccs waste mix	Profile mismatch with Stedin's dataset



Time clustering analysis

Time clustering was investigated as a method for reducing the computational burden of the optimisation model by replacing the full 8,760-hour annual time series with a smaller set of representative periods. Each representative period is assigned a weight reflecting the number of original hours it represents. Clustering was implemented using the `tsam` library [81], which is supported by Calliope. Four approaches were evaluated. Clustering quality was assessed using the root mean squared error (RMSE) between the original and reconstructed time series, computed per node and aggregated across all demand and supply profiles. A value of zero indicates perfect reconstruction; a value of 0.10 indicates that the reconstructed time series deviates from the original by an average of 10% of its standard deviation per timestep.

Approach 1: Standard k-medoid clustering

Standard k-medoid clustering was applied to the full set of hourly profiles across all 150 kV nodes, using cluster counts. K denotes the number of representative periods into which the full 8,760-hour annual time series is compressed. The following K values are tested: $K \in \{40, 60, 80, 100, 120, 140, 160, 200, 220\}$. Even at $K = 140$, the mean RMSE across nodes remained between 0.12 and 0.15, with several nodes (e.g. TH040, TH086, TH230) exceeding 0.15. The national 380 kV profiles showed particularly poor reconstruction (RMSE ≈ 0.20 – 0.24), reflecting the difficulty of simultaneously capturing local and national variability with a single set of representative days.

Approach 2: Contiguous segment clustering

Standard k-medoid clustering produces non-contiguous typical days, which can distort within-day dynamics relevant to storage dispatch. This approach instead divided the year into contiguous segments of fixed length $S \in \{4, 6, 8\}$ days before clustering, combined with $K \in \{60, 80, 100, 120, 140\}$ clusters. The best configuration ($K = 140$, $S = 8$) achieved a mean RMSE of 0.085. However, this requires $140 \times 8 \times 24 = 1,120$ representative timesteps, reducing the original time series by only a factor of approximately eight, which was insufficient to make the 332-node HV–MV optimisation tractable on the available hardware.

Approach 3: Extreme-period-aware clustering

Standard clustering tends to underrepresent statistical outliers such as peak demand days, high ramp events, and prolonged surplus or deficit periods. This approach extended Approach 2 by explicitly reserving a fixed number of extreme days, classified on six criteria: peak demand, maximum ramp rate, short-duration surplus, long-duration surplus, long-duration deficit, and simultaneous high loading across multiple nodes. The top 20 deficit days and top 20 surplus days were retained as individual representative periods alongside the clustered remainder. Tail-event representation improved modestly, but the overall RMSE did not improve significantly over Approach 2 (best result: 0.084 for $K = 140$, $S = 8$, $D = U = 20$), and the total number of representative timesteps increased further, worsening computational tractability.

Tail events refer to hours or periods at the extremes of the statistical distribution of demand and supply profiles, conditions that occur rarely but are relevant for capacity planning, as they determine the peak loads that flexibility technologies must be able to handle.

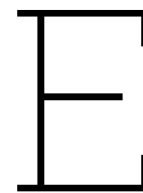
Approach 4: Stress-week selection

As an alternative to clustering, a small number of representative weeks were selected based on a DSO-relevant stress metric combining maximum transformer loading, number of overloaded hours, and cumulative overload volume. Weeks were ranked by their stress score, and a subset of the highest-stress weeks was selected, each assigned a weight proportional to the number of similar weeks in the full year. Acceptable reconstruction of the stress distribution required at least 10–15 weeks (1,680–2,520 timesteps), but the approach systematically under-represented average-stress conditions, introducing a bias towards over-investment in peak capacity.

Conclusion

All four approaches revealed a consistent trade-off between reconstruction accuracy and computational tractability. Achieving a mean RMSE below 0.10 across all nodes required approximately 1,000–1,200 representative timesteps, a reduction factor of seven to nine relative to the full hourly year.

Time clustering introduces a limitation for network planning: the non-chronological ordering of representative periods breaks the temporal continuity required for seasonal storage dispatch, and energy balance weights do not correctly propagate capacity constraints across aggregated periods. Time clustering was therefore not adopted in the final model. Instead, 3-hour temporal resampling of the full annual time series is applied, reducing the number of timesteps from 8,760 to 2,920 while preserving chronological structure.



Cost slack sensitivity analysis

This appendix presents the sensitivity analysis used to select the cost slack for the SPORES analysis. A cost slack of 10% is commonly applied in the SPORES literature [82] and serves as the starting point for this analysis. However, the scenario analysis presented in Section 6.4 reveals a cost difference of approximately 19% between the baseline and the high hydrogen price scenario, suggesting that a 10% slack may be too narrow to capture configurations that are genuinely relevant under alternative futures. To assess this, a sensitivity analysis is conducted comparing slack levels of 10% and 15%. For each level, five SPORES are generated using the Utrecht HV-MV model with broad exploration settings.

Baseline comparison

The cost-optimal baselines for both slack levels are nearly identical, confirming that the slack parameter does not affect the reference solution and that both analyses depart from the same cost-optimal configuration.

Solution space diversity

At 10% slack, the SPORES show limited variation in flexibility technology deployment. Battery storage and power-to-hydrogen capacity remain close to zero across most configurations, indicating that the 10% solution space is too narrow to reveal meaningful alternative configurations (Figure E.1). At 15% slack, a wider range of near-optimal solutions is found, with greater variation in battery deployment, power-to-hydrogen, and network reinforcement investments, as shown in Figures E.1 and E.3.

Network reinforcement

At both slack levels, the SPORES consistently plan total network reinforcement that exceeds the cost-optimal baseline, indicating that network investment is a structurally robust characteristic of near-optimal solutions regardless of the slack level applied (Figure E.2).

Cost slack selection

Based on this analysis, a cost slack of 15% is adopted for the SPORES analysis. This choice is supported by the expert interviews. The electrotechnical expert notes that Stedin's internal planning estimates traditionally carry a bandwidth of approximately 30%, and confirms that a slack of 15% is defensible and consistent with the modelling context, as a solution that is slightly more expensive but offers greater flexibility for future developments is justifiable in planning practice (B.1.6P). The system strategist similarly confirms that 15% is a reasonable and acceptable choice given the planning uncertainty involved (B.3.6J).

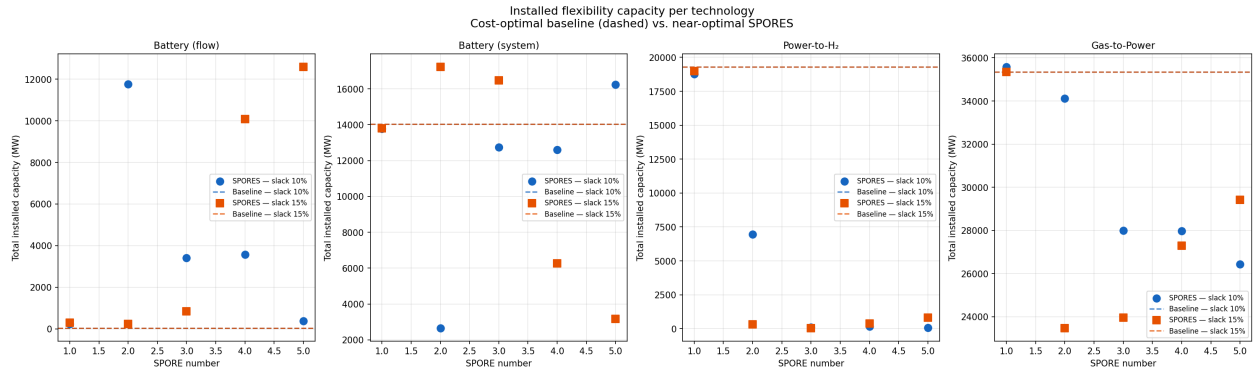


Figure E.1: Installed flexibility capacity per technology for the cost-optimal baseline (dashed line) and five near-optimal SPORES, compared across slack levels of 10% and 15%.

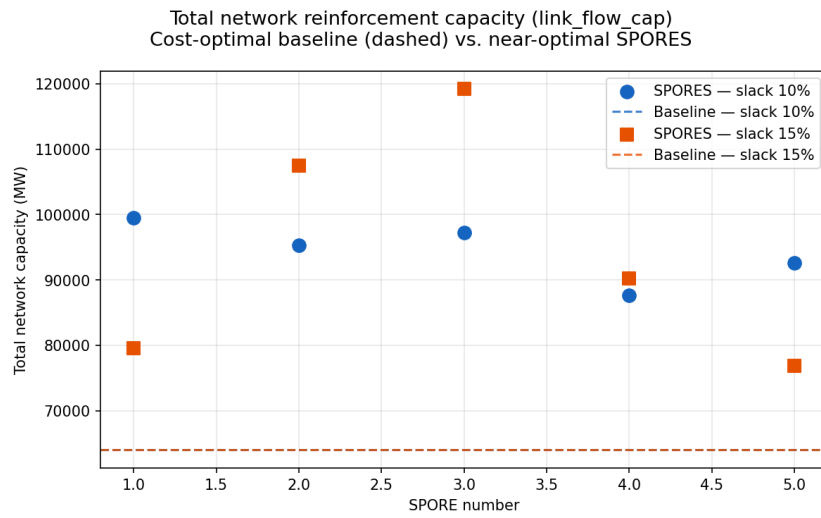


Figure E.2: Total network reinforcement capacity for the cost-optimal baseline (dashed line) and five near-optimal SPORES, compared across slack levels of 10% and 15%.

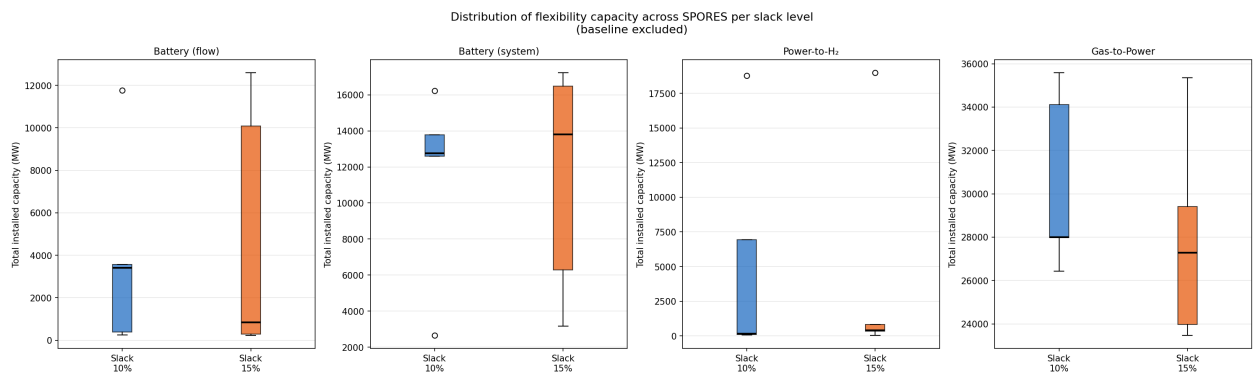
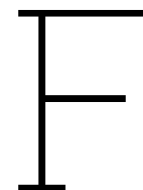


Figure E.3: Distribution of installed flexibility capacity across five SPORES per slack level (baseline excluded), showing the wider solution space obtained at 15% compared to 10% slack.



Distribution plots: justification for non-parametric tests

The statistical tests applied in the attributed structural robustness analysis rely on non-parametric methods, which do not assume that the data follow a normal distribution. This appendix provides the empirical justification for that choice by showing the actual distributions of the key input variables.

Figure F.1 shows the distributions of annual surplus hours and mean surplus block duration across all MV substations in the Utrecht model. The distribution of annual surplus hours is right-skewed: the majority of substations have between 1000 and 2500 surplus hours per year, while a small number show substantially higher values up to 7000 hours. The distribution of mean surplus block duration is highly concentrated around 810 hours with a small number of outliers at higher values. Both distributions deviate substantially from a normal distribution, justifying the use of the Mann-Whitney U test for MH6 and MH7.

Figure F.2 shows the distribution of phi coefficients across all MV substations, for both all 113 SPORES and the broad batch only. The distribution is bounded between -1 and +1 and concentrated on the negative side, with medians of -0.252 and -0.230 respectively. This non-normal, left-skewed distribution justifies the use of the Wilcoxon signed-rank test to assess whether the median phi differs significantly from zero.

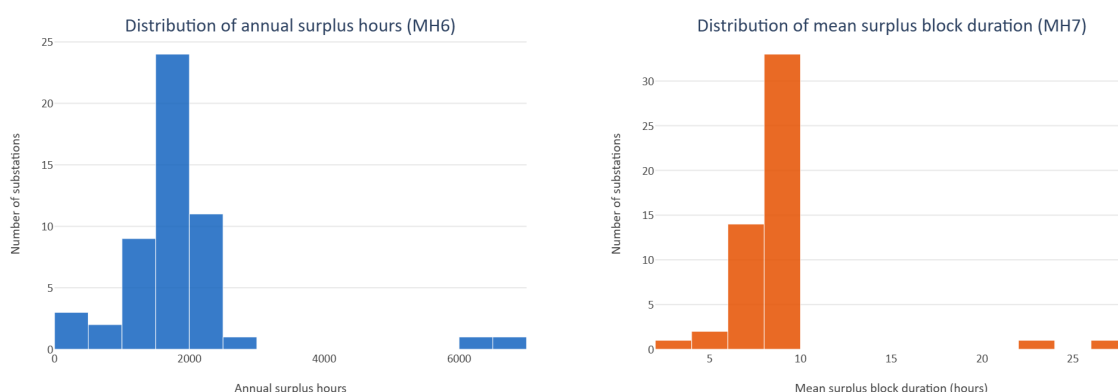


Figure F.1: Distribution of annual surplus hours (left) and mean surplus block duration (right) across MV substations in the Utrecht model. Both distributions are right-skewed, confirming that a normal distribution cannot be assumed and justifying the use of the Mann-Whitney U test.

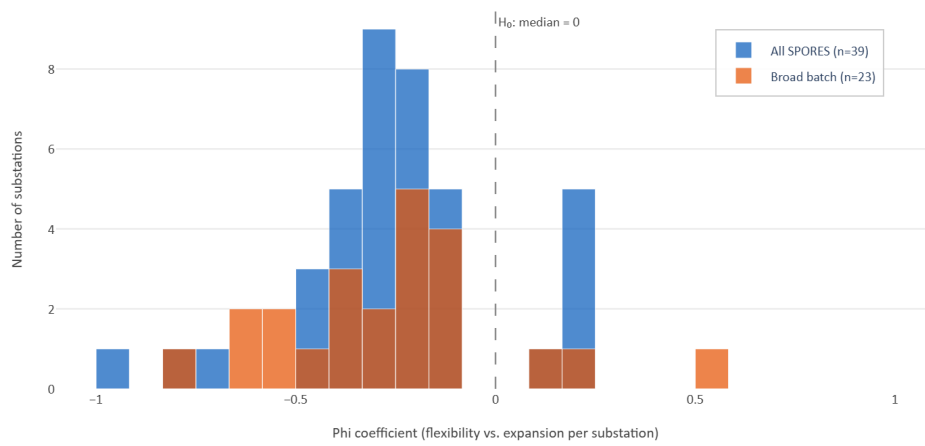


Figure F.2: Distribution of phi coefficients measuring the association between flexibility deployment and upstream link expansion per substation, across all 113 SPORES and the broad batch. The distribution is bounded and left-skewed, confirming that a parametric test is unsuitable and justifying the use of the Wilcoxon signed-rank test.



Expansion slots sensitivity analysis

This appendix shows the results of a sensitivity analysis in which the number of available transformer expansion slots is doubled across all substations in the HVMV model. This is done by doubling the `cap_flow_max` of each link. All other model parameters remain identical to the baseline configuration described in Chapter 5. The analysis addresses the question of whether the planning insights derived in Chapter 6 are sensitive to the assumption that physical expansion space is limited to the existing slot count.

For the analysis the HV–MV model and Utrecht provincial model are used as the basis for this comparison. The Utrecht model shows no change in cost-optimal outcomes between the baseline and the doubled-slot configuration. This confirms that the no-regret locations identified in that analysis are not artefacts of the slot constraint: the network structure at those substations leaves no room for upstream expansion regardless of how many slots are available, and flexibility deployment at those locations therefore remains the only feasible response under either configuration. Table G.1 summarises the aggregate investment outcomes for both model configurations.

Table G.1: Comparison of cost-optimal outcomes Baseline vs. 2× Expansion Slots (`cap_flow_max`) (HV–MV model). Percentage differences are relative to the Baseline.

Metric	Baseline	2× Slots	Δ
Total system cost (M / yr)	25.27	25.22	-0.05 (-0.2%)
Network expansion (MW)	797	6,966	+6,167 (+772%)
Expanded links (count)	33	108	+75
Total flexibility (GW)	60.19	58.2	-1.99 (-3.3%)
Vanadium redox flow battery (GW)	0	0	0
Lithium-ion battery (GW)	14.94	15.13	+0.2 (+1.3%)
Electrolyser (P2H) (GW)	14.19	12.05	-2.15 (-15.1%)
Hydrogen-to-power (GW)	31.05	31.01	-0.04 (-0.1%)

The most pronounced difference between the two configurations lies in network expansion. Total expanded capacity rises from 799 MW to 7 GW. This reflects the model exploiting the additional physical space to expand links that were previously slot-constrained. Despite this large increase in network investment, total flexibility capacity declines by only 3.3%. The main substitution occurs in electrolyser capacity, consistent with reduced need for local surplus absorption at substations where upstream expansion now allows surplus to be transported elsewhere in the network.

The screening index is applied to both configurations. Baseline recall is 100% (32.2% precision). For the 2C slots run, recall is to 93.9% (precision 68.1%). Of the 66 newly expanded links that had no baseline slots, 62 are identified as economic candidates by the screening index. The four remaining links are not missed on economic grounds: one carries no direct local overload and is expanded as a cascade effect of upstream network changes, two carry overloads too small to justify expansion over flexibility, and one falls marginally below the screening threshold at $I' = 0.97$.

Two conclusions follow. First, total system costs are robust to the slot assumption: doubling expansion capacity

reduces costs by only 0.2%, confirming that flexibility and network expansion are close substitutes at the relevant cost parameters and that the baseline slot count does not distort the investment logic. Second, the screening index reliably identifies where expansion pressure exists regardless of whether physical capacity is available: 84.8% of the expansions were already economically motivated in the baseline but physically blocked.

H

Extended results

Table H.1: Overview of MV substations by planning category. Flex freq = percentage of SPORES in which any flexibility is deployed. Exp freq = percentage of SPORES in which the upstream link is expanded. Demand and supply pressure = percentage of annual hours in which demand or supply exceeds `flow_cap_min` of the upstream link. Capacity values in MW.

Substation	Cat.	Flex freq	VRB	Li-ion	P2H	H2P	Exp freq	Flex med	P10–P90 flex	Exp med	P10–P90 exp	Dem. press.	Sup. press.
A1 — No-regret flex, no expansion													
ARK_13	A1	100%	50%	67%	4%	96%	0%	62	57–118	0	0–0	30.4%	13.3%
BLT_10	A1	100%	68%	43%	2%	97%	0%	88	80–143	0	0–0	46.5%	10.7%
VKV_10	A1	100%	54%	57%	3%	82%	0%	21	19–106	0	0–0	14.0%	10.5%
MIJ_10	A1	100%	38%	70%	4%	96%	0%	49	47–72	0	0–0	30.9%	9.0%
UBK_10	A1	100%	47%	42%	2%	95%	0%	26	25–56	0	0–0	20.6%	1.0%
UOV_10	A1	100%	61%	21%	2%	28%	0%	8	7–109	0	0–0	3.4%	0.0%
UMW_10	A1	100%	27%	57%	0%	23%	0%	18	17–136	0	0–0	4.5%	0.0%
GOR_13	A1	100%	78%	30%	0%	98%	0%	56	53–150	0	0–0	36.0%	4.7%
LRD_13	A1	100%	47%	73%	0%	96%	0%	33	31–113	0	0–0	27.9%	1.7%
VUA_13	A1	100%	65%	58%	4%	91%	0%	50	46–101	0	0–0	19.6%	12.3%
A2 — No-regret flex, expansion present													
HNH_10	A2	94.7%	67%	35%	2%	48%	58.8%	44	24–98	12	9–36	30.7%	9.4%
UJR_10	A2	93.9%	56%	41%	0%	49%	56.1%	52	27–120	12	10–54	28.0%	12.2%
BRV_10	A2	90.3%	59%	30%	3%	41%	65.8%	46	24–116	11	7–38	23.0%	9.4%
B1 — No-regret expansion, flex robust													
SDZ_10	B1	87.7%	43%	41%	7%	18%	90.3%	32	16–116	12	10–37	31.2%	7.4%
BLD_10	B1	77.2%	45%	25%	0%	23%	90.3%	28	15–135	29	18–45	48.4%	9.5%
HOU_10	B1	60.5%	25%	29%	3%	18%	91.2%	53	17–168	29	8–72	17.4%	16.4%
B2 — No-regret expansion, flex limited													
ARK_50	B2	50.9%	11%	20%	3%	25%	100%	429	20–912	118	105–238	0.0%	0.0%
VN1_10	B2	50.9%	15%	24%	4%	18%	97.4%	116	20–306	71	38–73	32.3%	4.2%
WAI_10	B2	47.4%	10%	17%	1%	33%	97.4%	108	24–262	45	18–76	36.0%	8.5%
BUN_10	B2	44.7%	9%	26%	0%	20%	96.5%	46	17–252	46	27–73	40.1%	7.0%
UKW_10	B2	41.2%	12%	19%	2%	20%	92.1%	176	46–396	63	23–76	22.0%	4.0%
VN2_10	B2	31.6%	4%	12%	0%	21%	98.2%	48	15–231	23	9–23	12.1%	0.1%
OUR_50	B2	30.7%	5%	21%	0%	8%	93.0%	156	24–447	27	7–87	0.0%	10.4%
DRB_10	B2	22.8%	3%	9%	0%	18%	97.4%	149	15–404	34	32–42	21.9%	10.4%
OUR_10	B2	21.9%	0%	11%	0%	11%	99.1%	99	14–257	46	33–46	30.8%	9.5%
Middle — Robust on one or both axes													
KNO_10	M	89.5%	55%	23%	3%	53%	57.9%	53	20–127	16	12–40	34.2%	8.4%
NWP_13	M	89.5%	43%	41%	4%	21%	34.2%	15	13–54	15	2–71	14.9%	10.1%
BAA_10	M	88.6%	50%	30%	5%	50%	56.1%	68	19–142	25	21–44	46.1%	11.7%
LOP_10	M	87.7%	28%	56%	3%	11%	14.0%	14	13–40	14	13–14	11.5%	11.1%
MNF_10	M	82.5%	60%	35%	0%	15%	85.1%	24	20–43	12	8–33	30.9%	15.5%
LEU_10	M	81.6%	45%	34%	2%	26%	43.0%	31	24–82	6	2–29	10.4%	8.3%
IJZ_10	M	75.4%	42%	20%	0%	21%	83.3%	21	17–116	12	8–29	20.6%	9%
DOO_10	M	74.6%	59%	11%	0%	25%	74.6%	14	10–77	10	8–21	27.4%	13.4%
AF3_10	M	74.6%	38%	18%	2%	43%	64.9%	36	10–170	19	8–21	19.6%	5.5%
ZEL_10	M	73.7%	47%	11%	2%	27%	78.1%	17	13–219	8	4–29	11.2%	4.6%
ZEW_10	M	71.9%	27%	25%	2%	32%	71.9%	24	9–134	15	4–75	14.5%	8.7%
AF5_10	M	70.2%	25%	35%	2%	27%	85.1%	28	15–290	35	17–76	32.2%	11%
JTP_10	M	69.3%	27%	25%	1%	26%	74.6%	20	8–73	6	3–14	15.4%	4.7%
AF2_10	M	65.8%	12%	31%	1%	35%	71.9%	45	12–114	27	12–27	33.9%	9.9%
AF3_10	M	65.8%	32%	18%	2%	21%	89.5%	22	11–198	23	8–40	19%	6.2%
VRS_10	M	64.9%	11%	33%	1%	30%	43.0%	15	8–201	8	8–76	1.4%	3.3%
AF4_10	M	58.8%	32%	17%	2%	17%	87.7%	8	6–83	10	4–11	17.4%	4.9%
MBK_10	M	53.5%	19%	25%	0%	17%	88.6%	41	13–121	32	10–32	23.9%	4.1%
UZD_10	M	50.9%	25%	19%	2%	17%	61.4%	10	6–103	10	7–10	7%	0%
NIE_10	M	46.5%	11%	22%	2%	16%	87.7%	247	14–521	7	7–219	2.1%	0%
SOE2_10	M	40.4%	5%	6%	1%	36%	88.6%	130	43–487	23	20–219	19.8%	8.2%
ARK_23	M	36.8%	5%	12%	5%	19%	88.6%	288	17–513	8	5–262	0%	0%
DRB_50	M	31.6%	2%	11%	1%	21%	82.5%	118	10–583	41	17–120	0%	0%
ULW_50	M	21.9%	2%	4%	1%	18%	75.4%	737	39–851	85	32–119	0%	0%
BRK_50	M	7.9%	2%	2%	4%	2%	86.0%	28	7–294	36	16–48	0%	0%

Network data

This appendix provides a complete overview of the network data used in the HV–MV model. It includes the full list of nodes and their geographic coordinates, a summary of the network links per voltage level combination, and an overview of the substations that were excluded from the model.

Excluded substations

Table I.1 lists the substations that were removed from the model prior to optimisation. Two categories of exclusions are distinguished: newly planned substations for which no demand or generation forecasts were available, and stations that are externally fed and therefore do not form part of the internal Stedin service area.

Table I.1: Substations excluded from the HV–MV model

Station code	Voltage	Category
NEW_23	23 kV	New substation
NEW_21	21 kV	New substation
NEW_10	10 kV	New substation
NEW_10	10 kV	New substation
GDP_21	21 kV	New substation
HEE_10	10 kV	External feed
SCW_10	10 kV	External feed
MSL1_10	10 kV	External feed
MSL2_10	10 kV	External feed
VOW_66	66 kV	External feed
TER_10	10 kV	External feed

Substations

Table I.2 lists all 332 substations included in the HV–MV model, ordered by voltage level from 380 kV down to 10 kV. For each node, the station code, voltage level, and geographic coordinates are provided. The single hydrogen node is included at the bottom of the table.

Table I.2: All substations in the HV–MV model

Station code	Voltage	Lat	Lon	Station code	Voltage	Lat	Lon
h2_hub	—	51.7027	4.5551	WT_380	380 kV	52.0159	4.3067
BWK_380	380 kV	52.0371	4.5295	MVL_380	380 kV	51.9557	4.0220
CST_380	380 kV	51.8141	4.7486	KIJ_380	380 kV	51.9143	4.6309
BKK_380	380 kV	52.1603	4.9877	SMH_380	380 kV	51.8392	4.2655
DIM_380	380 kV	52.3369	5.0143	RLL_380	380 kV	51.4245	4.2182
BSL_380	380 kV	51.4334	3.7276	ALW_150	150 kV	51.8491	4.6742
ZWK_150	150 kV	51.8778	4.5036	LLN_150	150 kV	51.9111	4.6277
STB_150	150 kV	51.7908	4.6743	GOU_150	150 kV	52.0077	4.7341
MWH_150	150 kV	51.8175	4.7107	DL_150	150 kV	51.9890	4.3675
ZOE_150	150 kV	52.0433	4.5183	BOT_150	150 kV	51.8700	4.2817
EUR_150	150 kV	51.9383	4.1466	OMM_150	150 kV	51.9553	4.5294
HVC_150	150 kV	52.0770	4.2896	HVO_150	150 kV	52.0751	4.3372
HVZ_150	150 kV	52.0420	4.2936	WAH_150	150 kV	51.8842	4.4269
OOD_150	150 kV	51.8749	4.3623	THW_150	150 kV	51.8847	4.2458
MVL_150	150 kV	51.9551	4.0245	GEE_150	150 kV	51.8631	4.2817
RCE_150	150 kV	51.9041	4.4606	FRK_150	150 kV	51.9115	4.4273
HVY_150	150 kV	52.0429	4.3601	TIN_150	150 kV	51.8924	4.1474
MDH_150	150 kV	51.7460	4.2017	ARK_150	150 kV	51.8719	4.9908
GBW_150	150 kV	51.8979	4.2795	GOP_150	150 kV	51.4901	3.8644
VLI_150	150 kV	51.4524	3.5916	WDP_150	150 kV	51.2642	3.8298
KRU_150	150 kV	51.4680	4.0316	OST_150	150 kV	51.3389	3.5091
MDB_150	150 kV	51.4883	3.6488	TRZ_150	150 kV	51.3318	3.7776
BOR_150	150 kV	51.4348	3.7290	RIL_150	150 kV	51.4260	4.2257
WAN_150	150 kV	51.4669	3.9646	VLO_150	150 kV	51.4500	3.6931
BRK_150	150 kV	52.1884	4.9924	OUR_150	150 kV	52.0650	5.0549
BUN_150	150 kV	52.2488	5.3934	VN1_150	150 kV	52.0235	5.5467
VN2_150	150 kV	52.0066	5.5789	DRB_150	150 kV	52.0574	5.2651
SOE_150	150 kV	52.1672	5.3408	NIE_150	150 kV	52.0509	5.1214
UMW_150	150 kV	52.1012	5.0782	ULW_150	150 kV	52.1042	5.0705
MVL_66	66 kV	51.9551	4.0245	YAK_66	66 kV	51.9722	4.0146
ALW_50	50 kV	51.8491	4.6742	LLN_50	50 kV	51.9111	4.6277
STB_50	50 kV	51.7908	4.6743	GOU_50	50 kV	52.0077	4.7341
MWH_50	50 kV	51.8175	4.7107	MDH_50	50 kV	51.7460	4.2017
ARK_50	50 kV	51.8719	4.9908	WDP_50	50 kV	51.2642	3.8298
KRU_50	50 kV	51.4680	4.0316	BOR_50	50 kV	51.4348	3.7290
BRK_50	50 kV	52.1884	4.9924	OUR_50	50 kV	52.0650	5.0549
DRB_50	50 kV	52.0574	5.2651	SOE_50	50 kV	52.1672	5.3408
NIE_50	50 kV	52.0509	5.1214	UMW_50	50 kV	52.1012	5.0782

Station code	Voltage	Lat	Lon	Station code	Voltage	Lat	Lon
ULW_50	50 kV	52.1042	5.0705	SGR_50	50 kV	51.7851	4.6174
HRD_50	50 kV	51.8229	4.8106	KLA_50	50 kV	51.7688	4.4490
SLV_50	50 kV	51.8852	4.6165	WAL_50	50 kV	51.8251	4.6609
OOL_50	50 kV	51.6991	4.3327	ZRZ_50	50 kV	51.6454	3.9313
SVG_50	50 kV	51.2313	3.8031	CAM_50	50 kV	51.3064	4.0194
OSL_50	50 kV	51.6559	4.0333	THN_50	50 kV	51.5477	4.0901
TZD_50	50 kV	51.3030	3.8495	GES_50	50 kV	51.5038	3.8796
VLO_30	30 kV	51.4500	3.6931	DL_25	25 kV	51.9890	4.3675
ZOE_25	25 kV	52.0433	4.5183	BOT_25	25 kV	51.8700	4.2817
EUR_25	25 kV	51.9383	4.1466	GRB_25	25 kV	51.8985	4.2735
OMM_25	25 kV	51.9553	4.5294	HVC_25	25 kV	52.0770	4.2896
HVO_25	25 kV	52.0751	4.3372	HVZ_25	25 kV	52.0420	4.2936
WAH_25	25 kV	51.8842	4.4269	OUD_25	25 kV	51.8749	4.3623
THW_25	25 kV	51.8847	4.2458	MVS1_25	25 kV	51.9551	4.0245
MVS2_25	25 kV	51.9551	4.0245	GEE_25	25 kV	51.8631	4.2817
RON_25	25 kV	51.9115	4.4273	RNS_25	25 kV	52.0429	4.3601
GWB_25	25 kV	51.8979	4.2795	HOV_25	25 kV	51.9624	4.4964
HOG_25	25 kV	51.8772	4.3568	SCW_25	25 kV	51.9089	4.3826
HOW_25	25 kV	51.9488	4.5466	SBR_25	25 kV	51.9469	4.4720
ZAM_25	25 kV	51.9246	4.5026	HGL_25	25 kV	52.0523	4.2774
DL2_25	25 kV	52.0087	4.3672	KDB_25	25 kV	51.9637	4.1057
YAK_25	25 kV	51.9722	4.0146	ZOE2_25	25 kV	52.0459	4.4915
PEW_25	25 kV	51.8953	4.3575	PEW2_25	25 kV	51.8931	4.4614
CNB_23	23 kV	51.8636	4.5038	ZWK_23	23 kV	51.8778	4.5036
ZO9_23	23 kV	52.0433	4.5183	BOT_23	23 kV	51.8700	4.2817
EUR_23	23 kV	51.9383	4.1466	GRB_23	23 kV	51.8985	4.2735
OMM_23	23 kV	51.9553	4.5294	WAH_23	23 kV	51.8842	4.4269
OUD_23	23 kV	51.8749	4.3623	MVL_23	23 kV	51.9551	4.0245
MVL_23_SP6_7	23 kV	51.9551	4.0245	RCE_23	23 kV	51.9041	4.4606
FRK_23	23 kV	51.9115	4.4273	HVY_23	23 kV	52.0429	4.3601
TIN_23	23 kV	51.8924	4.1474	ARK_23	23 kV	51.8719	4.9908
VLG_23	23 kV	51.9333	4.4679	SBE_23	23 kV	51.9488	4.5466
SBR_23	23 kV	51.9469	4.4720	ZAM_23	23 kV	51.9246	4.5026
ZO1_23	23 kV	52.0456	4.4913	HGL_23	23 kV	52.0523	4.2774
LSV_23	23 kV	52.0674	4.3955	DTP_23	23 kV	51.9925	4.3825
NOO_23	23 kV	52.0502	4.4109	RTA_23	23 kV	51.9504	4.4428
YAK_23	23 kV	51.9722	4.0146	PUT_23	23 kV	51.8986	4.5036
MDB4_21	21 kV	51.4883	3.6488	TRZ_21	21 kV	51.3318	3.7776
BOR_21	21 kV	51.4348	3.7290	RIL_21	21 kV	51.4260	4.2257

Station code	Voltage	Lat	Lon	Station code	Voltage	Lat	Lon
VLO_21	21 kV	51.4500	3.6931	THO_21	21 kV	51.5484	4.2203
HOU_21	21 kV	52.0080	5.1868	KDB_21	21 kV	51.9637	4.1057
LLZ_13	13 kV	51.9111	4.6277	STB_13	13 kV	51.7908	4.6743
MWH_13	13 kV	51.8175	4.7107	MDH_13	13 kV	51.7460	4.2017
MDH2_13	13 kV	51.7460	4.2017	ARK_13	13 kV	51.8719	4.9908
CAN_13	13 kV	51.9590	4.5812	CAI_13	13 kV	51.9386	4.5765
SGR_13	13 kV	51.7851	4.6174	GOR_13	13 kV	51.8317	4.9512
HRD_13	13 kV	51.8229	4.8106	KLA_13	13 kV	51.7688	4.4490
KRI_13	13 kV	51.9089	4.5920	LRD_13	13 kV	51.8919	5.0649
OBJ_13	13 kV	51.8162	4.4156	PAP_13	13 kV	51.8271	4.6968
RDK_13	13 kV	51.8688	4.5859	STL_13	13 kV	51.8045	4.0168
SWH_13	13 kV	51.8118	4.6154	VIA_13	13 kV	51.9804	5.0942
WAL_13	13 kV	51.8251	4.6609	ZWP_13	13 kV	51.8749	4.6401
DOK_13	13 kV	51.7838	4.6397	NWP_13	13 kV	51.9296	4.8753
ORL_13	13 kV	51.8143	4.6845	SLV_13	13 kV	51.8850	4.6168
TNR_10	10 kV	52.0456	4.3427	ZWK_10	10 kV	51.8778	4.5036
WAI_10	10 kV	52.0083	4.7325	DL_10	10 kV	51.9890	4.3675
BOT_10	10 kV	51.8700	4.2817	EUR_10	10 kV	51.9383	4.1466
GRB_10	10 kV	51.8985	4.2735	GOP1_10	10 kV	51.4901	3.8644
GOP2_10	10 kV	51.4901	3.8644	VL1_10	10 kV	51.4524	3.5916
WDP1_10	10 kV	51.2642	3.8298	WDP2_10	10 kV	51.2642	3.8298
KRU_10	10 kV	51.4680	4.0316	OST_10	10 kV	51.3389	3.5091
MDB1_10	10 kV	51.4883	3.6488	MDB2_10	10 kV	51.4883	3.6488
BOR1_10	10 kV	51.4348	3.7290	BOR2_10	10 kV	51.4348	3.7290
ROL1_10	10 kV	51.4260	4.2257	ROL2_10	10 kV	51.4260	4.2257
WAN_10	10 kV	51.4669	3.9646	THO_10	10 kV	51.5484	4.2203
BRK_10	10 kV	52.1884	4.9924	OUR_10	10 kV	52.0650	5.0549
BUN_10	10 kV	52.2488	5.3934	ZEW_10	10 kV	52.0869	5.2095
SDZ_10	10 kV	52.1582	5.2832	DOO_10	10 kV	52.0394	5.3457
MNF_10	10 kV	52.0442	4.9395	MBK_10	10 kV	52.1273	5.0269
LEU_10	10 kV	52.1203	5.4214	VRS_10	10 kV	52.0213	5.0997
LOP_10	10 kV	51.9847	4.9708	JTP_10	10 kV	52.0313	5.0878
BLT_10	10 kV	52.1233	5.1800	AF4_10	10 kV	52.1397	5.3459
VN1_10	10 kV	52.0235	5.5467	VN2_10	10 kV	52.0066	5.5789
AF1_10	10 kV	52.1576	5.3834	AF2_10	10 kV	52.1591	5.3778
AF3_10	10 kV	52.1564	5.4018	DRB_10	10 kV	52.0574	5.2651
SOE2_10	10 kV	52.1672	5.3408	NIE_10	10 kV	52.0509	5.1214
IJZ_10	10 kV	52.0259	5.0302	VKV_10	10 kV	52.2241	4.9813
MIJ_10	10 kV	52.2032	4.8712	AF5_10	10 kV	52.1763	5.4156

Station code	Voltage	Lat	Lon	Station code	Voltage	Lat	Lon
HOU_10	10 kV	52.0398	5.1490	ZEI_10	10 kV	52.1021	5.2516
HNH_10	10 kV	52.0789	4.8791	WBD_10	10 kV	51.9828	5.3405
UJR_10	10 kV	52.0823	5.1053	ULV_10	10 kV	52.0933	5.1078
UBK_10	10 kV	52.1029	5.1294	UOV_10	10 kV	52.1140	5.1080
USB_10	10 kV	52.0816	5.1630	UZD_10	10 kV	52.0738	5.1094
UMW_10	10 kV	52.1012	5.0782	BAA_10	10 kV	52.2173	5.2801
UKW_10	10 kV	52.1041	5.0650	VLG_10	10 kV	51.9333	4.4679
VHV_10	10 kV	51.9115	4.4328	PUT_10	10 kV	51.8987	4.5038
GRT_10	10 kV	51.8888	4.4708	GRW_10	10 kV	51.9624	4.4964
HOV_10	10 kV	51.8772	4.3568	SHL_10	10 kV	51.8381	4.3225
SCO_10	10 kV	51.9130	4.4126	VLO_10	10 kV	51.9079	4.3692
VLW_10	10 kV	51.9025	4.3240	DHA_10	10 kV	51.9639	4.1564
SPN_10	10 kV	51.9299	4.4181	VAK_10	10 kV	51.9258	4.4883
SCW_10	10 kV	51.9089	4.3826	KOD_10	10 kV	51.8759	4.4325
WLB_10	10 kV	51.8669	4.2234	HOW_10	10 kV	51.9488	4.5466
SBE_10	10 kV	51.9469	4.4720	IJM_10	10 kV	51.8935	4.5485
DL3_10	10 kV	52.0000	4.3432	HVS_10	10 kV	51.8355	4.1376
BMH_10	10 kV	51.8584	4.3660	SCN_10	10 kV	51.9339	4.3665
RCA_10	10 kV	51.9535	4.5623	DL6_10	10 kV	51.9888	4.3607
DL7_10	10 kV	51.9849	4.3436	DL10_10	10 kV	51.9943	4.3835
ZAM_10	10 kV	51.9246	4.5026	ZOE1_10	10 kV	52.0456	4.4913
ZOE2_10	10 kV	52.0532	4.5025	ZOE3_10	10 kV	52.0374	4.4740
ZOE4_10	10 kV	52.0568	4.4790	ZOE7_10	10 kV	52.0652	4.4736
ZOE8_10	10 kV	52.0663	4.4898	ZOE12_10	10 kV	52.0629	4.4552
ZOE13_10	10 kV	52.0638	4.5240	AVB_10	10 kV	52.0782	4.3342
APP_10	10 kV	52.0681	4.2512	BTS_10	10 kV	52.0756	4.3561
CAR_10	10 kV	52.0744	4.2853	VLW_10	10 kV	52.0523	4.2774
HTR_10	10 kV	52.0857	4.2715	JWS_10	10 kV	52.0574	4.3213
LGV_10	10 kV	52.0399	4.2508	NSG_10	10 kV	52.0866	4.3864
NSC_10	10 kV	52.0847	4.3115	TEL_10	10 kV	52.0608	4.3033
TRB_10	10 kV	52.0379	4.3241	VDB_10	10 kV	52.0988	4.3127
VJZ_10	10 kV	52.1047	4.2818	VLS_10	10 kV	52.0769	4.3029
WGS_10	10 kV	52.0704	4.3449	LSV_10	10 kV	52.0674	4.3955
ZOE14_10	10 kV	52.0744	4.5050	ZOE15_10	10 kV	52.0617	4.4955
BLD_10	10 kV	52.0246	4.6897	BOW_10	10 kV	52.0103	4.7037
BRV_10	10 kV	52.0712	4.7478	KNO_10	10 kV	51.9734	4.6295
KRW_10	10 kV	51.9373	4.8126	ZOE16_10	10 kV	52.0400	4.5018
ZOE17_10	10 kV	52.0472	4.4667	PIJ1_10	10 kV	52.0141	4.4404
PIJ2_10	10 kV	52.0238	4.4153	BRL1_10	10 kV	51.9754	4.4553

Station code	Voltage	Lat	Lon	Station code	Voltage	Lat	Lon
BRL2_10	10 kV	52.0062	4.4803	BLE1_10	10 kV	52.0027	4.5283
BLE2_10	10 kV	52.0305	4.5408	N001_10	10 kV	52.0432	4.3769
DL2_10	10 kV	52.0087	4.3672	ZOE19_10	10 kV	52.0533	4.5255
BSH_10	10 kV	51.9801	4.5012	PIJ3_10	10 kV	51.9954	4.4024
BRL3_10	10 kV	52.0128	4.4967	PIJ4_10	10 kV	52.0269	4.4447
ZRZ_10	10 kV	51.6454	3.9313	SVG1_10	10 kV	51.2313	3.8031
SVG2_10	10 kV	51.2313	3.8031	CAM_10	10 kV	51.3064	4.0194
OSL_10	10 kV	51.6559	4.0333	THN_10	10 kV	51.5477	4.0901
TZD1_10	10 kV	51.3030	3.8495	TZD2_10	10 kV	51.3030	3.8495
GES_10	10 kV	51.5038	3.8796	VLH_10	10 kV	51.9317	4.3511
DL4_10	10 kV	52.0174	4.3512	DL15_10	10 kV	51.9815	4.3706

Links

Table I.3 provides a complete overview of all transmission links in the HV–MV model, including the straight-line distance between each pair of nodes (excluding the tortuosity factor of 1.2).

Table I.3: All transmission links in the HV–MV model

From node	To node	Dist. (km)	From node	To node	Dist. (km)
BKK_380	DIM_380	19.73	BKK_380	BRK_150	3.14
BKK_380	VN2_150	43.98	BKK	ULW_150	8.43
BSL_380	RLL_380	34.13	BSL_380	GOP_150	11.41
BSL_380	KRU_150	21.48	BSL_380	MDB_150	8.20
BSL_380	TRZ_150	11.82	BSL_380	BOR_150	0.19
BSL_380	WAN_150	16.89	BSL_380	VLO_150	3.03
BWK_380	KIJ_380	15.34	BWK_380	ZOE_150	1.03
CST_380	KIJ_380	13.79	CST_380	MWH_150	2.64
CST_380	ARK_150	17.89	DIM_380	BRK_150	16.59
KIJ_380	BKK_380	36.72	KIJ_380	ALW_150	7.84
KIJ_380	LLN_150	0.42	KIJ_380	GOU_150	12.59
KIJ_380	OMM_150	8.34	KIJ_380	WAH_150	14.44
MVL_380	EUR_150	13.74	RLL_380	ALW_150	56.82
RLL_380	GOP_150	25.65	RLL_380	KRU_150	13.85
RLL_380	RIL_150	0.55	SMH_380	CST_380	33.42
SMH_380	MVL_380	0.00	SMH_380	MVL_150	21.01
SMH_380	GEE_150	2.89	WT_380	BWK_380	15.47
WT_380	DL_150	5.14	WT_380	HVC_150	6.90
WT_380	HVZ_150	3.04	WT_380	HVY_150	4.74
ALW_150	ALW_50	0.00	ALW_150	ARK_150	21.96
ZWK_150	ZWK_10	0.00	ZWK_150	ZWK_23	0.00

From node	To node	Dist. (km)	From node	To node	Dist. (km)
ZWK_150	WAH_150	5.33	LLN_150	ZWK_150	9.31
LLN_150	LLN_50	0.00	LLN_150	GOU_150	13.00
LLN_150	WAH_150	14.14	STB_150	STB_50	0.00
STB_150	MWH_150	3.89	GOU_150	GOU_50	0.00
MWH_150	ALW_150	4.33	MWH_150	MWH_50	0.00
MWH_150	ARK_150	20.23	DL_150	DL_10	0.00
DL_150	DL_25	0.00	DL_150	FRK_150	9.55
ZOE_150	ZO9_23	0.00	ZOE_150	ZOE_25	0.00
BOT_150	BOT_25	0.00	BOT_150	EUR_150	12.01
BOT_150	THW_150	2.97	EUR_150	EUR_25	0.00
EUR_150	THW_150	9.06	EUR_150	TIN_150	5.11
OMM_150	LLN_150	8.36	OMM_150	OMM_23	0.00
OMM_150	OMM_25	0.00	OMM_150	HOW_25	1.39
HVC_150	HVC_25	0.00	HVC_150	HVO_150	3.27
HVC_150	HVZ_150	3.91	HVO_150	HVO_25	0.00
HVZ_150	HVZ_25	0.00	WAH_150	WAH_25	0.00
WAH_150	OOD_150	4.57	WAH_150	RCE_150	3.21
OOD_150	BOT_150	5.57	OOD_150	OOD_25	0.00
THW_150	THW_25	0.00	THW_150	GBW_150	2.75
MVL_150	EUR_150	8.60	MVL_150	MVL_23	0.00
MVL_150	MVS1_25	0.00	MVL_150	MVS2_25	0.00
MVL_150	MVL_66	0.00	GEE_150	BOT_150	0.77
GEE_150	GEE_25	0.00	RCE_150	RCE_23	0.00
RCE_150	FRK_150	2.44	FRK_150	OMM_150	8.55
FRK_150	WAH_150	3.04	FRK_150	RON_25	0.00
HVY_150	DL_150	6.02	HVY_150	HVO_150	3.91
HVY_150	HVY_23	0.00	HVY_150	RNS_25	0.00
TIN_150	GEE_150	9.81	TIN_150	TIN_23	0.00
MDH_150	GEE_150	14.14	MDH_150	MDH_50	0.00
ARK_150	ARK_23	0.00	ARK_150	ARK_50	0.00
GBW_150	GWB_25	0.00	GOP_150	GOP1_10	0.00
GOP_150	GOP2_10	0.00	GOP_150	VLI_150	19.42
GOP_150	MDB_150	14.98	GOP_150	GES_50	1.86
VLI_150	VLI_10	0.00	VLI_150	BOR_150	9.75
WDP_150	WDP2_10	0.00	WDP_150	WDP_50	0.00
WDP_150	TRZ_150	8.36	KRU_150	KRU_50	0.00
KRU_150	WAN_150	4.66	OST_150	WDP_150	23.86
OST_150	OST_10	0.00	MDB_150	MDB1_10	0.00
MDB_150	MDB2_10	0.00	MDB_150	MDB4_21	0.00

From node	To node	Dist. (km)	From node	To node	Dist. (km)
MDB_150	BOR_150	8.15	TRZ_150	TRZ_21	0.00
TRZ_150	BOR_150	11.95	BOR_150	GOP_150	11.24
BOR_150	BOR1_10	0.00	BOR_150	BOR2_10	0.00
BOR_150	BOR_21	0.00	BOR_150	BOR_50	0.00
BOR_150	RIL_150	34.56	RIL_150	KRU_150	14.28
RIL_150	ROL1_10	0.00	RIL_150	ROL2_10	0.00
RIL_150	RIL_21	0.00	WAN_150	GOP_150	7.43
WAN_150	WAN_10	0.00	VLO_150	BOR_150	3.02
VLO_150	VLO_21	0.00	VLO_150	VLO_30	0.00
BRK_150	BRK_50	0.00	BRK_150	ULW_150	10.79
OUR_150	OUR_10	0.00	OUR_150	OUR_50	0.00
OUR_150	NIE_150	4.82	OUR_150	ULW_150	4.48
BUN_150	BUN_10	0.00	VN1_150	VN1_10	0.00
VN1_150	VN2_150	2.90	VN2_150	VN2_10	0.00
VN2_150	DRB_150	22.26	DRB_150	DRB_10	0.00
DRB_150	DRB_50	0.00	DRB_150	NIE_150	9.88
SOE_150	BUN_150	9.77	SOE_150	SOE2_10	0.00
SOE_150	SOE_50	0.00	SOE_150	ULW_150	19.79
NIE_150	NIE_10	0.00	NIE_150	NIE_50	0.00
UMW_150	UMW_50	0.00	ULW_150	UMW_150	0.62
ULW_150	ULW_50	0.00	MVL_66	YAK_66	2.03
YAK_66	YAK_23	0.00	YAK_66	YAK_25	0.00
ALW_50	PAP_13	2.91	ALW_50	ZWP_13	3.71
LLN_50	LLZ_13	0.00	LLN_50	CAI_13	4.66
LLN_50	KRI_13	2.47	LLN_50	SLV_50	2.98
STB_50	STB_13	0.00	STB_50	SGR_50	3.98
STB_50	KLA_50	15.74	STB_50	DOK_13	2.51
GOU_50	WAI_10	0.13	GOU_50	HNH_10	12.72
GOU_50	BLD_10	3.58	GOU_50	BOW_10	2.11
GOU_50	BRV_10	7.13	GOU_50	KNO_10	8.14
GOU_50	KRW_10	9.52	MWH_50	MWH_13	0.00
MWH_50	HRD_13	6.91	MWH_50	HRD_50	6.91
MWH_50	WAL_50	3.54	MWH_50	ORL_13	1.84
MDH_50	MDH_13	0.00	MDH_50	MDH_13	0.00
MDH_50	STL_13	14.33	MDH_50	OOL_50	10.45
ARK_50	ARK_13	0.00	ARK_50	GOR_13	5.24
ARK_50	LRD_13	5.56	ARK_50	VIA_13	14.01
WDP_50	WDP1_10	0.00	WDP_50	SVG_50	4.11
WDP_50	CAM_50	14.03	WDP_50	TZD_50	4.53

From node	To node	Dist. (km)	From node	To node	Dist. (km)
KRU_50	KRU_10	0.00	KRU_50	THN_50	9.75
BRK_50	BRK_10	0.00	BRK_50	VKV_10	4.05
BRK_50	MIJ_10	8.45	OUR_50	MNF_10	8.25
OUR_50	LOP_10	10.64	OUR_50	JTP_10	4.38
OUR_50	IJZ_10	4.67	DRB_50	ZEW_10	5.03
DRB_50	DOO_10	5.89	DRB_50	ZEI_10	5.06
DRB_50	WBD_10	9.79	SOE_50	SDZ_10	4.07
SOE_50	LEU_10	7.59	SOE_50	AF4_10	3.08
SOE_50	AF1_10	3.10	SOE_50	AF2_10	2.68
SOE_50	AF3_10	4.35	SOE_50	AF5_10	5.21
SOE_50	BAA_10	6.94	NIE_50	VRS_10	3.62
NIE_50	HOU_10	2.26	NIE_50	USB_10	4.45
NIE_50	HOU_21	6.56	UMW_50	BLT_10	7.39
UMW_50	UJR_10	2.81	UMW_50	UBK_10	3.51
UMW_50	UOV_10	2.48	UMW_50	UMW_10	0.00
ULW_50	MBK_10	3.94	ULW_50	ULV_10	2.83
ULW_50	UZD_10	4.31	ULW_50	UKW_10	0.37
SGR_50	SGR_13	0.00	KLA_50	KLA_13	0.00
KLA_50	OBJ_13	5.76	SLV_50	RDK_13	2.79
SLV_50	SLV_13	0.03	WAL_50	SWH_13	3.47
WAL_50	WAL_13	0.00	ZRZ_50	ZRZ_10	0.00
ZRZ_50	OSL_50	7.15	SVG_50	SVG1_10	0.00
SVG_50	SVG2_10	0.00	CAM_50	CAM_10	0.00
OSL_50	OSL_10	0.00	THN_50	THN_10	0.00
TZD_50	TZD1_10	0.00	TZD_50	TZD2_10	0.00
GES_50	ZRZ_50	16.15	GES_50	GES_10	0.00
DL_25	DL6_10	0.47	DL_25	DL7_10	1.71
DL_25	DL10_10	1.24	DL_25	ZOE3_10	9.08
DL_25	PIJ1_10	5.73	DL_25	PIJ2_10	5.07
DL_25	BRL1_10	6.22	DL_25	DL2_25	2.19
DL_25	PIJ3_10	2.50	DL_25	DTP_23	1.10
ZOE_25	ZOE14_10	3.58	ZOE_25	BLE1_10	4.56
ZOE_25	BLE2_10	2.10	ZOE_25	ZOE19_10	1.22
ZOE_25	BRL3_10	3.70	ZOE_25	PIJ4_10	5.37
ZOE_25	ZOE2_25	1.86	BOT_25	BOT_10	0.00
BOT_25	BOT_23	0.00	EUR_25	EUR_10	0.00
EUR_25	EUR_23	0.00	EUR_25	DHA_10	2.93
EUR_25	KDB_25	3.98	GRB_25	GRB_10	0.00
GRB_25	GRB_23	0.00	OMM_25	HOV_25	2.40

From node	To node	Dist. (km)	From node	To node	Dist. (km)
OMM_25	CAN_13	3.59	OMM_25	RCA_10	2.27
OMM_25	ZAM_25	3.88	HVC_25	HTR_10	1.58
HVC_25	NSC_10	1.72	HVC_25	VJZ_10	3.13
HVO_25	AVB_10	0.41	HVO_25	BTS_10	1.30
HVO_25	NSG_10	3.60	HVO_25	VDB_10	3.13
HVO_25	VLS_10	2.37	HVO_25	WGS_10	0.74
HVO_25	NOO_23	5.76	HVZ_25	APP_10	4.11
HVZ_25	CAR_10	3.65	HVZ_25	HGL_25	1.60
HVZ_25	JWS_10	2.55	HVZ_25	LGV_10	2.95
HVZ_25	TEL_10	2.19	WAH_25	WAH_23	0.00
WAH_25	KOD_10	1.00	WAH_25	IJM_10	8.44
WAH_25	PEW2_25	2.57	OUD_25	OUD_23	0.00
OUD_25	HOG_25	0.46	OUD_25	BMH_10	1.85
MVS1_25	MVL_23_SP6_7	0.00	GEE_25	SHL_10	3.96
GEE_25	WLB_10	4.04	GEE_25	HVS_10	10.40
RON_25	FRK_23	0.00	RON_25	SCO_10	1.03
RON_25	VLO_10	4.02	RON_25	VLW_10	7.18
RON_25	SPN_10	2.14	RON_25	SCW_25	3.09
RON_25	SCN_10	4.87	RON_25	RTA_23	4.45
RNS_25	TRB_10	2.53	RNS_25	NOO1_10	1.15
GWB_25	GRB_25	0.42	HOV_25	GRW_10	0.00
HOV_25	SBR_25	2.40	HOV_25	BSH_10	2.00
HOG_25	HOV_10	0.00	HOG_25	PEW_25	2.01
SCW_25	SCW_10	0.00	SBR_25	SBE_10	0.00
SBR_25	SBR_23	0.00	ZAM_25	VAK_10	0.99
ZAM_25	ZAM_10	0.00	ZAM_25	ZAM_23	0.00
HGL_25	VLW_10	0.00	HGL_25	HGL_23	0.00
DL2_25	DL3_10	1.91	DL2_25	DL2_10	0.00
KDB_25	KDB_21	0.00	ZOE2_25	ZOE1_10	0.03
ZOE2_25	ZO1_23	0.03	ZOE2_25	ZOE2_10	1.11
ZOE2_25	ZOE4_10	1.49	ZOE2_25	ZOE7_10	2.48
ZOE2_25	ZOE8_10	2.27	ZOE2_25	ZOE12_10	3.13
ZOE2_25	ZOE13_10	2.99	ZOE2_25	ZOE15_10	1.79
ZOE2_25	ZOE16_10	0.96	ZOE2_25	ZOE17_10	1.71
PEW2_25	PUT_10	2.99	PEW2_25	GRT_10	0.81
ZWK_23	CNB_23	1.58	ZWK_23	PUT_23	2.31
OMM_23	SBE_23	1.39	RCE_23	VLG_23	3.29
FRK_23	VHV_10	0.38	HVY_23	LSV_23	3.65
ARK_23	NWP_13	10.22	VLG_23	VLG_10	0.00

From node	To node	Dist. (km)	From node	To node	Dist. (km)
SBE_23	HOW_10	0.00	LSV_23	LSV_10	0.00
RIL_21	THO_21	13.62	THO_21	THO_10	0.00
DL_10	DL15_10	0.86	SCN_10	VLH_10	1.09
TRB_10	TNR_10	1.53	PIJ1_10	BRL2_10	2.88
DL2_10	DL4_10	1.47			
