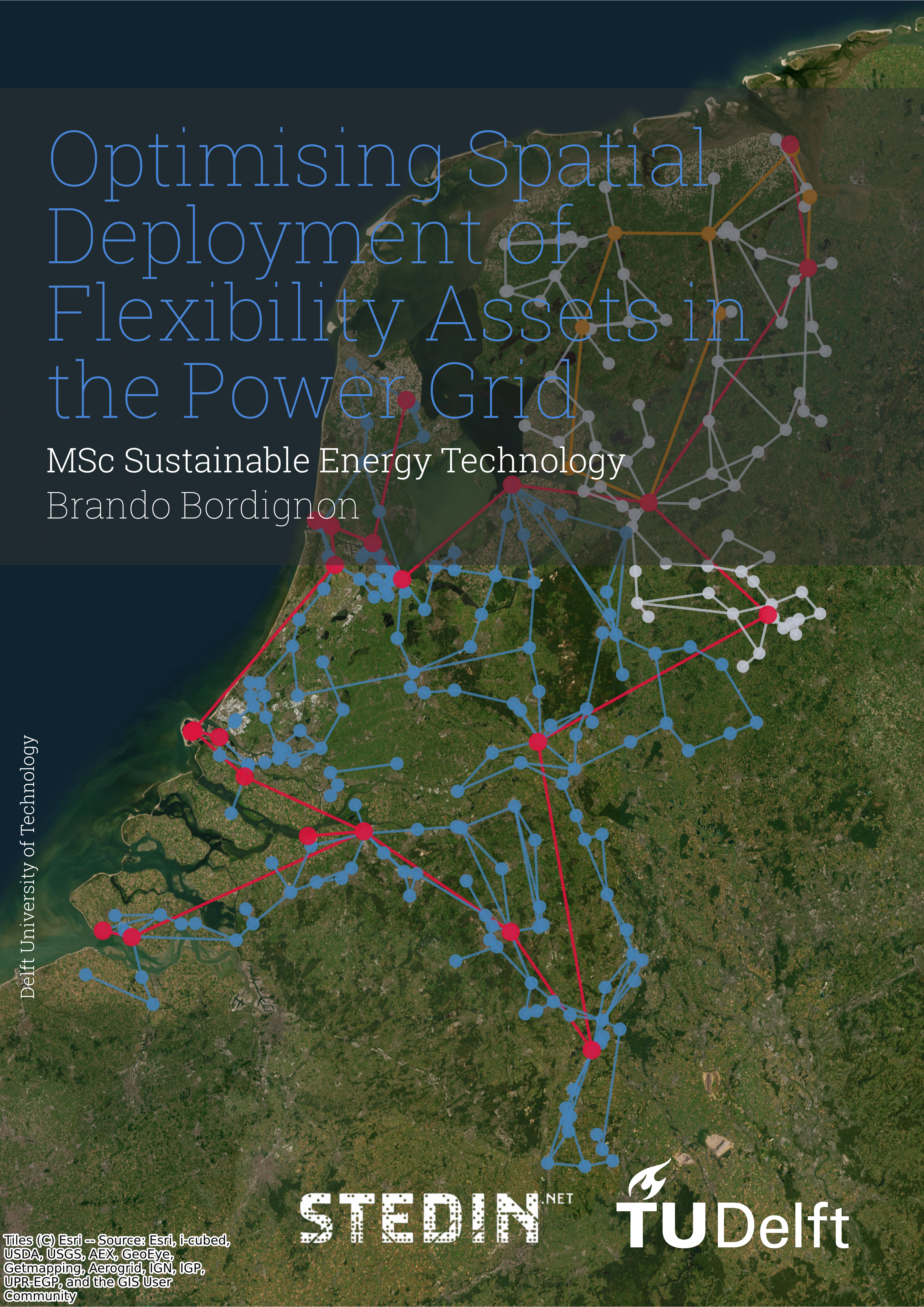
Optimising Spatial Deployment of Flexibility Assets in the Power Grid

MSc Sustainable Energy Technology

Brando Bordignon



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Optimising Spatial Deployment of Flexibility Assets in the Power Grid

by

Brando Bordignon

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Abstract

Renewable sources come with much more uncertainty. Fossil fuels created backbones of predictable flows under a relatively stable demand; however, tomorrow's energy system requires not only expansion, but anticipation. This shift forces a rethinking of what resilience truly means, and a viable path forward is to focus on flexibility, a spatially explicit design challenge in both principle and practice. This master's thesis, developed as a joint program between TU Delft and Stedin, takes the practical route. It approaches the challenge through a large and detailed application where flexibility is mapped across 283 high voltage substations and 359 transmission lines with projections to 2050. Decisions taken today will shape the reliability, security, and economic viability of tomorrow's power system. In the Netherlands, the II3050 report offers high level guidelines for grid development while it also makes clear the need for more operational detail: flexibility must be placed and sized with greater precision. And yet, that scale still remains undefined. This thesis addresses that gap. Using the open-source modelling framework Calliope, it builds a national model of the Dutch high voltage grid. It reconstructs its fully mapped topology and uses it as the structural foundation. From there, it builds a model to identify where and how much flexibility matters the most, resulting in cost-optimal and near-optimal portfolios of design alternatives. The goal is not only to chase the optimal outcome, but to identify solutions that consistently perform well. Modelling to generate alternatives (MGA) techniques are applied to the case through the SPORES method, which improves by also accounting for the spatially distinctive options rather than just costs. Supporting tools have been built to assess where technologies and locations recur most frequently across optimal portfolios and different scenarios. No-regrets analysis has been carefully performed to find those robust choices that hold their value even under varying system conditions.

Acknowledgments

It's interesting how the opening and the closing of this report share a common ground: they both offer a window to reflect. They are indeed meant to draw conclusion, naturally following a journey made by steps.

I am writing these felt acknowledgements while sit at the 13th floor of the Stedin office in Rotterdam Blaak. Today's particular weather makes it possible to neatly see deeply down the horizons. On the west side the enormous port of Rotterdam stands full of cranes and chimnneys, on the East the large new Maas river with water taxis speeding day and night. Looking up North I can see the EEMCS tower recognisable by its particular red stripe as well as the New and Old Churches in the Delft's historical centre.

This makes me wonder how cool it can get when, having the possibility, you make some decisions. And giving them time and discipline, they turn out to be right.

Moving out from the warm shell of comfort I've been living in, made me to put in practise everything my family taught me and while doing so, reconsidering and discovering newer version of myself. Thank you mum and dad, you always encouraged me to follow what I felt just right and motivated me towards reaching it with the simplest tool a parent can use, their example.

Within ad without the University, I met very passionate people.

Thank you Francesco, since our first talks your passion and commitment directly pushed me to prove myself better in relation to our research and beyond. You have been always available and ready to adjust the trajectory long projects like this, might fail to follow straight. Thank you as well Pedro to make me always questioning my findings in the search of the true whys. Warm acknowledgments to Michel and Michiel, you created a very enjoyable environment where I felt naturally flowing towards the end goals and not the other way around.

Brando
Delft, November 2025

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1 Introduction

Achieving climate neutrality by 2050 represents an ambitious yet feasible socio technical transformation in the Netherlands. The II3050 study, jointly developed by key Dutch grid operators, including TenneT, Gasunie, Stedin, and Alliander, has been conducted since 2019 to explore credible routes toward a climate neutral energy system by 2050 [4]. However, realising this vision takes several steps. For instance, a radical electrification of demand, a phase out of fossil fuel, a scale up of variable renewable energy sources (VRES) while boosting supportive storage options and conversions. To illustrate the magnitude of the change: the four II3050 scenarios estimate between 90 and 135 GW of combined wind and solar capacity by mid century [22], roughly a factor five growth compared with June 2025 installed capacity [1]. Delivering and harnessing this scale of generation will, in turn, demand the deployment of utility scale solutions that can collectively absorb, store, dispatch and convert electricity. Simultaneously with the development of dedicated hydrogen streams and end-use technologies capable of converting green hydrogen into power and heat with high efficiency.

Under the II3050 National Leadership scenario alone, residual demand analysis indicates that hourly deficits may peak at 35 to 50 GW, while hourly surpluses could exceed 95 GW [22]. Balancing such an energy system, without compromising security of supply or affordability, requires a well coordinated and cost effective deployment of flexibility resources across the power grid. However, balancing solutions that disregard the network capacity may lead to infeasible operational outcomes, particularly under problematic system conditions, such as network congestion in the Dutch context. Therefore, determining the location, type, and capacity of flexibility resources must explicitly account for the physical constraints and interactions within the transmission network, making this a complex optimisation problem. Representing the modelling framework and the network constraints makes optimisation essential. Against this, the present thesis develops a high resolution optimisation model aimed at identifying optimal and near optimal portfolios of spatially located flexibility assets, which, also accounting for grid dynamics, will offer decisional support and provide system wide overviews.

Recognising these needs while building on Stedin's call for a tool capable of performing detailed, hourly system analyses for 2050, this thesis was developed in collaboration with TUDelft. The available inputs at the starting point were national consumption projections and a preliminary map of high voltage substations. These datasets were substantially cleaned, expanded, and revised to serve both as the modelling foundation for this thesis and as a reusable base layer for future studies on the Dutch transmission grid. Indeed, the resulting grid dataset is intended to be widely applicable across different research questions that stem from a shared system setup. Likewise, the output model is expected to be equally valuable for other researchers looking to perform similar assessments or to expand the analysis by updating assumptions or integrating additional technologies.

Building on this foundation, a high resolution optimisation model was developed using the open source Calliope modelling system. The model includes 283 high voltage substations, which are treated as part of a single interconnected system. Ideal energy exchange is accounted between the four voltage levels (110kV, 150kV, 220kV, 380kV), allowing the model to assess how flexibility technologies could be optimally deployed while considering the network constraints of the interconnected power system.

1.1. Background and Motivation

The II3050 outlines four system scenarios for achieving climate neutrality by 2050. Across all of them, the need for system flexibility emerges as a structural and non optional feature of the next electricity system. Flexibility is expected to be provided through a combination of technologies: battery storage, hydrogen electrolysis, power to heat systems, power to gas and more. What remains uncertain, however, is how these assets should be dimensioned, distributed geographically, and integrated into the transmission grid under realistic and feasible operating conditions.

While national studies such as II3050 provide a solid baseline for long-term infrastructure planning, their estimation of flexibility requirements is derived from the *Energietransitiemodel (ETM)* [20], which operates at a single node national level. However, detailed network simulations are performed by TSOs and DSOs, but these are typically used for different purposes and not necessary for deriving the optimal spatial distribution of the predicted flexibility resources. Consequently, the spatial allocation of such assets in II3050 was based on a simplified grid representation, assessing national flexibility needs to regions or substations through proportional scaling methods rather than optimisation. The previous assessment methods translate long term scenario assumptions into hourly system profiles using historic weather data (based year 2012), simplified market modelling and a merit order dispatch of flexibility resources. This approach, however, ignores internal grid constraints and treats the Dutch electricity system as a single node. Flexibility requirements were indeed quantified using deterministic simulation techniques fed by national net load curves obtained by the ETM. Hence, they do not properly account for the transmission bottlenecks. As a result, the outcomes lack the potentially achievable level of detail useful to guide system design choices and spatial planning decisions at the operational level with foresight.

This thesis responds to this modelling gap by developing a different approach that shares with the former only the consumption predictions for demand and partially, the supply. It performs an optimisation over representative time slices, divided into one six-month period with six-hour intervals, to capture seasonal variations while maintaining computational feasibility on the DelftBlue supercomputer at TU Delft. Therefore, it uses the Calliope energy model tool [23], which makes straightforward and possible to build such models, making it feasible to obtain cost-optimal and near-optimal solutions. Moreover, it aims to find and assess which combinations of flexibility technologies are most effective and where these should be located to maximise system efficiency. Furthermore, the model goes beyond the optimal solution as it applies Modelling to Generate Alternatives (MGA) to identify near optimal configurations that propose systematically different near optimal system designs while remaining valid. The deliverables will provide and create a systematic overview space from which to perform research under tailored input configurations.

1.2. Problem Statement

The future Dutch power system, as envisioned by the II3050 outlook, will need to operate reliably under high levels of variability. The complexity of such a system not only increases the dependency on flexible resources to cope with unpredictability and uncertainty of RES, but also raises critical questions about their spatial location.

National assessments, such the II3050, quantify flexibility using price responsive mechanisms typical in a simplified market representation, which is blind to the physical constraints and spatial interactions within the grid. As a result, they lack sufficient resolution to evaluate system portfolios or to assess the potential effectiveness of capacity deployments at station level solutions in balancing the energy system. Moreover, system operators increasingly recognise the urgency of improving physical network capacities, but they remain constrained as the analytical tools available prevent efficient comparison of different technology mixes. This demands models that not only compute optimal dispatch or costs, but that also help to obtain and visualise complex results while providing confidence indicators. From a scientific perspective, these limitations also reveal methodological gaps in how flexibility is represented and optimised in spatially detailed energy system models, this will be further examined in Chapter 2.2, where other modelling approaches are discussed to highlight these shortcomings.

This thesis addresses these challenges by developing a spatially detailed optimisation framework that evaluates the performance of multiple flexibility portfolios across the entire high-voltage grid. It sets out to identify recurrent set of solutions that seeks to lay down effective energy modelling strategies.

1.3. Objectives and Research Questions

A more robust approach to assess flexibility is needed to improve confidence in energy system planning decisions. While simulations accounting for node imbalances and hourly prices have been tested, they do not fully capture the economic and operational potential of various flexibility resources. Given the uncertainties surrounding the development of these resources and the lack of precise analytical tools to evaluate different technology mixes, a comprehensive study is required to quantify trade-offs and support decision-making processes. This study aims to provide a different option that can withstand future challenges and support the country's energy planning.

This research is guided by the following question:

"What are the spatial distributions of the different flexibility technologies that could support the Dutch power system at 2050, and how can they be identified and visualised?"

While, the study further explores:

RQ1 – Which data are needed, and how can they be used to construct a model capable of performing energy planning decisions at the required spatial resolution?

RQ2-a – Once the cost-optimal solution is obtained, how can near-optimal desirable options be explored efficiently?

RQ2-b – How can these alternatives be transformed into no-regrets recommendations?

RQ3 – How can interactive visualisation make results more intuitive and actionable for stakeholders?

1.3.1. RQ1: Data and Model Construction

RQ1 – Which data are needed, and how can they be used to construct a model capable of performing energy planning decisions at the required spatial resolution?

The foundation of credible assessment also lies in the accurate representation of the underlying infrastructure. In practice, detailed description of the high-voltage grid, demand and generation for each station and techno-economic parameters needs to be fed in the optimisation model. However, no existing dataset combines these three dimensions in a unified format suitable for optimisation with Calliope. Input data given from Stedin were lacking line connection topologies, while other high-voltage model representations of the Dutch grid [30] were developed primarily for operational and technical assessments, aiming to verify the feasibility and performance of existing electrical connections. This narrows their scope to a valuable yet systematically different purpose compared to this work, as such models cannot be directly applied to long-term energy planning or optimisation of future flexibility deployment. Therefore, the data had to be found, harmonised and aligned with this research aim.

Following an extensive collection phase, the reconstructed high-voltage grid, the pre-processed demand and supply data, the specific technology prices and parameters, as well as the model building blocks, were identified as the data needed to foster a model capable of energy planning decisions with foresight. The Calliope modelling tool is therefore used to model the Dutch high voltage energy system, specifically tailored for the new more suitable material. The structural grid incorporates 283 substations and their interconnections. The demand and supply files describes interactions within stations and supply sources. The technology catalogues provides necessary cost estimates and the .yaml file allows to craft the model.

Nevertheless, RQ1 addresses the fundamental challenge of identifying essential data sources and translating them into a coherent, computationally tractable model. The outcome of RQ1 is a structured and reproducible workflow for energy system modelling. It establishes a methodological foundation that can be reused and adapted for future analyses starting from similar data conditions. This workflow introduces an optimal modelling approach that integrates technical, spatial, and economic dimensions within an executable sequence of steps. The workflow reported in Table 1.1 was applied to later address RQ2.

Table 1.1: Structured workflow developed to address RQ1 and enable reproducible energy system modelling.

Workflow step	Description
1. Grid Infrastructure Data	Definition of the spatial structure of the power system, including substations, voltage levels, and transmission links used to represent the reference baseline network topology.
2. Demand and supply data	Collection and preprocessing of demand and generation time series for each node, to provide homogeneous input attributes.
3. Technology and Cost Identification	Identification and specification of cost projection as well as technical burdens. Prices per MW - MWh, efficiencies, lifetime parameters and more.
4. Model build	Compilation of all data inputs into structured YAML configuration files, Calliope readable.

1.3.2. RQ2: Near-Optimal Solutions and No-regret

RQ2-a – Once the cost-optimal solution is obtained, how can near-optimal desirable options be explored efficiently?

RQ2-b – How can these alternatives be transformed into no-regrets recommendations?

Generating one solution, whether global or local, may not be sufficient. Former approaches, better analysed in Chapter 2.2, provides deterministic national benchmarks but lacks the exploratory and geographical depth required for robust flexibility planning. They identify what is most favourable given one set of assumptions with heuristic methods, and they don't account for what remains viable across many plausible futures. Therefore, to ensure a more effective portfolio, recent mathematical advancements can be incorporated to expand beyond traditional forecasting methods. For instance, different near-optimal solutions that differ in system designs while meeting system requirements, can be analysed. Recent work [17] states "finding a 'cost-otpimal' planning strategy provides only a false sense of certainity". Additionally, "it would be sensible to explicitly look for technically feasible and economically comparable cost alternatives to the sought optimum". RQ2 addresses the methodological gap left by previous approaches by introducing a three-stage framework that not only generates diverse near-optimal solutions but also synthesises them into robust investment recommendations

Stage 1: generating near-optimal alternatives

The first stage applies modelling to generate alternatives (MGA), a technique that systematically explores the solution space surrounding the cost optimum. By iteratively maximising the difference from previous solutions while maintaining costs within a specified tolerance (e.g., within an x-percentile deviation from the minimum feasible system cost - slack), MGA generates hundreds of alternative configurations. Each represents a different way to achieve similar system performance through varied technology combinations. MGA interprets the broader mathematical and computational practice, indeed, this research project adopts the SPORES method [18] to grasp all the benefits of the MGA and expand them efficiently beyond just cost differences, introducing spatially distinctive options exploration. MGA explores different technology mixes, while SPORES also look at where technologies are built.

Applying MGA through the SPORES method may identify near-optimal solutions that overcome the rigidity of traditional single-outcome optimisation, which often stems from overlooking alternative valuable configurations, relying on uncertain technology cost assumptions, and maintaining a narrow cost-based focus.

Stage 2: computational efforts

Running the full-scale model, comprising 283 substations and their transmission links, requires the use of a high-performance computing environment. This step represents a one-time computational effort carried out by the TUDelft DelftBlue supercomputer. It executes the entire optimisation that generates the complete near-optimal solution spaces. From this single run, a representative set of alternative system configurations is extracted and stored.

Each configuration is exported into a structured collection of output files. These files are the analytical backbone of the post-processing phase, as they drive the further exploration of system behaviours without rerunning the full model. This decoupling of the computational execution from the post interpretation, allows subsequent analyses to be performed efficiently.

Stage 3: alternatives into no-regret recommendations

The third stage transforms this file collection of alternatives into actionable no-regret insights. The goal is to identify recurrent system designs, those that consistently appear near the optimum despite minor changes in the input. Static methods are employed to cross-reference the results to identify system components that consistently appear as part of optimal solutions across all configurations. This involves, statistical analysis of technology deployment across all near-optimal solutions, calculating appearance frequencies for each technology-location combination as well as a classification of investments into confidence indicators: ”no-regret” (appearing in >90% of solutions), ”robust” (50-90%), and ”considerable” (<50%). This identifies which types of flexibility and at which certain network nodes frequently recur, meaning finding which system design conditions vary the least.

These consistently high-performing components become core investments, or ”no-regret” options. The outcome is a well performing set of decision tools, that increase the interpretable accuracy of the model’s findings.

1.3.3. RQ3: interactive visualisation

RQ3 – How can interactive visualisation make results more intuitive and actionable for stakeholders?

Clear, fast and organised communication by energy planning models, in a sector that faces rapid changes and stirs in trajectories, is essential. RQ3 explores the most straightforward yet exhaustive and accessible way to fill the last steps of energy modelling: exporting the findings. RQ3 has been motivated by the ambition to redefine the way energy modelling results are communicated and, therefore, valued. Beyond delivering, it also seeks to bridge the gap between technical and practical. The aim is to contribute to academia and stakeholders’ interests with a tool that confidently expands the benefits of the ongoing mathematical innovations within energy system modelling.

The visualisation platform is an interactive environment in which any change in assumptions or parameters dynamically alters the displayed system outcomes, including the near-optimal and no-regret outputs generated in RQ2. The platform builds upon an initial version previously developed by the supervisory team, which has been subsequently adapted, expanded, and refined in this work to interface with the new model outputs and enhance user interaction and interpretability. Its redevelopment was essential also to improve the computational and refreshing speed.

2
Context and Previous Work

This chapter aims to introduce the calculation methods and tools previously used in the II3050 report to estimate flexibility requirements in the Dutch energy system by 2050 as well as to analyse former applications to highlight the scientific relevance and positioning of this research. The energy transition goals will be outlined, followed by an explanation of the methodology currently in use, which is based on hourly simulations using a merit order approach and annual climate profiles fed into the ETM. Finally, the main limitations of this approach are discussed, including the lack of optimisation methods and the omission of grid dynamics.

2.1. The II3050 Report and Energy Transition Goals

In line with national and European goals, the Netherlands aims to achieve carbon neutrality by 2050. The National Climate Act establishes major objectives, including a completely CO_2 neutral electrical system and a 49% reduction in CO_2 emissions by 2030 and 95% by 2050 [6]. EU frameworks, such as Fit for 55 and REPowerEU, advocate for energy diversification, deep decarbonization, and a significant reduction in reliance on fossil fuels [5].

The Dutch grid operators want to know how the energy transition and carbon neutrality impacts the electrical grid towards 2050. It's about providing energy to the appropriate location on schedule, managing supplies, determining the required space to modify the power infrastructure appropriately, while considering the associated costs. Based on four long term scenarios, the Dutch operators jointly collaborated under Netbeheer Nederland to develop the II3050 report [21], which presents deliverables providing insights into system costs, spatial requirements, and infrastructure development, including quantified estimates of physical capacity needs.

2.1.1. Flexibility Needs in the Dutch Power System

By 2050, the dynamic of energy flows will be radically different from today. Figure 2.1 report the key energy system figures in the National Leadership scenario 2050,

Energy use (final total incl. non-energetic)		Flexibility	
Reduction in final energy	26%	Batteries	60 GW / 0.7 TWh
% renewable energy	84%	Power to gas; H_2 storage	45 GW / 14 TWh
Degree of self-sufficiency	89%	Power to heat; Heat storage	11 GW / 11 TWh
Share of electrification	56%	Interconnection	18.8 GW
Share of hydrogen	23%	Dispatchable power	18 GW
Share of biomass	6%		
Energy production from renewable sources		**CO_2 and carbon (total incl. LULUCF)**	
Offshore wind	72 GW	Emission reduction by 2040	82%
Solar power	173 GW	Emission reduction by 2050	96%
Onshore wind	20 GW	Carbon use by industry	27 Mt C

Figure 2.1: Key energy system figures in the National Leadership scenario in 2050

reference flag of this project. Greater variability is predicted in supply and demand due to meteorological factors and intense electrification driving peaks in demand [21]. This might be in terms of short-term fluctuation, such as intra-day dependability, and in the form of larger seasonal imbalances. Moreover, the II3050 report highlights inconsistencies between where the electricity is produced and where it is consumed [21]. For instance, offshore wind farms are far from consumption centres. Similarly, large industrial scale electrolysers, may be located in coastal areas where abundant green energy will be available. But far away from where hydrogen demand could emerge for mobility or industrial applications.

Such a system requires a profound development of supportive technologies. A radical rethinking of flexibility, not as a complementary asset but as a main actor. According to projections from the II3050 study, the Netherlands will need to absorb electricity surpluses rising from 5 TWh in 2019 to an average of 225 TWh by 2050, and must also deal with shortages growing from 3 TWh to 90 TWh per year over the same period [22]. These requirements must be met. All levels of the energy system must develop, implement, and integrate a broad range of flexibility resources in order to meet these challenges. This includes adopting technologies that are either not fully commercially available yet or only marginally present in the existing system, such as fuel cells, hydrogen turbines, electrolyzers (alkaline, PEM, and SOEC types), and utility-scale batteries. However, these asset distributions at the grid level and their geographic deployment have to be carefully planned to prevent rising grid congestion due to higher demand. A lack of coordination between technologies and location can overload the existing infrastructure, fostering undesired outcomes.

Furthermore, the future energy demand profiles will also be different; the electrification of transport, deployment of heat pumps, as well as weather uncertainty, will constantly contribute to increasing volatility in demand profiles. For these reasons, imbalances between the supply and demand of energy from different energy carriers happen frequently. Solar and wind energy are inherently uncontrollable, and this mismatch calls for a flexible energy system that adjusts supply dynamically rather than passively following fixed demand profiles. To address this, the II3050 report sets out a series of strategic recommendations. The focus is all about accelerating. The deployment and integration of flexibility solutions across all voltage levels and energy sectors must become a reality. Specifically [21]:

- *Build flexibility through innovation, and incentives.* Policy support is needed to ensure that flexible technologies are available. Timely and wise investment will avoid price peaks and ensure system security.
- *Guaranteeing that flexibility resources contribute to balancing the energy system and preventing congestion at all voltage levels.* Current incentives do not ensure that storage, electrolysers, or flexible loads are sited where they help the most. Policy must ensure deployment contributes to solving rather than worsening congestion at all voltage levels.
- *Accelerate the development of hydrogen infrastructure and storage* Salt caverns for hydrogen must be operational by 2030, with continued expansion after. Otherwise, electrolysers will fail to provide a flexible reservoir match with variable energy sources.
- *Strengthen European coordination and integration.* Deep collaboration with European partners is essential to align interconnectors, hydrogen pipelines, gas networks, and the offshore grid. Rapid implementation of EU policy into national regulation. Standardise CO_2 reduction accounting methods between EU countries.

Above all, the II3050 report suggests that flexibility in the energy system can no longer be confined only to electrons flowing, but instead, on the ideal and strategic interaction between electrical and molecular energy carriers. Technologies that can adjust consumption in real time, such as demand-side response, smart charging, and batteries, are examples of electrical flexibility [4]. On the molecular level, it involves transforming electricity into forms that can be stored, like heat or hydrogen (through electrolysis). All of this aligns well with the ambition of this master's thesis.

2.1.2. II3050 Workflow

It's now clear that flexible support is essential for the future Dutch energy system. It's no longer a nice to have, but rather a critical part. The next section builds the workflow which was previously in use to quantify flexibility in the II3050 report. It examines the data sources, modelling tools, results and points to several methodological limitations. Content is derived from the II3050 appendix and from information gathered during group project meetings.

The ETM is an open-source modelling tool developed to simulate the Dutch energy system. For each scenario, it generates detailed 8760-hour demand and supply profiles for each wanted category. It carries out a deterministic energy flow type of calculation. It is based on predefined efficiencies, capacities, and assumptions; all inputs are predefined and fixed, fostering results directly based on these values. The resulting profiles are structured by carrier, type (demand, supply, storage, exchange, flexibility), and sector. However, the ETM does not have an underlying energy grid topology. Table 2.1 gives an overview of the categories.

Table 2.1: Categories Overview

Type	Category	Examples
Demand	Buildings	Buildings, Buildings_hp_electric/hybrid
Demand	Households	Households, Households_hp_electric/hybrid
Demand	Transport	Bus, Car, Train, Truck, Van, Other
Demand	Other	Agriculture, Heat_network, Industry, Other
Exchange	International	BE, DK, DE, NO, UK connections
Exchange	General	Import/Export
System_flex	Storage	Battery (households/vehicle), Hydro
System_flex	Gas	Gas CHP/Large, Hydrogen
Supply	Renewable	Solar (4 types), Wind (2 types), Hydro, Biomass
Supply	Conventional	Nuclear, Coal, Waste, Other

The II3050 research process set out four distinctive scenarios. Each of them reflects a different socio-political vision and translates it into assumptions about how the Netherlands will decarbonise by 2050. While they are built around key structural assumptions such as intensive electrification, they differ to some extent:

- *Decentralised Initiatives (DEC)*. Citizens and regions take the lead, pushing a bottom-up transition with massive local PV and onshore wind, but limited coordination and weak industrial policy. Flexibility is mostly decentralised.
- *National Leadership (NAT)*. The state centrally directs the energy mix, prioritising offshore wind (72 GW), nuclear, and hydrogen production for heavy industry and grid balancing. The system is highly electrified, with strong deployment of H2 storage (45 GW) and dispatchable power (18 GW).
- *European Integration (EUR)*. EU-wide coordination drives investment in shared infrastructure and renewable trade; Dutch flexibility leans on interconnection (28.8 GW) and carbon capture storage, with lower national storage (46%). Biomass and BECCS play a stronger role in industry.
- *International Trade (INT)*. The Netherlands bets on importing carriers like hydrogen, acting as a logistics hub. Domestic production is modest, but the system is exposed to global market risks and depends heavily on cross-border flexibility and trade flows.

Once being defined, the four scenarios were translated into quantitative input for the Energy Transition Model (ETM). To summarise the workflow, Figure 2.2 sketches how ETM national outputs obtained by demand and supply market clearing dynamics, are translated into substation-level inputs for subsequent analyses.

At first, to obtain the aggregated national demand and supply files, the ETM uses a simplified market-based approach built on the concept of the merit-order dispatch. In each hour, different technologies submit bids based on their willingness to accept prices for generation, or willingness to pay in case of demand. Power producers bid at lowest at their Marginal Costs (MC), which reflects the least acceptable

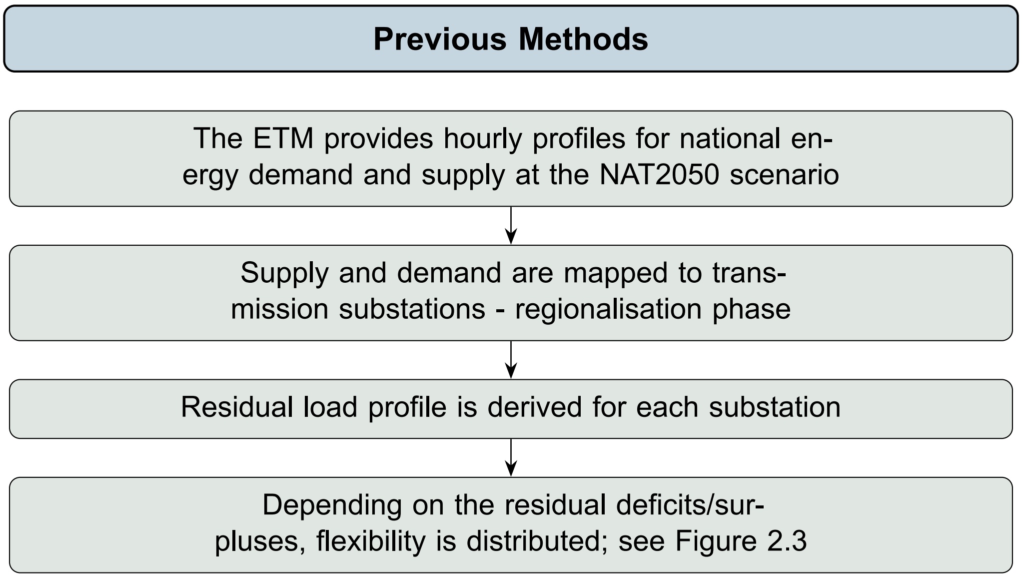


Figure 2.2: Schematic of the previous workflow used to derive substation time series from ETM outputs.

price to run the plant (fuel, maintenance) to meet a certain required demand. Renewables can bid very low marginal costs as it's cheap to run them. The ETM then ranks these offers and selects them, assessing which resource is more convenient to deploy, respecting this order (from cheapest to most expensive) until the system is balanced. This is how it decides which resource is used, when, and at what price the market is cleared. It follows straightforward Demand & Supply dynamics. In addition, the model assumes a copper plate setup, meaning it ignores internal transmission constraints and therefore energy can flow freely across the system. Between zones (like the Netherlands and neighbouring countries), the ETM includes hourly trade flows based on interconnection capacity and relative electricity prices. This process fosters hourly prices that are sorted as a result of balancing demand and supply with the economic parameter pre defined in the scenario stage. These aggregated files are then used to determine at a station level, how much flexibility is needed and, what type.

After generating hourly national aggregated profiles for supply and demand, the II3050 workflow proceeds to calculate the actual flexibility needs in the system at the station level. This is done by comparing, hour by hour, the residual load curve per station, meaning power demand deficits and generation surpluses. A general example is offered in Figure 2.3. The figure illustrates how flexibility technologies are assigned according to the residual load profile previously obtained. When the residual load shows positive peaks, battery systems are sized to absorb that value of excess generation. During negative troughs, gas-to-power technologies are dimensioned too. Considering periods with higher and more prolonged variations, power-to-gas systems are sized. The resulting flexibility contributions at the station level are then quantified and reported in structured tables, normalised between 0 and 1 with respect to the total national values identified by their sum.

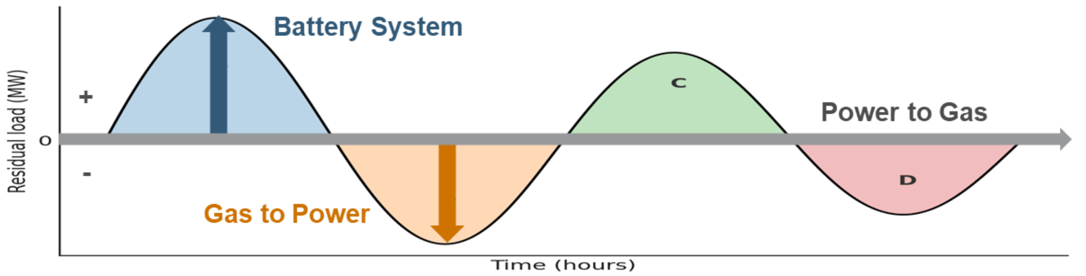


Figure 2.3: Flexibility sizing process previously adopted in the II3050 starting from the residual load curve per station. Battery and gas-to-power capacities are derived directly from short-term positive and negative peaks, while power-to-gas systems are dimensioned from longer variations periods.

2.2. Review of Existing Approaches

This section reviews the main modelling approaches previously applied to assess flexibility in the Dutch energy systems, identifying their methodological scope, limitations, and underlying assumptions. It concludes by remarking the remaining scientific and practical gaps that motivate the development of this thesis.

II3050

The II3050 approach to flexibility remains structurally and mathematically constrained. This limitation arises primarily from the deterministic nature of the Energy Transition Model (ETM) and the simply heuristic allocation applied during the regionalisation and net load curve phases. The ETM uses fixed profiles and simplified economic dispatch in order to obtain the national demand and supply curve. It is indeed deterministic, as it allows to investigate only one single solution stemming from the fixed inputs. Moreover, it treats the Dutch energy system as a single node bus with no network topology included. Additionally, the framework does not accommodate recent mathematical advancements that enable the generation of alternative system configurations.

Simulation and optimisation serve different purposes, and each comes with trade-offs. Simulation-based energy models, such as the ETM, focus on reproducing system operation given different inputs, but do not optimise decisions across technologies and geographical nodes. Furthermore, the ETM has been used for national calculations, while the regionalisation phase was carried out using heuristic calculation tools (as reported in the third block of figure 2.2). The primary limitation of the current approach lies in the assumption that each node operates as an isolated system, which neglects potential synergies arising from inter-node interactions. For instance, when a node is assessed independently, the deployment of a battery storage system may appear economically unjustified. However, in a multi-node context, if a neighbouring node exhibits surplus generation but lacks adequate flexibility, the installation of storage capacity in the first node could optimally improve the energy balancing.

Optimisation, when deciding how many and which flex resources to deploy, offers the advantage of finding solutions that may be innovative or original because they are not based on assumptions that reflect current dispatching rules and typical traditional planning approaches (e.g. a region with high solar potential but low local demand could host additional PV capacity to supply neighbouring areas, which an optimisation model would capture by considering system-wide benefits rather than local assumptions). Nevertheless, a cost-based optimiser such as Calliope, although it is expected to be similar to a merit order in some cases, will make "unexpected" choices because it can make more complex considerations, also due to the larger number of variables while subject to binding system constraints (requirements). For instance, it may positively anticipate specific operating conditions and account for potential synergies across nodes and technologies within the system.

These limitations highlight a clear methodological gap: current approaches fail to capture inter-node synergies, rely on heuristic regionalisation, and restrict the exploration of alternative configurations due to their deterministic nature. However, optimisation frameworks such as Calliope makes straightforward to build energy system models capable to address these shortcomings while bringing results. This master's thesis improve the research by simultaneously introducing the benefits of optimisation and enhances them by developing an ad-hoc network that allows geographically in-depth considerations not attempted before.

FLEXNET

Similar attempts to quantify the national flexibility needs with foresight can be found through different agencies employing different research methods. For instance, the TNO published in 2022 a revised version of the FLEXNET project [26], formerly compiled by several Dutch DSOs. The scope was to analyse demand and supply of flexibility in the Dutch power system up to 2050 at both the national and regional levels. In this case, the COMPETES [29] model used, introduced a full optimisation framework compared to the simulation-based methods discussed earlier. Specifically, it consists of two major modules: a capacity expansion module formulated as a linear program to determine the least-cost combination of new generation and transmission assets under perfect competition, and a unit commitment-economic dispatch module formulated as a relaxed mixed-integer program to minimise short-term operational costs while accounting for flexibility requirements, investment costs, and load constraints of generation technologies. This represents a significant methodological advancement, as it incorporates an optimisation-based framework rather than relying on deterministic simulation approaches.

However, despite the introduction of optimisation methods, COMPETES still fails to account for the spatial granularity required to assess detailed substation level dispatches necessary to provide geographically in-depth directions. COMPETES does indeed perform well at the level of EU countries (outputs are typically expressed in aggregated indicators, i.e flows in Wh), but it cannot be applied to more detailed evaluations of internal national patterns, specifically where tailored network constraints (bringing intra-node synergies) deeply shape model outcomes. This limitation leaves an analytical gap between European-National level flexibility assessments and the operational granularity achievable with the introduced model.

Open Data Based Model of the Dutch High-Voltage Power System

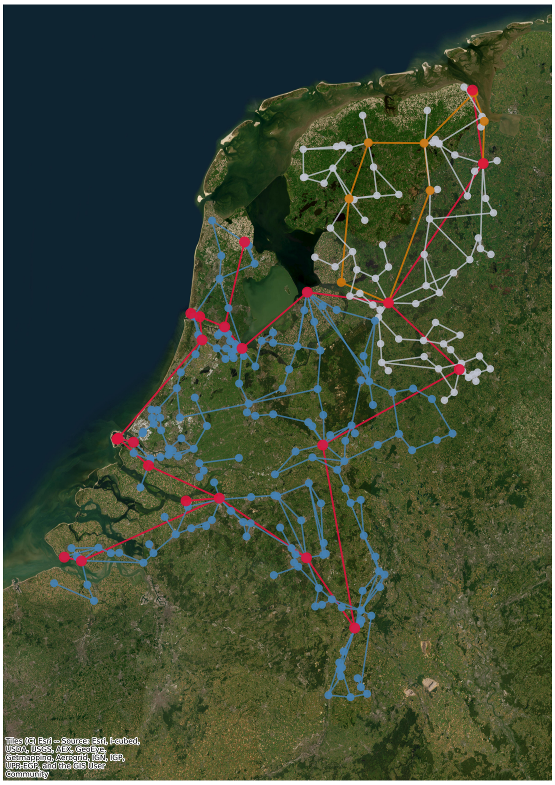
Authors in [30] built and compiled an open-source model of the 2021 high voltage power grid. The system is implemented in Pandapower, a Python library that allows to run power and optimal power flow assessments. Contributions lie in demonstrating how open data (publicly available online) can replicate the behaviour of a real transmission system. It reconstructs the 110kV to 380kV transmission network with real grid topology, electrical parameters, and generator characteristics for the years 2018 and 2021. It is a useful and precise tool that offers a realistic and in-depth operational replica of the Dutch high voltage system. It is easily applicable and, depending on the selected input parameters, technical feasibility studies can be carried through operation simulations. Rigorous electrical assessment (voltages, line loadings, dispatch given fixed assets and costs) can therefore be done with a large geographical detail introduced by this work. System technical parameters, as well as their variation, can be therefore inspected under varying scenarios.

However, its scope is inherently limited to simulating existing conditions. It cannot support forward-looking planning decisions, such as determining where and how much flexibility should be deployed under future scenarios making it not suitable to academically address the research questions presented in Section 1.3. In this regard, future developments could bridge the two approaches by coupling the newly introduced energy planning framework with a power flow validation tool, such as the one introduced above [30]. This would surely combine the parameters accuracy of operational models with the decision-oriented capacity of optimisation frameworks.

2.3. Scale of Former Calliope Models

Calliope is an open-source software designed by authors in [24] to support the development and solution of complex optimisation models, particularly in the context of energy systems planning and analysis. It facilitates their implementation and solution. Former applications have typically been applied at broader spatial scales, adopting national or multi-regional models partitioned into roughly a dozen zones, such as the 12 provinces in the Netherlands. In contrast, this study introduces a substation resolution to better reflect real system behaviour. At coarser levels, transmission is often represented by a small set of power lines, which do not necessary follow existing layouts. Moreover, previous models, lacking explicit network topology at a narrower scale, produced system design outputs that were partially unable to refine results by accounting for intra-station transmission capacities across the entire network with larger geographical details. For the Netherlands, datasets pointing at a substation level of the high voltage grid have not been standard practice in energy modelling, so former analyses have relied on aggregated geographies and simplified network constraints when compared to large scope of this research (283 substations and dedicated connection lines).

This project raises the resolution to the level of the entire high voltage transmission system itself. It represents 283 substations, interconnected by 359 lines, together



(a) Substation-level dataset of the Dutch high-voltage grid, developed in this thesis. It visualises 283 transmission stations and their interconnections, input to the new Calliope model.

(b) Previous Calliope application of the Netherlands (adapted from [12], where the system is represented at the provincial scale.

Figure 2.4: Comparison between the substation-resolved network model (left) and a previous province-level Calliope application (right).

with 27 inter voltage transformer links coupling the 380 kV, 220 kV, 150 kV and 110 kV networks. Each element of the network is reported with explicit operational attributes distinguishing transformer nodes, under construction assets, and non active connector nodes that may be added to the optimisation problem during future work, results are reported in Section 4.1. Used as a basis input for Calliope, this new structure (considering its improve spatial accuracy) expands the scope of energy modelling analyses as results and interactions could therefore be of greater relevance for stakeholders. To illustrate this shift in focus, Figure 2.4 includes a comparison between a standard Calliope base model introduced by authors in [12] and the new model developed trough this research.

The field of Energy Modelling Systems is undergoing a rapid phase of expansion, driven by both the growing complexity of energy transitions but also the increasing demand for supporting tools. During the period of this thesis project, these interests became tangible as we were invited to actively participate in settings outside the academic scope of the project, reflecting a genuine recognition of the value of the research approach developed throughout.

3 Methodology

This chapter sets out the methods that enable the transition from former simulation-based analysis to a full optimisation framework. The reported methodology is adopted in order to address the research questions presented in Section 1.3. Starting from the collection and preparation phase, the methodology introduces the mathematical background at the foundation of the model's ability to produce optimal and near-optimal outcomes. In addition, it explains what tools have been created and introduced to intuitively and practically support the presentation of the results.

3.1. Data Collection and Preparation

3.1.1. Network Dataset

As this is a collaborative project with a network operator, access to detailed power grid datasets has been granted. However, considering the foundation of this study is to approach the former simulation differently, a combination of property and public resources was needed to tailor it to the new optimisation structure. The starting point consisted of a list of substations provided by Stedin, which included locations (coordinates) and descriptive attributes (voltage level, regional code) but no information on the physical relations and connections between them. Therefore, it required substantial enrichment before it could be used in the model to address the gaps left by previous work and highlighted in Section 2.2.

Two main challenges emerged at this stage. First, the dataset provided only a partial view of the infrastructure, as substations that were crucial for transmission links were not presented. These were added manually, drawing on previous work and publicly available information [30] [9] [28] . Second, the absence of explicit power line connections meant that the network topology had to be reconstructed from scratch. To this extent, building a new and more robust dataset was needed. In doing so, the purposes of this project expanded as, providing a solid foundation for those seeking a similar structure to support their own research became a relevant goal.

In order to do so, several resources and techniques have been deployed. The starting point was a dataset provided by Stedin, which contained a list of 271 substations. However, no information regarding the network topology was included. To fill this gap, previous work proved particularly valuable.

The following sources were used: the *Open Data Based Model of the Dutch High-Voltage Power System* available through the TU Delft Research Portal [30], the online high-voltage map from HoogspanningsNet [9], and the official grid maps published by TenneT [28]. Building on these resources, all substations from the Stedin dataset were manually connected one-to-one, creating the grid topology. This was done by analysing Google Earth *.kmz* files and manually drawing the corresponding transmission lines, including their new and more accurate coordinates. The process was further validated by cross-checking with the work of TUDelft researchers [30] and comparing it with the network layouts published by TenneT. This allowed a realistic reconstruction of the grid topology. This entire work is available through an Excel file, namely the PowerNetDataset. The resulting topology will be later presented in Chapter 4.1.

The reconstructed network topology underwent extensive validation to ensure accuracy and consistency:

- all station coordinates were cross-referenced with publicly available TenneT network maps and OpenStreetMap data to confirm location accuracy;
- line connections were validated against transmission links to ensure physically realistic network paths;
- each line segment was verified to connect stations of the same voltage level,
- designated transformer locations were geographically individuated and aligned with naming;
- station roles (active, connector, under construction) were validated based on current and planned operational characteristics.

Power Grid Capacity

The grid topology reconstructed in this work represents substations and transmission lines between them. However, for modelling purposes, at each link must be assigned a maximum power transfer capacity. In this model, capacity values were derived from voltage level and literature-based ranges of values, cross referencing with work from [8] [11]. Specifically, each transmission line between nodes was assigned a power capacity consistent with standard operating ranges according to nominal voltage (110, 150, 220, and 380 kV) and compared with European capacity distributions reported in [8]. It's worth considering that the model accounts power capacity constraints rather than detailed power flow analysis. This simplification follows a common practice in energy system planning models, where the aim is to capture large-scale spatial allocation and infrastructure needs rather than detailed operational physics. Even if relevant, introducing optimal power flow (OPF) equations would significantly increase computational complexity and runtime without substantially directly affecting strategic-level insights, focus of this research approach. Nonetheless, power flow calculations aspects are typically addressed in operational studies such as [30], while future planning models such the one introduced in this work, focus instead on energy balance under simplified yet representative transmission constraint which are a key novelty, distinguishing from previous works reviewed in Section 2.2.

3.1.2. ETM supply and demand input files

The Energy Transition Model (ETM) was used by the II3050 research team to generate hourly national projections of electricity demand and technology-specific supply for 2050. A known limitation of the ETM is its single-node representation of the Netherlands, which prevents the distribution of projected quantities across substations and transmission lines, both of which have limited capacities that can lead to congestion or unfeasible balancing decisions. To address this, the authors performed a regionalisation step: starting from national totals, hourly profiles were allocated to individual transmission stations using documented assumptions on where demand is expected to occur and where each technology is expected to be present, given the spatial development of resources and projects. The result is, for every node in the grid, a realistic hourly demand pattern and an hourly supply pattern consistent with the national trajectories under the NAT2050 scenario assumptions.

The regionalised dataset contains the following station-level categories for demand and supply. The list below reflects the incoming structure before any modelling consolidation and post-processing that will be presented later in the text.

Table 3.1: Station-level categories after ETM regionalisation (carrier fixed to electricity).

Category	
Demand categories (16)	
Agriculture	Buildings
Buildings heat pump (electric)	Buildings heat pump (hybrid)
Heat network	Households
Households heat pump (electric)	Households heat pump (hybrid)
Industry	Other demand
Transport bus	Transport car
Transport other	Transport train
Transport truck	Transport van
Supply categories (12)	
Biomass	Hydro (run-of-river)
Power plant coal	Power plant nuclear
Power plant other	Power plant waste
Solar PV (buildings)	Solar PV (field)
Solar PV (households)	Solar PV (offshore)
Wind offshore	Wind onshore

Input data Re-organisation

The raw material previously presented and reported in Table 3.1, required substantial re-organisation to become model-ready. Similar labels were grouped, naming was harmonised, and each sub-series was checked and kept at the appropriate substation. For demand, all categories associated with a given station were combined into a single hourly demand profile per station. For supply, the many detailed labels were consolidated into six transparent technology families that match how assets connect to the grid and how results are interpreted.

The generation portfolio available at the outset, included several technology categories mapped to their respective connection substations. Dispatchable power plants made of: conventional thermal and biomass-based units, large gas, CHP, hydrogen-fired plants, coal, other thermal sources, and waste-to-energy. Nuclear power is included as a separate category. Renewable generation from utility-scale and large distributed solar PV installations (covering buildings, fields, households), together along with offshore and onshore wind technologies.

The outcome is a complete set of time series files, resulting in a node-resolved detailed dataset. Every one of the active 271 stations has an hourly demand profile, and all these profiles are compiled into a single national demand file. Here, each column stands for the aggregated hourly station demand. On the supply side, every active station has an hourly generation profile by technology, resulting in 271 different time series files. In there, columns represent the seven above-mentioned supply categories. Non-active connector stations remain in the network for topology only and therefore carry zero demand and zero supply by construction. Stations marked as under construction are included with full capabilities, in both demand and supply, to reflect their role in the 2050 outlook.

Supply categories

The original supply categories were consolidated into six technologies, two of which merge several source categories. This keeps the model transparent while preserving the essential behaviour of the system. Table 3.2 summarises the families and gives examples of the source categories that feed into each group.

Each family retains the hourly shape provided by ETM. The re-arranging process produces station-level series that are both internally consistent and straightforward to interpret in the optimisation. Table 3.3 illustrates the shared header structure for the 271 post-processed supply files corresponding to active substations.

Input model files

Two input sets are provided to the optimisation, both at hourly 2050 resolution and covering the 271 active substations:

- **Supply (per station):** `techs_supply_{stationID}.csv` — one file for each active substation (271 files). Each file contains the common header shown in Table 3.3.
- **Demand (all stations together):** `full_net_demand.csv` — one matrix with *hourly 2050 timesteps* as the first column and one column per active substation (271 columns in total).

Table 3.2: Supply technology families and typical constituent categories

Technology	Examples of source categories
Dispatchable Power Plants	Conventional thermal units (e.g., gas and coal where present), combined heat and power where applicable, biomass units, and waste plants mapped to their connection substations.
Nuclear Power	All nuclear output connected to the transmission grid.
Solar PV	Utility scale and large distributed PV that injects at transmission/sub-transmission nodes.
Wind Offshore	Offshore wind parks and landing points connected to the high voltage network.
Wind Onshore	Onshore wind connected at 110–150 kV substations.

Table 3.3: Schema of a station-level supply CSV (commonly shared by all 271 files).

timesteps	dispatchable_pp	hydro_ror	power_plant_nuclear	solar_pv	wind_offshore	wind_onshore
2050-01-01 00:00:00	0.0	0.0	0.0	0.0	0.0	0.0

In the demand file, column headers use substation codes; the carrier is electricity only, and figures are in MW. Altogether, the model imports 272 CSV tailored files: 271 station-level supply files and 1 multi-station demand file. File processing was performed using automated Python functions that standardise structure, nomenclature, and time indexing, creating model-ready files. The optimisation model imports these inputs and maps them to the corresponding grid nodes and technologies, for which specific Calliope lines of code were implemented.

3.1.3. Cost and Technical Data

Other than network topology and energy profiles, the model requires technology related parameters that account for both economic and technical specifications. These inputs assign values to the optimisation variables, which are the core components of the objective function. In long term planning is usually a good practice to find cost estimates that reflect expected prices years earlier than the forecasted ones. This will therefore increase the accuracy by looking at relatively closer time windows. In this research, the flexible deployment is predicted for the year 2050. Nevertheless, the prices adopted refer to 2040.

To maintain consistency between the assumptions and conventions used to determine certain cost categories, it was precautiously decided to consider relatively few sources. This has guaranteed a precise differentiation between the prices of the technologies and, being so, it positively impacted the model's ability to diversify the solutions.

The Danish Energy Agency produces statistics, key data, projections, analysis and technology catalogues, publicly available for download in their website [2]. While

the others offer an important overview and knowledge of the energy sector, for the scope of this project, the technology catalogues served an important role. The data sheets are continuously updated as technologies evolve as well as if the data changes significantly or if errors are found. The date for the latest update of the ones considered is February 2025; all the cost data are in 2020 EURO [2].
Among the many, three stood for their relevance:

1. **Technology data for energy storage**
   Provides cost and performance benchmarks for battery systems and other storage technologies. `technology_data_for_el_and_dh_-_0017_1.xlsx`
2. **Technology data for renewable fuels**
   Offers techno-economic parameters for biofuels, hydrogen, and other renewable carriers. `Technology_datasheet_for_energy_storage_--_0010.xlsx`
3. **Technology data for generation of electricity and district Heating**
   Covers investment costs, efficiencies, and operating characteristics of major generation technologies. Includes both conventional and renewable options. `data_sheets_for_renewable_fuels.xlsx`

Costs Tech Parameters

Table 3.4 presents the operational cost inputs to the model for each technology. The accompanying descriptions facilitate locating the specific technologies in the technical catalogue [2] anticipated above, where they are listed under similar designation. Prices are reported in 2020 EUR, and technical units are homogeneous. Again, the prices selected are forecasted estimates to the year 2040. Operational costs include variable O&M (and, where relevant, fuel costs).

Table 3.4: Technology cost assumptions used in optimisation model.

Technology	Description	CAPEX	OPEX	Ref.
GENERATION				
Solar PV	Utility-scale photovoltaic systems (2040)	320	8.1 kEUR/MW/yr + 1.06e-5 kEUR/MWh	[3]
Onshore Wind	Onshore wind turbines (2040)	1,110	15.97 kEUR/MW/yr + 0.00198 kEUR/MWh	[3]
Offshore Wind	Fixed-bottom offshore wind, AC connected (2040)	2,141	32 kEUR/MW/yr + 0.00345 kEUR/MWh	[3]
Hydro	Run-of-river hydroelectric	2,000	80 kEUR/MW/yr + 0.002 kEUR/MWh	[3]
Nuclear Power Plant	Generation III nuclear reactor (2040)	8,594	0.00355 kEUR/MWh + fuel 0.00341 kEUR/MWh	[3]
Dispatchable PP	Biomass, waste, and other dispatchable sources	2,500	50 kEUR/MW/yr + 0.045 kEUR/MWh	[2]
CONVERSION				
Power to Hydrogen	Electrolyser system (2040)	425	4% of CAPEX per year	[2]
Hydrogen to Power	Hydrogen turbine / CCGT	905	3.34 kEUR/MW/yr	[2]
Hydrogen Import	Hydrogen import terminal	—	0.231 kEUR/MWh	[2]
Hydrogen Export	Hydrogen export facility	—	0 kEUR/MWh	[2]
STORAGE				
Large Battery Storage	Vanadium Redox Flow battery (2040)	390†	2.92 kEUR/MW/yr	[1]
Battery Storage	Lithium-ion battery system (2040)	299†	8.67 kEUR/MW/yr	[1]
Hydrogen Storage	Underground storage caverns	—	Storage losses 1% per year	[1]
DEMAND & BALANCING				
Curtailment	Renewable energy curtailment / power shedding	—	—	—
Load Demand	Electricity system load demand	—	—	—
Loss of Load	Value of Lost Load (VOLL) penalty	—	10,000 EUR/MWh	—

Notes: CAPEX (Capital Expenditure) in kEUR/MW for generation and conversion technologies. OPEX (Operational Expenditure) includes fixed costs in kEUR/MW/yr and variable costs in kEUR/MWh. †Battery storage costs in kEUR/MWh.
References: [1] Energy Storage Catalogue, [2] Renewable Fuels Catalogue, [3] Electricity and District Heating Catalogue.

Technology Tech Parameters

Table 3.5 reports the main technical parameters used in the model. The values include lifetimes, efficiencies, and operational constraints, which determine the performance and comparability of the considered supply, storage, conversion, and demand technologies.

Table 3.5: Technical parameters adopted in the model.

Technology	Parameter	Value
SUPPLY TECHNOLOGIES		
Solar PV	flow_out_eff	1.0
	lifetime	40
Onshore Wind	lifetime	28.5
Offshore Wind	lifetime	27.5
Hydro	flow_out_eff	0.90
	lifetime	40
Nuclear Power Plant	flow_out_eff	0.326
	flow_ramping	0.5
	lifetime	40
Dispatchable Power Plant	flow_out_eff	0.4
	lifetime	25
Loss of load	lifetime	1
Hydrogen import	flow_cap_max	inf
STORAGE TECHNOLOGIES		
Large Battery Storage	lifetime	35
	flow_out_eff	0.91
	flow_in_eff	0.91
	flow_cap_per_storage_cap_max	0.08
	storage_discharge_depth	0.11
	storage_loss	6.25e-05
Battery Storage	lifetime	30
	flow_out_eff	0.985
	flow_in_eff	0.975
	flow_cap_per_storage_cap_max	0.25
	storage_discharge_depth	0.11
	storage_loss	4.17e-05
Hydrogen storage	storage_cap_max	inf
	flow_out_eff	1
	flow_in_eff	0.99
	storage_loss	0.01

Continues on next page

Technology	Parameter	Value
	storage_initial	0.5
	lifetime	30
CONVERSION TECHNOLOGIES		
Power to Hydrogen	lifetime	25
	flow_out_eff	0.653
Hydrogen to Power	lifetime	25
	flow_out_eff	0.57
	flow_ramping	0.8
DEMAND TECHNOLOGIES		
Curtailment	resource_use_max	20000
Hydrogen export	resource_use_max	20000

3.2. Linear Programming

After having discussed and identified the methodology to retrieve the input components necessary for the new model, this section aims to expand and clarify why optimisation and the mathematics behind it. Here, we are specifically dealing with the modelling of energy systems. However, the same mathematical methods are widely applicable and applied in a variety of optimisation problems, each fostering different outcomes but following a common logic.

Energy system modelling is a discipline used to generate results and insights regarding the balancing of energy systems at different scales [27]. It can be applied within a wide range, spanning from households (utilities) and neighbourhoods to national and beyond. In general, there are many interconnected components that together actively participate, while following supply and demand dynamics. As noted by Lund et al. [7] the general purpose of ESM is ' ..to guide the design, planning, and implementation of future energy systems'. Building upon this concepts, recent mathematical and computational developments expands their utility by also looking beyond the optimal outcome [18].

The following paragraph introduces a simple yet exhaustive example of a convex optimisation problem representative of the Linear Programming (LP), supported by author-generated figures (snapshots from an interactive tool) designed to clarify the key concepts necessary for grasping the methodological focus and terminology implied during this research.

3.2.1. Convex Optimisation

The mathematical structure underlying most energy system models can be expressed as a convex optimisation problem. In linear programming, both the objective function and all constraints are linear and, in its simplest form, the problem consists in finding the combination of decision variables $\mathbf{x}$ that minimises a given objective function $f(\mathbf{x})$, subject to a set of linear constraints that define the feasible space of solutions:

$$\begin{aligned} \min_{\mathbf{x}} \quad & f(\mathbf{x}) = \mathbf{c}^\top \mathbf{x} \\ \text{s.t.} \quad & \mathbf{A}\mathbf{x} \leq \mathbf{b}, \\ & \mathbf{x} \geq 0 \end{aligned} \tag{3.1}$$

where $\mathbf{c}$ is the cost vector, $\mathbf{A}$ and $\mathbf{b}$ represent the constraint matrix and boundary vector, and $\mathbf{x}$ is the vector of decision variables (e.g., investments in generation, storage, or flexibility to deploy).

The visualisation in Figure 3.1 provides a three-dimensional representation of this mathematical framework from the interactive tool. The curved surface $f(x_1, x_2)$ represents the objective function through a quadratic convex form, included for illustrative purposes to help the reader intuitively grasp the underlying optimisation concept. The optimal point $\mathbf{x}^*$ (marked in red) corresponds to the lowest point on the surface within the feasible region, where $f(\mathbf{x}^*) = f^*$.

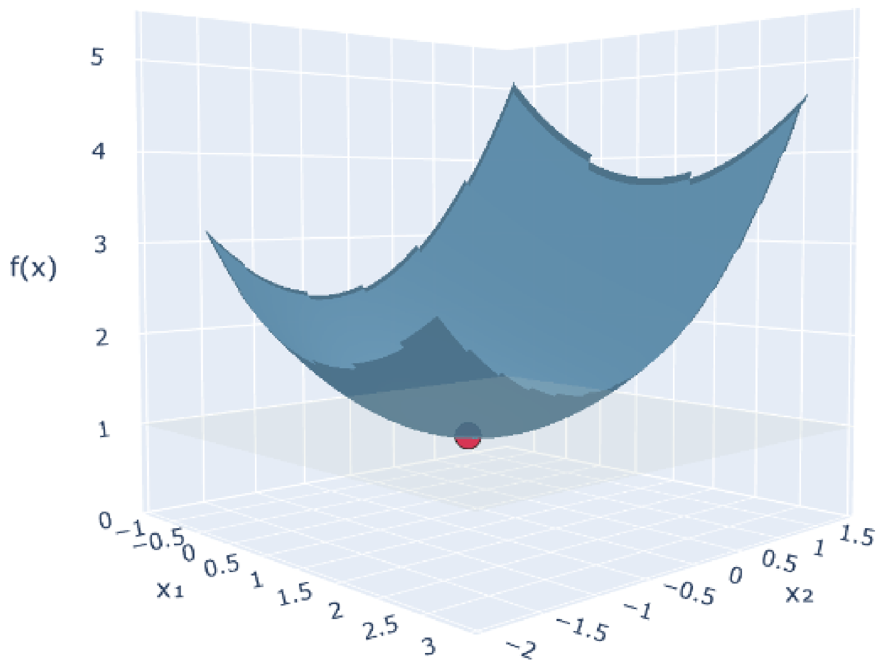


Figure 3.1: Three-dimensional author compiled visualisation of a convex objective function $f(\mathbf{x})$ defined over two decision variables x_1 and x_2 with $\varepsilon = 0$. The surface represents the feasible search space of the optimisation problem, while the red point indicates the global minimum.

To explore alternative combinations that lead to nearly optimal outcomes, the concept of *near-optimal feasible space* is introduced. By relaxing the optimality condition through a small tolerance ε, the near-optimal region can be defined as:

$$\mathcal{X}_\varepsilon = \{\mathbf{x} \in \mathcal{X}_{\text{feas}} \mid f(\mathbf{x}) \leq (1+\varepsilon) f^*\} \tag{3.2}$$

This set contains all feasible solutions whose objective value lies within a fraction ε above the optimal cost. In the following graph, the optimal surface due to a shift in the ε is displayed. As ε increases, the plane moves upward, expanding the near-optimal feasible region (coloured). The illustration adopts a quadratic convex function for clarity.

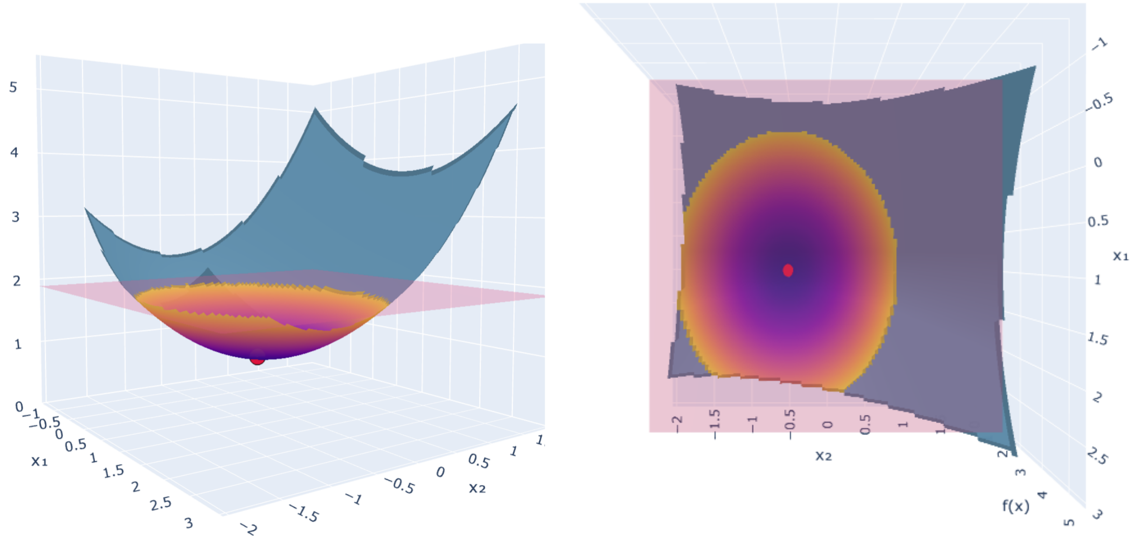


Figure 3.2: Representation of the near-optimal feasible region. The left panel shows the objective function $f(x)$ as a convex surface, with the red point indicating the global optimum. The coloured layer below the paraboloid represents all feasible solutions whose objective value lies within the tolerance $(1 + \varepsilon)f^*$. The right panel provides the top view of the same surface, showing how the near-optimal region expands as the tolerance ε increases when compared to Figure 3.1. Note that the convex paraboloid shown here is used for visualisation purposes.

Such representation is particularly useful as it allows to visualise the near-optimal area, where configurations of technologies may achieve almost identical costs with the optimal one but lead to distinct spatial distributions. The screenshots above were taken from an interactive environment developed by the author, where adjusting the value of ε dynamically with a slider, shifts the near-optimal region, visually illustrating how the feasible area expands as the tolerance increases. This research stretches the boundaries of the optimal area to find different sets of near-optimal alternatives representative of systematic different flexibility distributions.

Flexibility in Calliope

In Calliope [24], the decision on how much flexibility capacity to install and where to locate it is formulated as part of a linear programming problem. The model introduces a set of decision variables that represent the desired system behaviours under defined requirements (constraints).

In Calliope, flexibility emerges as an outcome of the optimisation process, determined through the model's space of the decision variables. The framework defines variables such as flow_cap (installed capacity) and flow_in/flow_out (dispatch levels) for each technology, node, and energy carrier. The objective function minimises total system costs, including investment, operational, and penalty terms for unmet demand or curtailed supply. Flexibility is therefore allocated only where it contributes to lowering the system's overall cost while maintaining feasibility under all operational constraints.

3.3. MGA with HSJ and SPORES

From the methodological point of view, this research project implements modelling to generate alternatives (MGA) through the SPORES algorithm developed by authors in [19], simply, a different way to generate those alternatives. First instances of the MGA techniques appeared back in the 80's as a result of a common acknowledgement that "structural uncertainty in optimisation models will always exist" [3]. Therefore, early developers of MGA started broadening the inspection of the results, leading to a "..realisation that all models are highly simplified versions of reality, and that feasible, near-optimal solutions returned by optimisation models are likely to be as useful as the optimal result" [3].

Theoretically, MGA begins from the optimal solution and systematically investigates neighbouring feasible configurations. Instead of searching the entire solution space, it deliberately restricts, iterations after iterations, the exploration to a controlled area close to the optimum. Therefore, alternative system designs that achieve nearly equivalent performance are identified.

Practically, it adopts Hop, Skip, and Jump algorithm (HSJ) as the structural basis behind the conceptual implementation of MGA [10]. The mathematical structure and notation presented are derived from the original formulation by Brill et al. [10], whose HSJ method represented the structural procedure to implement the newly developed MGA concept. The interpretation, however, aligned with this project's focus on exploring flexibility within near-optimal decision spaces and it will help the reader to understand the novelties proposed by the SPORES algorithm used in this research [19].

Hop , Skip and Jump

Within the early literature on MGA, the HSJ approach [10] offers a mechanism to produce solutions that are both good and deliberately, different from a given optimum.

Let X be the feasible set defined by the constraints, and let $f_j(x)$ denote the objective function. HSJ stems from the optimal solution $x^{(0)}$, by searching for alternatives that satisfy requirements, fostering a swift in the decision pattern.

Let's define $K = \{k : \; x_k^{(0)} > 0\}$, as the set of all the decision variables that are nonzero in the optimal configuration. HSJ then introduces and solves the minimisation of the sum of all the non-zero decision variables in K. Those variables are part of the optimal solution. Respectively, HSJ solves:

$$\min_{x \in X} \; p(x) = \sum_{k \in K} x_k \quad \text{s.t.} \quad f_j(x) \leq T_j \;\; \forall j, \tag{3.3}$$

where T_j are target bounds (e.g., $T_{\text{cost}} = (1+\varepsilon)\, f_{\text{cost}}(x^{(0)})$ for some tolerance $\varepsilon > 0$). The objective of (3.3) penalises the reuse of variables active in the optimal configuration (K), steering the optimisation towards a feasible solution that satisfies the target bounds (T_j) while differing in its composition. In straightforward terms, if k points to node–technology capacity choices, minimising $\sum_{k \in K} x_k$ discourages re-using the same set of choices and promotes alternative spatial deployments. The process reported on the right of Picture 3.3, points to intuitively explain how HSJ iteratively identify and updates the penalty weights in the optimisation runs.

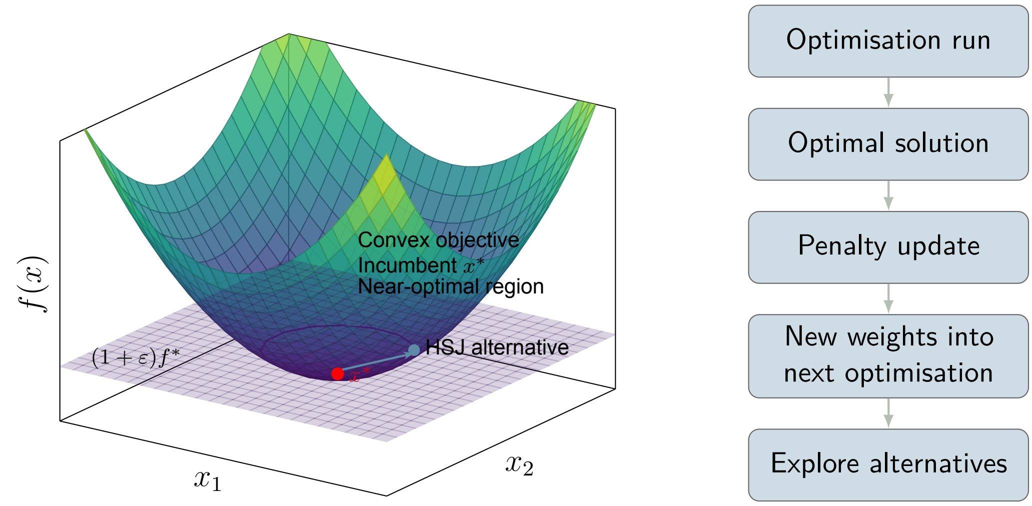


Figure 3.3: On the left, HSJ schematic on a convex objective. The red point marks the optimum x^*. The feasible plane at $(1+\varepsilon)f^*$ bounds the near-optimal set. HSJ seeks a feasible point that remains under this cost target while differing from x^* in its decision pattern; here, a representative alternative (blue) lies on the near-optimal "ring," fostering a move away (motioned by minimising the set of variables at the optimum) from the single solution towards the near-optimality. The right panel outlines the iterative process of assigning penalties and exploring less-penalised alternatives. Together, they represent the conceptual foundation of the HSJ method.

In the context of this work, the iterative search aims to identify and diversify feasible system configurations on how flexibility appears across near-optimal regions of the solution space. By relaxing the narrow 'dominance' of the cost-optimal solution, the logic allows flex technologies to appear where they add systemic overall value and support beyond the global optimum. The resulting set of solutions thus serves as a structured investigation of near-optimal flexibility deployments.

SPORES

The spores method extends the HSJ principle introducing two main differentiations. First, a different treatment of penalties and, the introduction of multiple-direction investigation techniques to better explore the near optimal space [16]. Compared to the HSJ method, rather than directly minimise the sum of active decision variables (X set in the former example), SPORES introduces a new penalty classification to account for the more spatially distributed options (geographically diversified) that evolve iteratively after each optimisation run. In addition, it allows the iteration process to start, or better, to run by anchoring [16] to near-optimal points located far from the cost optimal, which near optimal region would otherwise remain unexplored. These alternatives, previously hard to reach with traditional methods, now become new optimisation centres. SPORES was introduced by authors in 2020

[19] driven by the intention to incorporate spatial reasoning rather than focusing solely on costs. The supporting mathematical definitions introduced in [19] and further recalled in [16] and [14] are here reported to support the methodological framework adopted in this thesis to generate the spatial deployments of flexible assets while answering RQ2.

The following overview helps interpret the assigned and updated spatial penalty weights to generate near-optimal and spatially differentiated solutions. The guiding common logic seeks to penalise what has already been used, so that the next sub-optimisation problem is pushed towards different decision spaces that were 'underused' (see Figure 3.4). Finding the optimal solution reveals, for example, the installed capacity $x_{\mathrm{cap}}(i,j)$ for each technology i at location j (e.g. a battery at node j). For each pair, the algorithm assigns a positive penalty weight $w_{ij}^{(n)}$ (see equation 3.4), which increases as the technology has already been used extensively in that location. It is therefore summed with the weight from the previous iteration $w_{ij}^{(n-1)}$. Here $x_{\mathrm{cap},ij}^{(n)}$ is the capacity chosen at iteration n, and $x_{\mathrm{cap},ij}^{\max}$ is the maximum potential at that site. The update rule in Equation 3.4 implies that the penalty weight increases proportionally to the capacity already deployed. This mechanism can be summarised as follows: **large deployment $\Rightarrow$ larger increment of the weight $\Rightarrow$ stronger future penalty at next iteration.**

$$w_{ij}^{(n)} = w_{ij}^{(n-1)} + \frac{x_{\mathrm{cap},ij}^{(n)}}{x_{\mathrm{cap},ij}^{\max}} \tag{3.4}$$

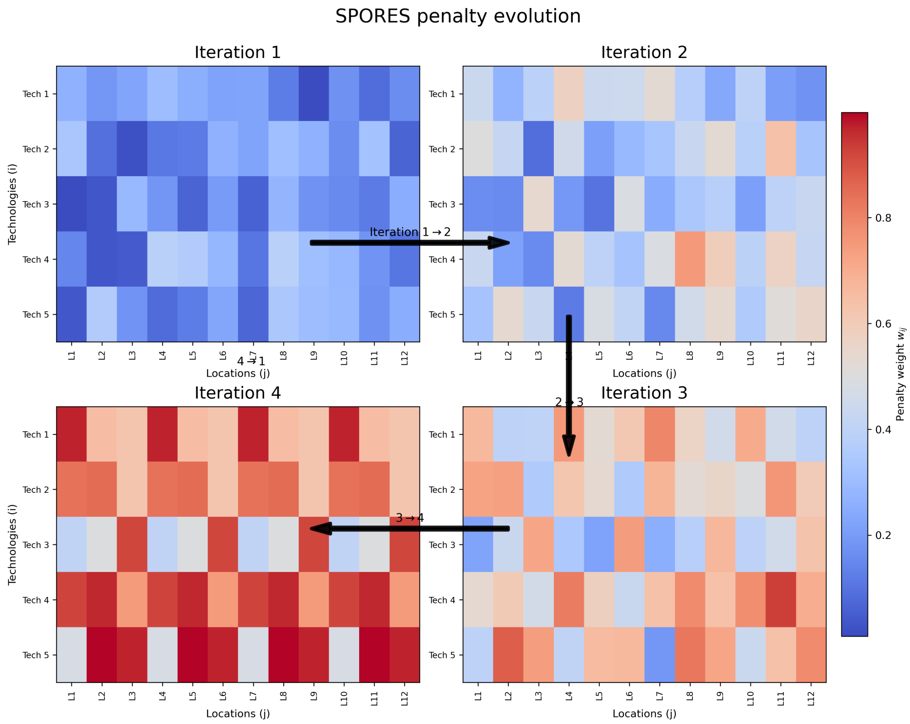


Figure 3.4: Spatial penalty weights w_{ij} by technology (i) and location (j) across iterations. Iteration 4 can be seen as a memory of all the prior spatially-distinctive choices.

Figure 3.4 is an author-compiled penalty heatmap based on random entries. It visualises the evolution of spatial weights across four SPORES iterations. Each cell represents a technology–location pair (i, j), with a colour intensity that reflects the penalty accumulated by former steps ($w_{ij}^{(n)}$). Darker cells mean points that, as a result of being largely deployed in previous iterations, are now strongly discouraged approaching the next one. On the contrary, clearer cells indicate less explored sites that, for this reason, remain attractive for future iterations. The algorithm progressively 'learns' in the arrow motion. At the end, the accumulated penalties of iteration 4 can be seen as a memory of all the prior spatially-distinctive choices. Meaning at each iteration $n+1$, SPORES solves the new weighted optimisation problem, so the model prefers less-penalised configurations while keeping total cost within the near-optimal slack s:

$$\begin{aligned} \min_{x} \quad & Y \;=\; \sum_{i,j} w_{ij}^{(n)}\, x_{\text{cap},ij} \\ \text{s.t.} \quad & \text{system constraints } Ax \le b,\; x \ge 0, \\ & \text{total cost } \;\le\; (1+s)\,\text{(least-cost)}, \end{aligned} \tag{3.5}$$

While this offers supporting mathematical understanding, the weighting process used in the SPORES generation relative to this research, attributes random penalties values during the inspection loops. This comes with benefits such as improving the spatial dissimilarity of iterative runs [16]. For instance, instead of incrementally reinforcing over previous penalties, it applies randomise perturbations to the weight assignments procedures at each iteration, defined as:

$$w_{ij}^{(n)} = w_{ij}^{(n-1)} + r_{ij}, \quad \text{with } r_{ij} = U(0, 100) \tag{3.6}$$

At each iteration, small random changes are added to the weights of each technology–location pair, pushing the model to explore new areas of the solution space . This helps generate a wider and more spatially distinct set of near-optimal designs.

In its general mathematical form, the SPORES - MGA problem can be expressed as:

$$\min Y = a \cdot \sum_{j} \sum_{i} w_{ij} x_{ij}^{\text{cap}} \;\pm\; b \cdot \sum_{j} x_{ij}^{\text{cap}} \quad \text{s.t.} \quad \begin{cases} \text{cost}_n \le (1+s)\,\text{cost}_0 \\ Ax \le b,\; x \ge 0 \end{cases} \tag{3.7}$$

Here, i and j represent the technology and location indices, respectively; x_{ij}^{cap} is the capacity decision variable for each technology–location pair. Coefficients a and b weight the two explicit objectives. The first term applies spatial and technological penalties through the weights w_{ij}, discouraging the repeated use of previously locations and promoting spatial distinctiveness between consecutive runs. This corresponds to the "spatial and technological distinctiveness" stage **a.** in Figure 3.5, where the algorithm explicitly diversifies siting patterns while remaining within the near-optimal cost range.

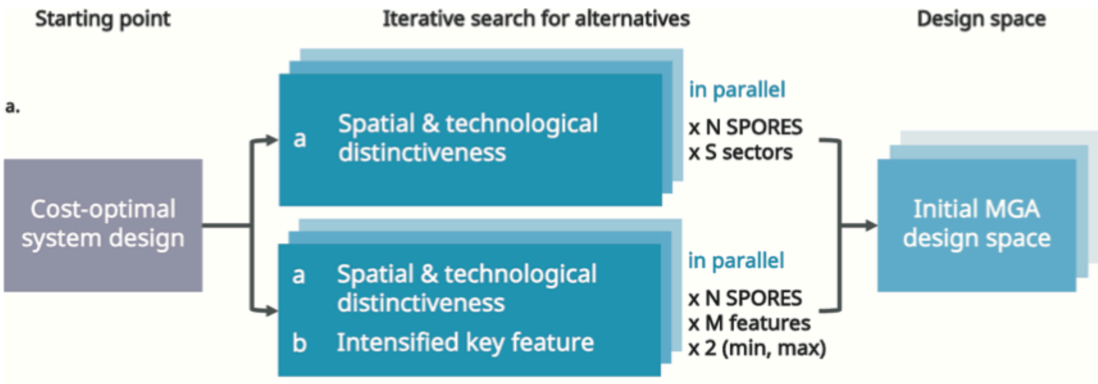


Figure 3.5: Stylised representation of the SPORES algorithm, in its standard formulation. Retrieved from [14]

The second term introduces an intensification factor, controlled by the $\pm b$ parameter. This component defines the so-called "intensified key feature" batches (**b.**), which focus the optimisation on increasing or decreasing the deployment of a specific technology. These intensifications pushes the system's response and map different regions of the feasible decision space. For $b > 0$, the model minimises the share of the selected technology, while for $b < 0$, it maximises it. When $b = 0$, the formulation reduces to a single-objective search driven only by spatial diversity [14].

Parallel search batches

The model futures four main flexible technologies for optimal and near optimal capacity allocations: Battery Storage, Large Battery Storage, Power to Hydrogen and Hydrogen to Power.

In this research the SPORES framework has been applied to perform a parallel search for near-optimal alternatives by executing independent optimisation batches anchored to different regions of the feasible decision space [19]. Each batch defines a distinct direction of exploration by modifying the weighting structure or introducing secondary objectives linked to the deployment of specific flexibility technologies (see point **b** of Figure3.5). This parallel configuration allows simultaneous searches across several system designs, each targeting a unique technological configuration within the same near-optimal cost region.

In this study, eleven parallel batches are implemented (see Table 3.6 for reference), each representing a different search direction. The baseline runs include the `net_model` and `mode_define` configurations, which generate the initial cost-optimal and the firsts near-optimal set of alternatives without technology-specific intensifications (only the cost slack). The following batches are designed to explore alternative system configurations by either maximising or minimising the capacity of specific flexibility technologies. These include:

- `bat_flow_max` and `bat_flow_min` for large storage,
- `bat_system_max` and `bat_system_min` for battery storage,

- gas2power_max and gas2power_min for hydrogen to power, and
- p2h2_max and p2h2_min for power to hydrogren.

Each of these batches produces eleven SPORES alternatives, obtained through successive iterations of the weighting procedure. Together, they form a parallel exploration of the near-optimal solution space, where each run investigates a distinct combination of technology intensifications and spatial penalties. Two additional batches, h2_integer and h2_random, are introduced to test different penalty assignment methods for hydrogen-related flexibility. The integer method applies a deterministic threshold-based weight increment [16], assigning a fixed value (e.g., 100) to technologies whose deployment exceeds a minimum capacity threshold; this approach generates four SPORES alternatives.

Table 3.6: Overview of SPORES batches, scoring methods, and corresponding numeric distinction.

Batch name	Scoring method	SPORES per batch	Spores .. to ..
net_model	Cost-optimal	-	0
mode_define	Random	11	1-11
bat_flow_max	Random	11	12-22
bat_flow_min	Random	11	23-33
bat_system_max	Random	11	34-44
bat_system_min	Random	11	45-55
gas2power_max	Random	11	56-66
gas2power_min	Random	11	67-77
p2h2_max	Random	11	78-88
p2h2_min	Random	11	89-99
h2_integer	Integer	4	100-103
h2_random	Random	11	104-114
Tot. SPORES	—	**114**	**115**

Across all batches, the model produces a total of 114 independent SPORES runs, all computed in parallel under a consistent cost-slack constraint of 10% the nominal cost optimal value. Accounting for the cost-optimal solution the model prints 115 systematic different ways to distribute the flexible supporting technologies.

SPORES scenarios

Considering the SPORES framework is not part of the built-in Calliope functionalities, this model uses an external script developed by the supervisory team, together along with costume maths and scenarios. The GitHub repository can be found in [13]. The structure of this framework is governed by three main components: the spores.yaml configuration file, the spores_algorithm.py functions, and a series of Python batch scripts, each dedicated to a specific technology and direction of intensification as decipted in Table 3.6. The spores.yaml file defines the scenarios and parameter sets used in the optimisation runs. Each scenario specifies how the model should intensify, meaning whether a given technology is to be favoured or penalised in the subsequent iteration.

The mathematics core is implemented in spores_algorithm.py, where the function run_spores() automates the generation of near-optimal runs. For each iteration, it computes a new cost-weight structure and applies the corresponding scoring method (either integer or random), according to the scenario definition. The updated penalty weights are then passed to the next optimisation run, building a chain of iterative steps that progressively results in a diversification of alternatives. Each near-optimal batch (listed in Table 3.6) is then executed through an independent Python script. Each script retrieves the model structure, defined scenarios, and spores parameters, and calls the functions through:

```
spores_results, spores_scores, backend = run_spores(...)
```

Each call produces one SPORE (a single near-optimal systematic different system design) which is saved in easily accessible CSV format. Multiple consecutive runs form a batch sequence of SPORES per technology scenario. A total of 11 SPORES batches were executed. For each flexibility technology, two distinct sub-series were defined, each implementing higher or lower deployment through positive or negative intensification factors, see Table 3.6. The intensification factor $(\pm b)$ (see Figure3.5) defines the direction of preference in the penalty update. As mentioned above, $+b$ penalises the corresponding technology, leading to lower deployment in the next iteration while, $-b$ promotes the same technology, leading to higher deployment in the next iteration.

3.4. Interface

Authors in [15] emphasises that the true tangible value of MGA lies not only in generating diverse near-optimal alternatives but in presenting them through interactive environments that allow experts, stakeholders and developers to interpret, compare, and explore model outcomes. Translating this idea into practice, the former interface developed by the author's supervisor was redesigned to tailored needs due to the new model larger scope, therefore: improve interpretation, responsiveness (refreshing rates) and exploration. It is indeed worth noticing that all the model results are available with one click in a single collective environment that is not locked to the model but to its output files. Reproducibility, new time windows, new techs, different supply and demands patterns fostering different outcomes could therefore easily be represented by the same environment indeed under different scenarios.

Practically, the interactive dashboard was developed using Plotly Dash, a Python framework for building web-based analytical applications. The interface backend files consists of two main modules: `load_interface.py` manages data loading, user interactions , and callbacks (updating visuals depending on input system preferences), while `plotting_utils.py` handles all the visualisation logic from the files reading. A useful methodological choice was to implement dynamic capacity filtering in the presence analysis through sliders; users can select the portion of interest (e.g. flexible technologies with capacity >200MW) and therefore explore the new-adapted solution space, gaining different (more tailored) conclusions. Instantly all linked visualisations updates. In addition, provincial aggregation (stemming from coordinates approximations) can help to reveal regional technology preferences.

3.4.1. Design: Near-optimal Designs

Each element in the Near optimal design page is introduced to allow direct exploration of the flexibility results obtained by the Calliope runs in the DelftBlue supercomputer. It consists of the technology filters, the normalised capacity deployment scatterplot, the geographical network map, and the dispatch and capacity ranking panels. The dispatch at node graph is particularly valuable to inspect the transmission synergies with the neighbouring sub-stations.

Select Spore The first page opens with a dropdown menu that allows users to select specific SPORE configurations of interest. This feature supports targeted inspection of individual near-optimal alternatives. For reference, Table 3.6 lists all SPORE batches and their corresponding scoring methods, helping users identify which SPOREs originate from different parallel search directions.

Technology Filter and SPORES selection panel The filter panel allows users to interactively select the deployment range of each flexibility technology through normalised capacity sliders. Adjusting these sliders dynamically filters the solutions shown in the Normalised Capacity Deployment plot. Each point in the scatterplot represents a SPORE alternative, and only those whose deployment of a selected technology falls within the chosen range remain visible. This enables the user to isolate specific capacity thresholds and visually identify how different near-optimal solutions distribute technologies across the system.

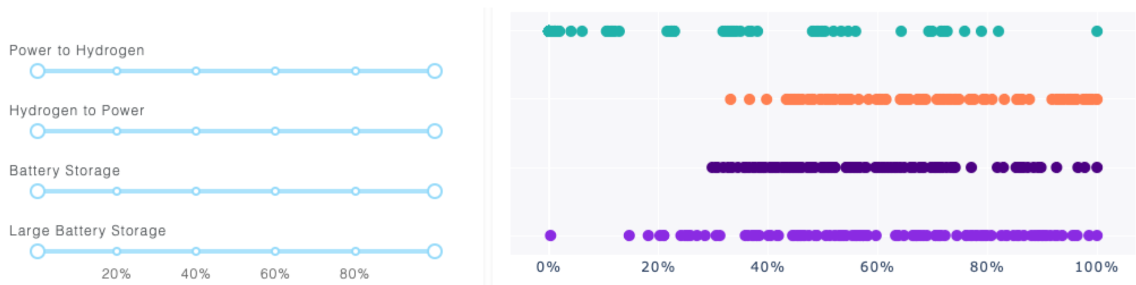


Figure 3.6: Interactive filtering and normalised capacity deployment visualisation. The sliders on the left allow users to filter SPORE alternatives based on the normalised deployment level of each flexibility technology. The scatterplot on the right updates dynamically, displaying only the SPORES whose installed capacity for the selected technologies falls within the chosen range.

Network Map The network map builds from the topology previously introduced in Figure 2.4a and adds sizing bubbles as well as different colours to assess , at geographical node level, how the optimal and the different near-optimal portfolios of flexible capacities are distributed. Upon filtering, it also displays the exogenous supply dispatch at the national tissue.

Dispatch This graph illustrates the 6-hourly balance of generation and consumption across all nodes for a selected SPORE. Each coloured layer represents the flow contribution of a specific technology, while the black line denotes total load demand. The graph updates dynamically with each SPORE selection also accounting for variations between neighbouring substations.

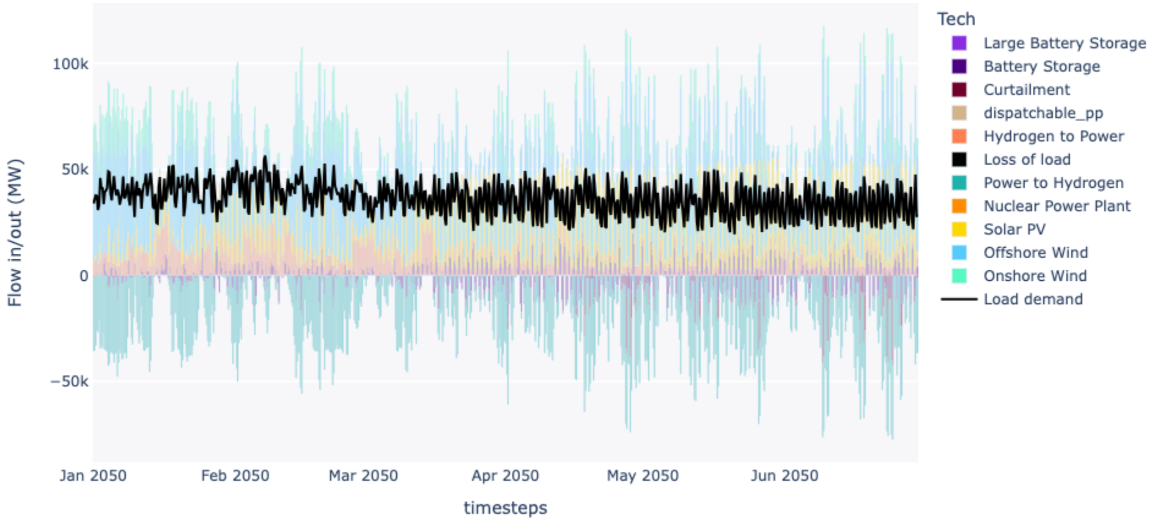


Figure 3.7: Dispatch view for power carrier across all nodes. Each coloured area corresponds to a technology's hourly flow contribution, while the black curve represents total load demand. The plot updates with each SPORE selection, allowing comparison of dispatch patterns and flow interactions between adjacent substations.

Capacity deployment The capacity chart ranks the substations according to their installed flexibility capacity for the selected SPORE. Each bar is divided by technology, showing the relative contribution of each flexible technology. The graph dynamically updates with every SPORE selection, as well as the Top 20, 50, 100, or all the nodes.

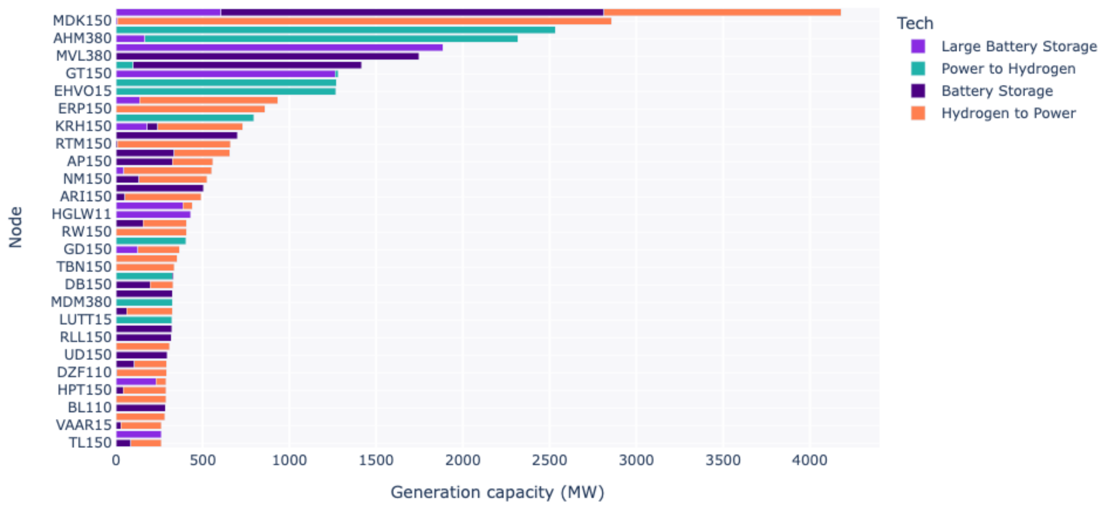


Figure 3.8: Flexible capacity deployment for the top 50 substations in the selected SPORE.

3.4.2. Design: No-regrets Alternatives

This subsection first introduces the presence analysis to formalise the mathematical foundations behind the visual outputs. It then presents the design of the second section of the interactive platform, where no-regret alternatives are explored through dynamic graphical representations.

Presence Analysis

The 'no-regret' analysis on the second page of the interactive platform is motivated by the quantification of how often each flexibility technology appears at a specific node across the entire near-optimal set of configurations (cost-optimal plus 114 near-optimal alternatives). This kind of newly-introduced presence analysis represents a valuable outcome that can be derived from an MGA adoption to traditional optimisation problems. Starting from the vast number of alternative configurations, this methodology effectively points at the most feasible options coming from different search strategies. This could help planners or developers to identify what pushes the model (supply, network, weather or maybe cost drivers) towards 'more recurrent' choices. This could also help, depending on system input interests, to identify which technology appears to be the most suitable. A node–technology appearances matrix is therefore specifically introduced see Figure 3.11. Its rows represent network nodes and columns represent flexibility technologies while the values in each cell are the percentage of appearances of the four fixed technologies per node per tech per entire set of solutions.

This methodology is not part of standard practice but was specifically developed by the author in response to the distinctive nature of the results due to their novelty and particularly, quantities. It well aligns to the ongoing evolution of the MGA framework itself, which calls for new methods to interpret complex (and many) solution spaces.

Practically, the method considers the set of near-optimal designs S, nodes N, and technologies T. For each design, node and tech (s, n, t), a binary (1, 0) indicator is assigned according to whether the installed capacity flow_cap(s, n, t) is deployed. Therefore, this defines the presence condition as:

$$\text{present}(s, n, t) = \begin{cases} 1, & \text{if flow\_cap}(s, n, t) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{3.8}$$

The frequency of presence for each node–technology pair (n, t) is then calculated as the proportion of near-optimal configurations (spores) in which the technology is active, expressed as a percentage:

$$\text{presence\_pct}(n, t) = \frac{\sum_{s \in S} \text{present}(s, n, t)}{N_S} \times 100 \tag{3.9}$$

where N_S represents the total number of spores under consideration for the given selection.

The output is new dataset that can be reshaped into a node–technology appearances matrix, where each row corresponds to a network node and each column to a flexibility technology. The resulting values, ranging from 0 to 100, indicate how frequently each technology is installed across all near-optimal configurations. A value of 100% indicates that a technology is always present at that node and in each of the many configurations, while 0% implies that it never appears in any of the scenarios analysed.

It came in handy to introduce a means of these frequency presences to assess how structurally suitable (ready) each substation is for hosting flexibility assets. It measures how 'favourable' a substation is, according to the many systematically different near-optimal portfolios. Defined as 'infrastructure readiness index - IRI, it measures the average presence frequency of flexibility technologies at each node:

$$\text{IRI}(n) = \frac{1}{|T|} \sum_{t \in T} \text{presence\_pct}(n, t) \tag{3.10}$$

where $|T|$ is the number of flexibility technologies considered. The IRI expresses the overall maturity of a node's willingness to install a flexibility supportive infrastructure. Nodes with high IRI can be seen as robust investment locations, as they consistently accommodate flex resources.

Equation 3.11 illustrates a representative snippet of the frequency matrix. In there, each cell expresses how often a given flexibility option is installed. The last row reports the corresponding Infrastructure Resilience Index (IRI), obtained as the average of each column.

$$\text{Presence} = \begin{bmatrix} 85.0 & 42.0 & 91.7 & 77.8 \\ 100.0 & 65.0 & 94.2 & 88.3 \\ 74.0 & 30.0 & 82.1 & 66.0 \\ 58.3 & 0.0 & 71.2 & 55.8 \\ 90.5 & 48.1 & 86.7 & 79.3 \\ 66.7 & 10.0 & 60.3 & 45.0 \end{bmatrix} \tag{3.11}$$

Example of node–technology frequency matrix. Each row corresponds to a network node (e.g. EHO380, MDM380, VSG150, ZBM150, BRW110, OM150) and each column to a flexibility technology. Values represent the percentage of alternatives in which each technology is active.

No-regret Alternatives

The no regret investment page offers decisional support with the post interpretation of the results. It applies a systematic point of view and creates insights considering the cost optimal and the near optimal solutions as a whole. The displayed figures are built upon the mathematical concepts of the presence matrix introduced above, where the percentage of appearances of the four fixed technologies across the entire node-level dataset is found. Frequencies, presences, confidence, and regional analysis all stem from how many times, in the 115 optimal and near-optimal configurations, a specific technology appears at the determined node. For instance, how many times at node X is an electrolyser deployed in the 115 systematic different designs? By acknowledging the potential of these insights, a variety of supporting visual materials offering different interpretations has been built to directly address RQ3 presented in Section 1.3.

Presence threshold (MW) All the no regret analytical tools presented below are interconnected through the presence threshold slider, which defines the minimum installed capacity considered in the analysis. It allows dynamic filtering and it updates all the subsequent visualisations according to the selected threshold value. The default setting (0 MW) displays the full range of flexibility deployments across the near optimal solution space. However, by increasing the threshold, only nodes with installed capacities exceeding the selected minimum are shown. This introduces another practical layer of results exploration.

Figure 3.9: Presence threshold slider controlling the minimum capacity included in all no regret analysis tools.

Frequency of appearance -heatmap At first it is depicted a visual representation of the presence matrix through the deployment of a heatmap. Colour intensities trace the most robust node-technologies pairs while accounting for the entire dataset on a scale from 0 to 100% , meaning that technology is present in that node above the entire solution space ... % of the times. Each column, therefore, stands for the flexible technology, while rows account for the 271 active nodes. Zoomed-in windows of the heatmap allow for increasing the visual detail of the nodes and analysing the deployment at the node level. In Figure 3.11, nodes showing darker shades across the four technologies can be interpreted as more robust in terms of flexibility presence. Additionally, by pointing over each cell, the user can also visualise the exact share of a specific technology at a given node; Node, Technology and Presence values are therefore displayed while pointing at each cell.

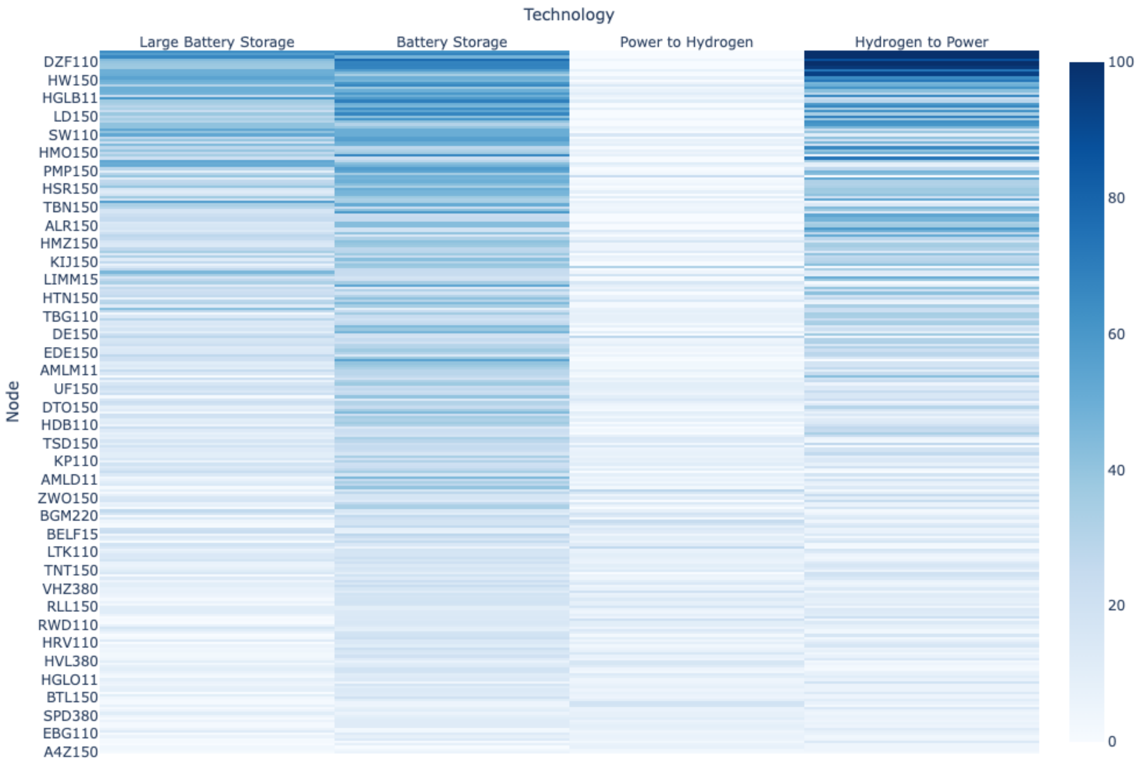


Figure 3.10: Heat map displaying the frequency of appearance with gradient colours

Investment readiness index As introduced above, the infrastructure readiness index (IRI) measures the average presence frequency of flexibility technologies at each node. The following graph is its representation. Higher values identify nodes that consistently emerge considering he four flexible technologies as favourable locations.

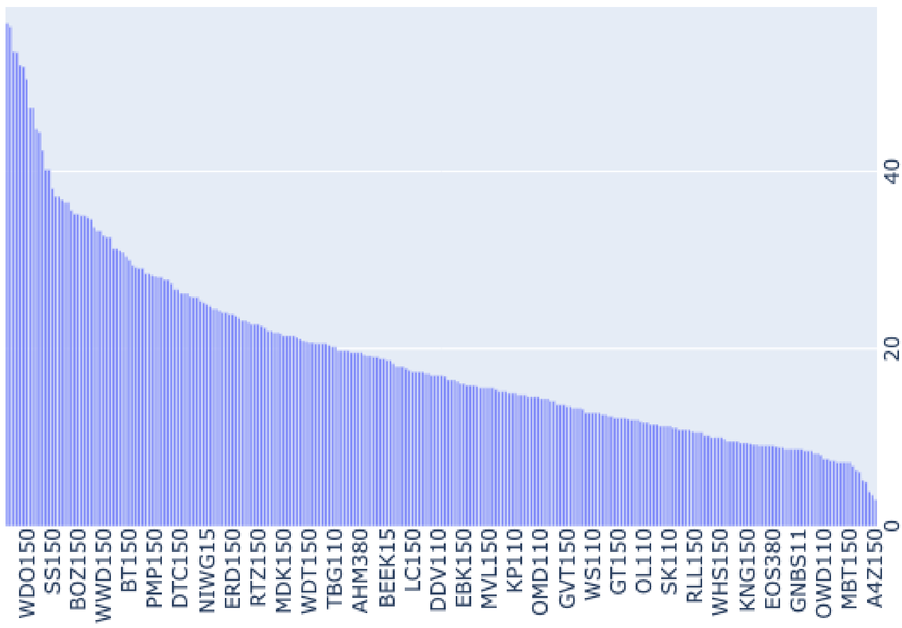


Figure 3.11: Average presence frequency of flexibility technologies at each node

Presence intensity map In Figure 3.12 the overall SPORES generated per node per tech, translate onto the national tissue. The bubble size stands for larger values of the presence matrix; the legend reports average bubble sizes related to three level of appearances percentages. There, the parameters from the presence matrix are traced back to their coordinates and the national layout is used again not anymore to display the capacity but rather their presence scores. The diameter of the nodes helps to grasp their relevance, larger markers represents more recurrent installations across the near optimal solution space. This no regret supporting tool is particularly valuable from a system perspective, it indeed identifies regional clusters and allows for narrowing the flexibility potential to provinces that therefore will need greater attention.

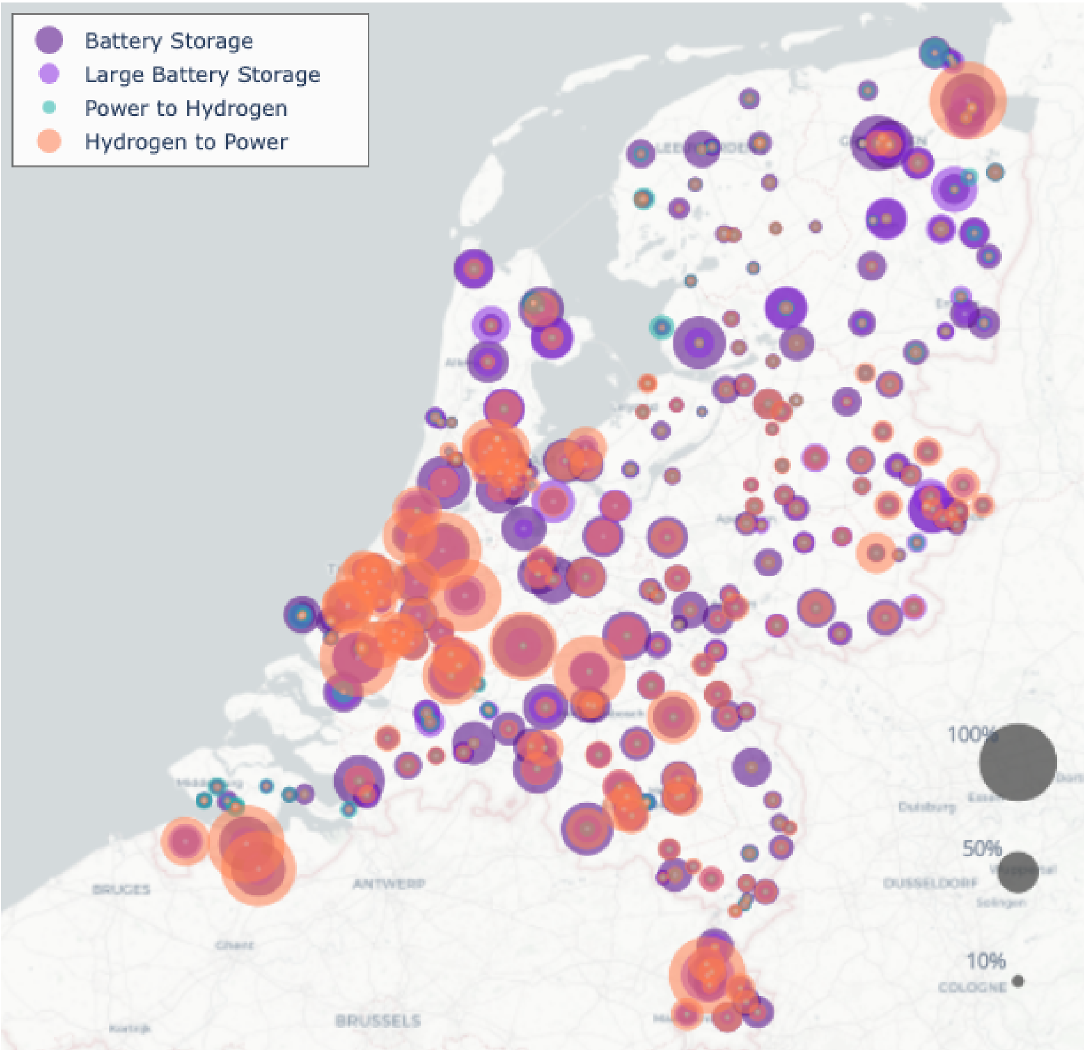


Figure 3.12: Spatial frequency of flexibility technology deployment across all near-optimal solutions. Marker size represents the frequency of appearance per technology, as derived from the presence matrix. Legend helps the reader to grasp their meaning.

Confidence distribution This classification in the no regret page distributes the 271 active nodes between three confidence groups. No-Regret (technologies appearing in more than 90% of feasible solutions), Robust (50–90%), and Considerable (below 50%). Each bar represents the number of nodes where a given technology falls within a specific confidence level. Systematic conclusion will be drawn later in the text. Figure 3.13 reports a representation for reader's reference.

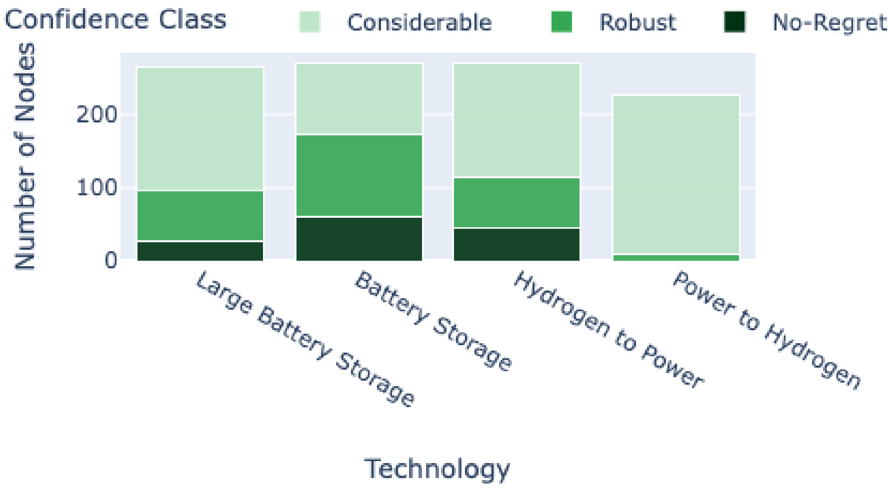


Figure 3.13: Distribution of confidence classes by technology across all near-optimal solutions. No- Regret (technologies appearing in more than 90% of feasible solutions),Robust (50–90%), and Considerable (below 50%).

Regional deployment mix Lastly, the focus narrowed down from the national perspective to reach the regional level. Therefore, geographical boundaries were introduced at the coordinates level to both filter the spatial deployment and the presence of the configurations in the cost optimal and near optimal spaces. Resulting in a flexibility distribution between the 12 Dutch provinces. A portion of the tool is shown in Figure 3.14.

PROVINCIAL TECHNOLOGY PRESENCE OVERVIEW

Average presence frequency of flexibility technologies aggregated by province

PROVINCE	NODES	BATTERY	LARGE BATTERY	P2H2	H2P	AVG PRESENCE
Zuid-Holland	42	37.1%	26.9%	4.3%	**42.5%**	**27.7%**
Flevoland	8	**32.2%**	26.9%	3.1%	31.3%	**23.4%**
Noord-Brabant	43	**31.8%**	19.2%	7.5%	25.1%	**20.9%**
Zeeland	11	24.4%	16.0%	11.9%	**26.3%**	**19.7%**
Groningen	17	**31.3%**	22.4%	10.3%	14.4%	**19.6%**
Gelderland	17	**30.4%**	17.3%	7.1%	22.3%	**19.3%**

Figure 3.14: Provincial average presence frequency of flexibility technologies across near-optimal solutions

4 Results

4.1. Dataset and Model (RQ1)

This section reports the outputs of the data preparation and adjustment process needed to enable the building of the high-resolution energy system model used in this research project. The resulting network topology (in terms of network maps and dataset), as well as the processed demand and supply profiles, represent the outcomes of this first phase. Together, they allow to draw the spatially detailed foundation upon which the flexibility solutions explored in the subsequent sections are built.

4.1.1. Grid Infrastructure Data

The newly obtained PowerNetDataset represents the Dutch high-voltage transmission network, comprising 283 transmission stations, 359 transmission lines, and 27 different voltage-level interconnections (transformation points). This comprehensive dataset forms the backbone of the new optimisation model. It therefore represents the network as it stands, together with the infrastructure currently being built. The transmission network operates at four distinct voltage levels: 110 kV and 150 kV, classified as High Voltage, and 220 kV and 380 kV, classified as Extra-High Voltage. The 283 stations in the dataset are categorised into three functional groups based on their state and functionalities:

The 283 stations in the dataset are classified into four categories:

1. **Active - 271 stations**: Fully operational nodes that participate in the optimisation model with both generation and demand data.
2. **Under construction - 10 stations)**: a subset of the active group. Even though not present yet, these stations are modelled with full capabilities to reflect their expected role in future demand and supply forecasts towards 2050. They consist of 5 new 150 kV and 5 new 380 kV installations, all planned to be operated by TenneT.

3. **Transformation - 51 stations**: substations that enable interconnection between different voltage levels, ensuring the flow of power across the 110, 150, 220, and 380 kV layers of the grid. Of these, 42 are active, while 9 serve purely as transformers, highlighting the need to be identified and included.
4. **Connector - 12 stations)**: stations with no active participation that serve as purely structural connectors in the dataset. They are included to preserve network topology but are excluded from optimisation.

Table 4.1 presents the distribution of stations by voltage level and characteristic.

Table 4.1: Distribution of Transmission Stations by Voltage Level and Characteristics

Characteristic	110 kV	150 kV	220 kV	380 kV	Total
Active Stations	79	171	3	18	271
Under Construction	0	5	0	5	10
Transformation Stations	9	15	8	19	51
Connector Stations	2	0	6	4	12
Total Stations	**81**	**171**	**9**	**22**	**283**

The distribution shows a concentration of stations at the 150 kV level (171 stations, 60.4%), which forms the backbone of the regional transmission network. The 110 kV level (81 stations, 28.6%) serves as the interface with distribution networks, while the 380 kV level (22 stations, 7.8%) provides the extra-high voltage backbone for long-distance transmission. The 220 kV level, with only 9 stations (3.2%), is mainly utilised for long-distance electricity transmission in the north-eastern region of the Netherlands

Table 4.2 presents a snippet of the entire dataset, reporting geographical coordinates and operational characteristics. The colours distinguish between categories:

- Red indicates stations under construction (UC, all also active).
- Green indicates transformation stations (T), i.e. substations enabling exchanges between different voltage levels.
- Blue indicates connector stations (C), i.e. non-active stations that preserve the network topology without participating in optimisation.

Table 4.2: New PowerNet Transmission Stations Dataset (283 stations)
Active (A) – 271 ; Under Construction (UC, subset of A) – 10 ; Transformation Stations (T) – 51 ; Connector Stations (C, non-active) – 12

Station ID	Code	Longitude (°E)	Latitude (°N)	Voltage (kV)	Operator	Flags
b001	AMLM11	6.630	52.357	110	Enexis	A
b002	MSKZ11	7.031	52.914	110	Enexis	A
b003	RWD110	5.744	53.104	110	Liander	A
b004	SKS110	5.774	53.196	110	Liander	A

Continued on next page

Table 4.2 – continued from previous page

Station ID	Code	Longitude	Latitude	Voltage	Operator	Flags
b005	MEE110	6.946	53.124	110	Enexis	A+T
...	...	...	...	...	...	...
b254	HSW220	6.188	52.532	220	–	T
b255	MDN220	6.946	53.124	220	–	T
...	...	...	...	...	...	...
b264	HCL110	6.110	52.470	110	–	C
b265	LSM110	5.874	53.190	110	–	C
b268	A10380	5.016	52.338	380	TenneT	A+UC
b269	A4Z150	4.876	52.429	150	TenneT	A+UC
b270	AGP150	5.069	52.775	150	TenneT	A+UC
b271	AHM380	4.014	51.952	380	TenneT	A+UC
b272	HVL380	3.591	51.450	380	TenneT	A+UC
b273	KRH150	5.798	50.971	150	TenneT	A+UC
b274	POM380	4.567	51.689	380	TenneT	A+UC
b275	SLD150	4.823	52.393	150	TenneT	A+UC
b276	SPD380	4.678	52.473	380	TenneT	A+UC
b277	WSP150	5.030	52.305	150	TenneT	A+UC

Grid Operator Distribution

The Dutch transmission network involves multiple grid operators with distinct operational responsibilities. TenneT, as the national Transmission System Operator (TSO), manages the high-voltage backbone, while Distribution System Operators (DSOs), which Stedin is part of, handle regional networks. Table 4.3 shows the distribution of stations by operator, however, each DSO station typically corresponds to a paired TSO substation at the same interface node, standing for the physical connection point where electricity is transferred from the transmission to the distribution network (all the DSO stations also have a TSO counterpart).

Table 4.3: Station distribution by grid operator. The listed DSO stations represent the primary connection points to the transmission network managed by TenneT. Each DSO station typically corresponds to a paired TSO substation at the same interface node, where electricity is handed over from the transmission to the distribution network

Grid Operator	Type	Number of Stations
Enexis	DSO	112
Liander	DSO	76
Stedin	DSO	44
TenneT	TSO	47
WestlandInfra	Regional DSO	2
Tbd	–	2
Total		**283**

Transmission

The physical connections between stations are represented by 359 transmission lines spanning a total of 5,048 kilometres. These lines operate at the same four voltage levels as the stations they connect; voltage consistency within each network segment is therefore checked. Table 4.4 summarizes the transmission line characteristics by voltage level.

Table 4.4: Total number of transmission lines by voltage level

Voltage Level	Number of Lines
380 kV	87
220 kV	42
150 kV	98
110 kV	132
Total	**359**

The 380 kV lines form the backbone of the transmission system, characterised by longer average distances as they connect major generation centers with load hubs. In contrast, the 110 kV lines serve more localised distribution functions, resulting in shorter average lengths. The complete line dataset, including origin-destination pairs and exact distances, is available in the supplementary materials.

Voltage Interconnections

Critical to the multi-voltage network operation are 27 transformation bridges that enable power flow between different voltage levels. These interconnections, detailed in Table 4.5, primarily consist of transformer stations with minimal geographic separation between voltage terminals within the same substation complex. The average separation distance of 0.128 km reflects the typical spacing within transformer stations as well as the accuracy of this new dataset. For modelling purposes, the transformer stations have been represented as virtual transmission links without losses, enabling unrestricted power transfer between different zones (virtual cables).

Table 4.6 provides a comprehensive overview of the new PowerNetDataset characteristics. This dataset is a significant advancement over previously available materials, providing researchers with a complete and validated representation of the Dutch transmission network suitable for further studies. If used properly, it will prove useful as a foundation for future analyses and contribute to a better understanding of the challenges to then create new opportunities in the Dutch power system.

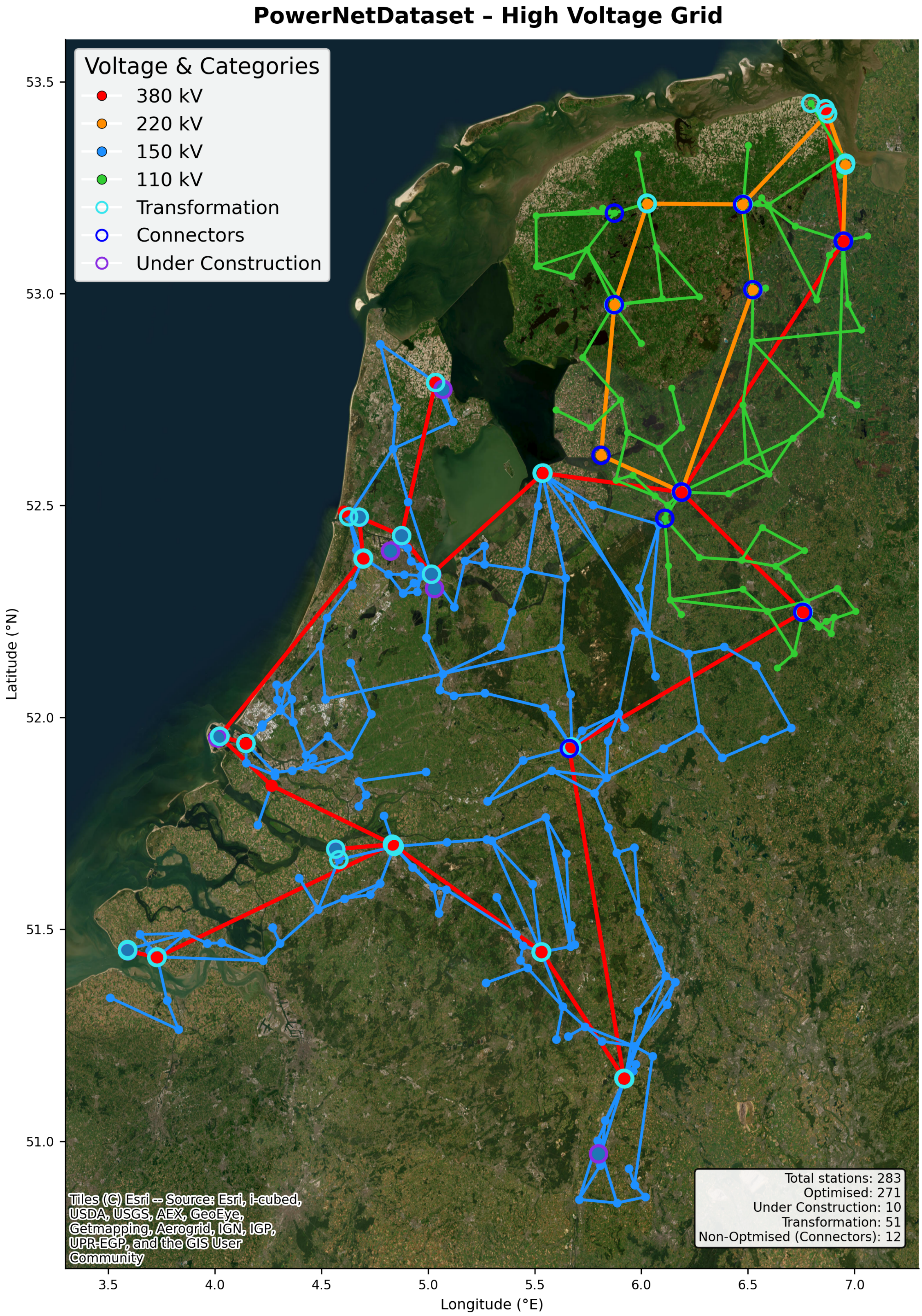


Figure 4.1: PowerNet representation of the Dutch high voltage transmission network. The map shows 283 stations interconnected by 359 transmission lines across four voltage levels: 380 kV (red), 220 kV (orange), 150 kV (blue), and 110 kV (green). Stations with connector function are highlighted with green borders, while stations under construction are marked with red borders.

Table 4.5: Voltage Level Interconnections and Transformer Stations

Station A	kV	Station B	kV	Distance (km)	Type
MDM150	150	MDM380	380	0.000	Transformer
MEE110	110	MDN220	220	0.025	Transformer
MDN220	220	MDN380	380	0.179	Transformer
DIM150	150	A10380	380	0.026	Transformer
OZN380	380	A4Z150	150	0.045	Transformer
ERP150	150	ERP380	380	0.052	Transformer
ZYV220	220	ZYV110	110	0.084	Transformer
MVL150	150	MVL380	380	0.125	Transformer
HSW220	220	ZWO380	380	0.135	Transformer
ZLH110	110	HSW220	220	0.136	Transformer
EHVO15	150	EHO380	380	0.177	Transformer
BSL150	150	BSL380	380	0.184	Transformer
BGM110	110	BGM220	220	0.184	Transformer
OHK110	110	ODH220	220	0.187	Transformer
HGLO11	110	HGL380	380	0.207	Transformer
VVL110	110	VVL220	220	0.236	Transformer
LLS150	150	LLS380	380	0.270	Transformer
MBT150	150	MBT380	380	0.292	Transformer
VSG150	150	HVL380	380	0.303	Transformer
VHZ150	150	VHZ380	380	0.304	Transformer
DZW110	110	WEW220	220	0.496	Transformer
GT150	150	GT380	380	0.829	Transformer
DOD150	150	DOD380	380	0.918	Transformer
RBB220	220	EOS380	380	1.517	Transformer
EHM110	110	RBB220	220	2.020	Transformer
MDK150	150	POM380	380	2.942	Transformer
VLN150	150	SPD380	380	3.000	Transformer

4.1.2. Model Build

In line with RQ1, this subsection describes how the required data were organised to construct a model capable of supporting energy planning decisions at high spatial resolution. Here, the above-mentioned set of information was used to create the model's core component files. Together, they cover node and technology definitions, connections within different voltage levels, supporting import material and both the power and hydrogen transmission networks. This process resulted in a fully functional optimisation model, readable by Calliope, and thus designed to address the remaining research questions. The model architecture leverages YAML (a human-friendly data serialisation standard for all programming languages [25]) format files, chosen for their compatibility with the Calliope optimisation tool.

The developed Calliope model relies on a structured set of interconnected configuration files. Figure 4.2 defines the model used in this research. Here, each YAML

Table 4.6: Poweret summary

Network Component	Count
Stations	
Total	283
Active	271
Under Construction (still Active)	10
Connector Stations (non-active)	12
Transformation points	
Transformation	51
Infrastructure	
Transmission lines	359
Total network length	5,048 km
Voltage level interconnections	27
Voltage Levels	
380 kV	22 stations
220 kV	9 stations
150 kV	171 stations
110 kV	81 stations

file describes a specific component of the system and is linked through a central `model.yaml` file, which manages the overall configuration, calls the mathematical solver, and specifies the optimisation time window. However, each file serves a different purpose within the model architecture.

To execute the model, Calliope [25] must be properly installed and configured. The framework requires Python (version 3.10–3.12), several scientific libraries such as Pyomo, Pandas, and Xarray, and a compatible optimisation solver such as CBC, GLPK, Gurobi, and CPLEX. In this research, the environment was managed through Conda and the Gurobi solver, properly tweaked following resolution requirements. The following paragraphs investigate these specific files, reflecting the assumptions carried out to build them.

```
model_files
├── model.yaml
├── nodes.yaml
├── techs.yaml
├── connection.yaml
├── imports.yaml
├── transmission.yaml
├── transmission_h2.ya
├── scenarios
│   └── spores.yaml
└── timeseries
```

Figure 4.2: Structure of the model_files directory.

Model.yaml

The model.yaml file performs several core functions: it imports all files, configures the temporal and operational settings, and specifies the solver and model parameters for the optimisation algorithm.

```
import:
```

```
  - "techs.yaml"            # Technology definitions and costs
  - "nodes.yaml"            # 283 substations with constraints
  - "transmission.yaml"     # Power line connections
  - "transmission_h2.yaml"  # Hydrogen network topology
  - "connection.yaml"       # Voltage level bridges
  - "imports.yaml"          # Temporal data (demand/supply)
  - "scenarios/spores.yaml" # SPORE scenario definitions
```

Time resolution of the optimisation is defined as follows:

```
config:
  init:
    name: Flexibility Model
    calliope_version: 0.7.0
    time_subset: ["2050-01-01", "2050-06-30"]
    time_resample: 6h
```

It operates in plan mode, meaning it optimises capacity investments and operational dispatch jointly.

```
build:
  ensure_feasibility: true  # Enables unmet demand slack variable
  mode: plan                # Joint investment-operation optimisation
```

The ensure feasibility introduces slack variables (auxiliary constraints) for unmet demand, with the goal to avoid infeasibilities. It makes unmet demand extremely expensive, so the optimiser will only leave some demand unsupplied if it's truly impossible to meet it otherwise. Solver parameters were tuned for computational stability and efficiency.

```
solve:
  solver: gurobi
  zero_threshold: 1e-10
  solver_options:
    DualReductions: 0
    Presolve: 0
    Threads: 6
    Method: 2
    Crossover: 0
    FeasibilityTol: 1e-3
    OptimalityTol: 1e-4
    BarConvTol: 1e-4
```

Total system costs are minimised through a unified monetary objective function. By doing so, all cost components are aggregated into a single monetary metric.

```
parameters:
  objective_cost_weights:
    data: 1
    index: monetary
    dims: costs
```

Nodes.yaml

The nodes.yaml file translates the substations in the dataset into the nodes of the model. It defines the technologies available at each node, and any node constraints. It uses a useful calliope setting, such as, a set of reusable templates to avoid duplication during definition.

It came in handy to define three distinctive templates: standard_node_techs, used for fully operational nodes; pass_through_node_techs, applied to connector substations (not part of the optimisation); and h2_hub_techs, used for the hydrogen hub. Templates are referenced by each node through the key template.

```
templates:
  standard_node_techs:
    techs: {export_h2, lost_load, dispatchable_pp, hydro_ror,
   power_plant_nuclear, solar_pv, wind_offshore, wind_onshore,
   battery_flow, battery_system, power_2_h2, gas_2_power, curtailment,
   demand_power}

  pass_through_node_techs:
    techs: {}

  h2_hub_techs:
    techs: {storage_h2, export_h2, import_h2}
```

The hydrogen hub acts as the central point for storage and hydrogen flow exchange.

```
nodes:
  h2_hub:
    longitude: 5.5
    latitude: 52.3
    station_code: H2HUB
    template: "h2_hub_techs"
    techs:
      storage_h2:
        flow_cap_per_storage_cap_max: 0.001
        storage_cap_max: 43300000
        storage_loss: 0.001
      export_h2:
        flow_cap_max: 50000
      import_h2:
        flow_cap_max: 50000
```

Each node entry contains geographical coordinates, a station identifier, a reference template, and specific technology constraints.
When flow_cap_max = flow_cap_min, the capacity at that node is fixed rather than optimised, meaning the model treats it as non investment parameter (fixed). The following structure repeats across the 283 substations in the dataset, each with its respective parameters.

```
nodes:
```

```
WD0150:  "# Westdorpe 150kV"
  longitude: 3.82931993
  latitude: 51.26374943
  station_code: WD0150
  voltage level: 150
  template: "standard_node_techs"
  techs:
    solar_pv:
      flow_cap_max: 887.74
      flow_cap_min: 887.74
    wind_onshore:
      flow_cap_max: 127.44
      flow_cap_min: 127.44
```

Techs.yaml

This section reports the flexible technologies and the h2 stream supporting components used in the optimisation. Generation (supply) technologies are defined with their costs and parameters as well, but are not reported here, as they do not participate in optimisation (treated as given). Fixing a capacity at a node is done in nodes.yaml for the relevant technology; the model then treats that capacity as given rather than an investment decision.

Both battery variants are modelled as storage technologies (carrier_in=carrier_out) with round-trip efficiency, depth-of-discharge and losses; capacity costs are applied to the energy component. Power to Hydrogen and Hydrogen to Power are conversion units (different carriers in/out). More specifics are reported in the following code snippets. As mentioned in detail in section 3.1.3, tech and costs estimates come from the Danish Energy Agency Catalogue.

```
battery_flow:                       # Vanadium Redox Battery - DEA2040
  name: "Battery Flow"
  base_tech: storage
  carrier_in: power
  carrier_out: power
  template: interest_rate_setter
  lifetime: 35                          # [years]
  flow_out_eff: 0.91                    # discharge efficiency
  flow_in_eff: 0.91                     # charge efficiency
  flow_cap_per_storage_cap_max: 0.08    # 12.5h autonomy
  storage_discharge_depth: 0.11         # 89% usable capacity
  storage_loss: 0.0000625               # [1% per hour]
  cost_storage_cap:
    data: 390.30                        # kEUR per MWh (CAPEX)
  cost_om_annual:
    data: 2.92                          # kEUR per MW per year (O&M)

battery_system:                     # Lithium-ion Battery - DEA2040
  name: "Battery System"
  base_tech: storage
```

```
    carrier_in: power
    carrier_out: power
    color: "#4B0082"
    template: interest_rate_setter
    lifetime: 30                         # [years]
    flow_out_eff: 0.985                  # discharge efficiency
    flow_in_eff: 0.975                   # charge efficiency
    flow_cap_per_storage_cap_max: 0.25   #  4h autonomy
    storage_discharge_depth: 0.11        # 89% usable capacity
    storage_loss: 0.0000417              # [per hour]
    cost_storage_cap:
      data: 299.16                       # kEUR per MWh (CAPEX)
    cost_om_annual:
      data: 8.67                         # kEUR per MW per year (O&M)

power_2_h2:                          # AEC 100 MW Electrolyser - DEA2040
    name: "Power to  H"
    base_tech: conversion
    carrier_in: power
    carrier_out: hydrogen
    template: interest_rate_setter
    lifetime: 25                         # [years]
    flow_out_eff: 0.653
    cost_flow_cap:
      data: 425.00                       # kEUR per MW (CAPEX)
    cost_om_annual_investment_fraction:
      data: 0.04                         # % of investment per year (O&M)

  gas_2_power:                       # Hydrogen Turbine - DEA 2040
    name: "Gas to Power"
    base_tech: conversion
    carrier_in: hydrogen
    carrier_out: power
    template: interest_rate_setter
    lifetime: 25                         # [years]
    flow_out_eff: 0.57                   # hydrogen → power efficiency
    flow_ramping: 0.8                    # operational flexibility
    cost_flow_cap:
      data: 904.78                       # kEUR per MW (CAPEX)
    cost_om_annual:
      data: 3.34                         # kEUR per MW per year (O&M)
```

The import_h2 technology allows the model to request hydrogen from external systems whenever it is convenient to do so. Hydrogen storage creates a national sink that balances hydrogen supply and demand internally across all substations.

```
  import_h2:
    name: "Hydrogen Import"
    base_tech: supply
    carrier_out: hydrogen
```

```
    flow_cap_max: inf
    cost_flow_in:
      data: 0.231 # keuro /MWh

  export_h2:
    name: "Export  H"
    base_tech: demand
    carrier_in: hydrogen
    resource_use_max: 20000
    cost_flow_in:
      data: 0                       # kEUR per MWh

  storage_h2:                       # DEA2040
    name: "Hydrogen Storage"
    base_tech: storage
    carrier_in: hydrogen
    carrier_out: hydrogen
    storage_cap_max: inf
    flow_out_eff: 1                 # DEA Round-trip efficiency
    flow_in_eff: 0.99
    storage_loss: 0.01              # Daily loss rate
    storage_initial: 0.5            # Start at 50%
    lifetime: 30
```

Curtailment and lost load provide "last-resort" flexibility; the latter is purposely heavily penalised.

```
curtailment:
  base_tech: demand
  carrier_in: power
  resource_use_max: 20000

lost_load:
  base_tech: supply
  carrier_out: power
  lifetime: 20
  cost_flow_out: 1e4
```

Transmission.yaml

The transmission.yaml file defines the four voltage connections between substations. Each template specifies the available voltage level, nominal transfer capacity, efficiency, and associated cost per unit of installed capacity and operation. The configuration is based on the Net Transfer Capacity (NTC) principle, which expresses the maximum permissible power exchange between two connected nodes while maintaining grid security.

The NTC for each transmission line is defined as:

$$\text{NTC}_{i,j} = V_{ij} \cdot I_{ij} \cdot \sqrt{3} \cdot \cos\phi \tag{4.1}$$

where V_{ij} is the line-to-line voltage between nodes i and j, I_{ij} is the maximum allowable current, and $\cos\phi$ represents the power factor (typically close to unity for transmission systems). This product determines the upper bound for active power transfer in megawatts. The (n−1) security criterion has also been applied to account for system reliability

The file defines four transmission templates corresponding to the Dutch transmission voltage levels: 380 kV, 220 kV, 150 kV, and 110 kV. Each template specifies the base capacity cost, efficiency, and flow constraints.

```
templates:
  transmission_110kv:
    name: "110 kV AC power transmission"
    base_tech: transmission
    carrier_in: power
    carrier_out: power
    flow_out_eff_per_distance: 0.99995
    lifetime: 60              # years
    flow_cap_min: 94.69       # V_L = 110 kV, I = 710 A, (n-1) -> 0.7
    flow_cap_max: 94.69

  transmission_150kv:
    name: "150 kV AC power transmission"
    base_tech: transmission
    carrier_in: power
    carrier_out: power
    flow_out_eff_per_distance: 0.99995
    lifetime: 60
    flow_cap_min: 145.49      # V_L = 150 kV, I = 800 A, (n-1) -> 0.7
    flow_cap_max: 145.49

  transmission_220kv:
    name: "220 kV AC power transmission"
    base_tech: transmission
    carrier_in: power
    carrier_out: power
    flow_out_eff_per_distance: 0.99995
    lifetime: 60
    flow_cap_min: 699.91      # V_L = 220 kV, I = 2 624 A, (n-1) -> 0.7
    flow_cap_max: 699.91

  transmission_380kv:
    name: "380 kV AC power transmission"
    base_tech: transmission
    carrier_in: power
    carrier_out: power
    flow_out_eff_per_distance: 0.99995
    lifetime: 60
    flow_cap_min: 1188.67     # V_L = 380 kV, I = 2 580 A, (n-1) -> 0.7
    flow_cap_max: 1188.67
```

Each connection between substations uses one of these templates, ensuring consistency in voltage-level modelling and cost assumptions. Each bidirectional link is defined once and automatically replicated in the opposite direction by Calliope. An example connection between two neighbouring substations (Amersfoort–Apeldoorn) is shown below:

```
links:

  AMFA15, APDO15:                    # Amersfoort   Apeldoorn (150 kV)
    template: 150KV_template
    length: 49.2                     # km
    flow_cap_max: 1000               # MW (nominal)
    flow_cap_min: -1000              # bidirectional
```

Transmission_h2.yaml

In the hydrogen configuration, all the 283 substations are connected to the central h2_hub. The model optimally decides which transmission should be operated depending on the willingness to install a relevant conversion technology in the nodes. Transmission links follow a similar topology to the above-reported configuration.

```
templates:
  transmission_h2:
    name: "Hydrogen transmission pipeline"
    base_tech: transmission
    carrier_in: hydrogen
    carrier_out: hydrogen
    color: "#FF00FF"
    flow_out_eff_per_distance: 1
    flow_cap_min: 0
    flow_cap_max: 5000
```

Connectors.yaml

This yaml file serves to establish the links between the four different voltage levels. There, voltage transformation happens in real life, and these points allow the model to relocate deficits or surpluses of power within different topology layers. BY modelling these bridges as virtual_cables with unit efficiency, any bottleneck related to transformation losses is removed.

```
templates:
  virtual_cable:
    base_tech: transmission
    carrier_in: power
    carrier_out: power
    flow_out_eff_per_distance: 1      # zero-loss (distance = 0 km)
    lifetime: 60
```

Connectors.yaml

Finally, the import.yaml attributes at each of the 271 active substations, their relevant post-processed supply files, while also importing the comprehensive national demand.

```
datatables:
  supply_A10380:
    data: timeseries/techs_supply_A10380.csv
    rows: timesteps
    columns: [techs]
    add_dims:
      nodes: [A10380]
      parameters: source_use_equals
```

4.2. Spatial Deployment of Flexible Assets

The interactive platform serves as the environment where all results are visualised. At this point readers are invited to consult Appendix A, which provides screenshots of the interface to help connect the way results are exported. This environment makes cost-optimal, near-optimal and no-regrets results easily available and synchronised within each other. It runs upon Python files and the csvs files stemming from the mga-spores configurations. The csvs files available as the input to the platform come from the outputs of parallel different runs performed by Calliope and the DelftBlue supercomputer. Divided in two main pages, it distributes the results between exploration of the system design and their collective interpretations. Exploration focuses on navigating the range of system designs generated by the SPORES algorithm. It includes cost-optimal and near-optimal solutions, allowing users to select configurations based on specific system interests, explore them geographically, and analyse dispatch and power exchanges at the single node level. Interpretation, on the other hand, provides visual insights from different readings of the presence matrix (see section 3.4) to understand patterns and relationships among technologies across all the scenarios as well as graphical representations. In addition, confidence class analysis is present together along with a regionalisation presence table distribution of flexible dispatches in the twelve Dutch provinces.

This section will report the system findings by naturally using the platform functionalities. The cost-optimal configuration (spore 0) will be presented both in its exploration and interpretation dimensions, drawing overall conclusions on the geographical interdependencies of the optimal solution by analysing spatial patterns and the technological dispatch in relation to local supply conditions.

Cost-optimal configuration (Spore 0)

Table 4.7 reports the capacity outputs of the flexible technologies in the cost-optimal configuration, obtained from the initial model run prior to any near-optimal exploration. This configuration identifies a portfolio composed of four flexibility options and they represents the least cost available portfolio in order to balance the energy system. The national wide installed cost optimal flexible capacity reaches 136 GW, distributed across three of the four available flexible technologies. Power to hydrogen represents the largest share, with 60 GW of electrolysers deployed mainly across northern and coastal regions as well as inner land high-res (highly renewable) points. Hydrogen to power follows with 55 GW, while battery storage accounts for 22 GW. Large battery does not appear in this configuration, as its contribution remains less optimal while accounting for cost minimisation, they are indeed more expensive to deploy when compare to the other electrical storage alternative and offers lower discharge efficiencies. This specific design, lacking of larger storage options, offers a good window from where, benefits of MGA could be of great value to expand the systematic exploration at other near-optimal alternatives.

Technology	Capacity [GW]
● Power to Hydrogen	60.00
● Hydrogen to Power	55.00
● Battery Storage	22.00
● Large Battery Storage	0.00
TOTAL	**137.0**

Table 4.7: Flexible capacity in the cost-optimal configuration (Spore 0).

Figure 4.3 offers a first systematic overview of the optimal decision variables laid on top of the new network topology. The figure represents the spatial allocation of flexibility assets within the high-voltage grid and it represents the base case before any penalty or intensification is introduced; it defines the benchmark compared to which the spores alternatives are generated. In Figure 4.3 each coloured bubble corresponds to a specific technology, while its position is the geographic location of the substation where the asset is dispatched. The bubble size denotes the installed power capacity with size ranges for reading references. Figure 4.3 reveals distinct deployment patterns. For instance, looking at Figure4.4 hydrogen to power capacity is concentrated in the station nodes of the Randstad area in the Netherlands, respectively the Noord Holland, Zuid Holland and Zeeland area. It also appears in the south region of the Limburg province. Therefore, it has a strong recurrent technology deployment in energy intensive regions. Power to hydrogen in Figure **??** appears as well in Zuid Holland, due to the large offshore wind installations (see Figure 4.6c) and, more widely, in Noord Brabant. It is worth noticing that Figure 4.6c displays several large offshore generation nodes positioned inland. This 'counterintuitive' distribution comes from assumptions embedded in the ETM, where offshore wind landing points are not constrained directly immediate to coastline. Instead, they are allocated according to broader research directions about the technical and economic feasibility of long-distance transmission cables. The general idea was indeed to directly serve major industrial centres with abundant offshore wind supply. The model positively aligns with these assumptions, and it coherently incorporate them into its spatial allocation logic. Figure 4.5 clearly matches this logic as hydrogen is largely installed in those landing points (see bubble sizes >1GW). In Figure 4.6 battery units emerge sparsely in the national area but they tend to cluster similarly to p2h2 supporting technologies. The Randstad area is again involved due to its need of supporting technologies to cope with high demand and, interesting peaks also appears in the Eindhoven region consistent with high RES supply deployment as supported in Figure 4.6c and 4.6a as well as the North and North-East Groningen with high shares of wind onshore and consistent solar supply, see Figure 4.6d 4.6a.

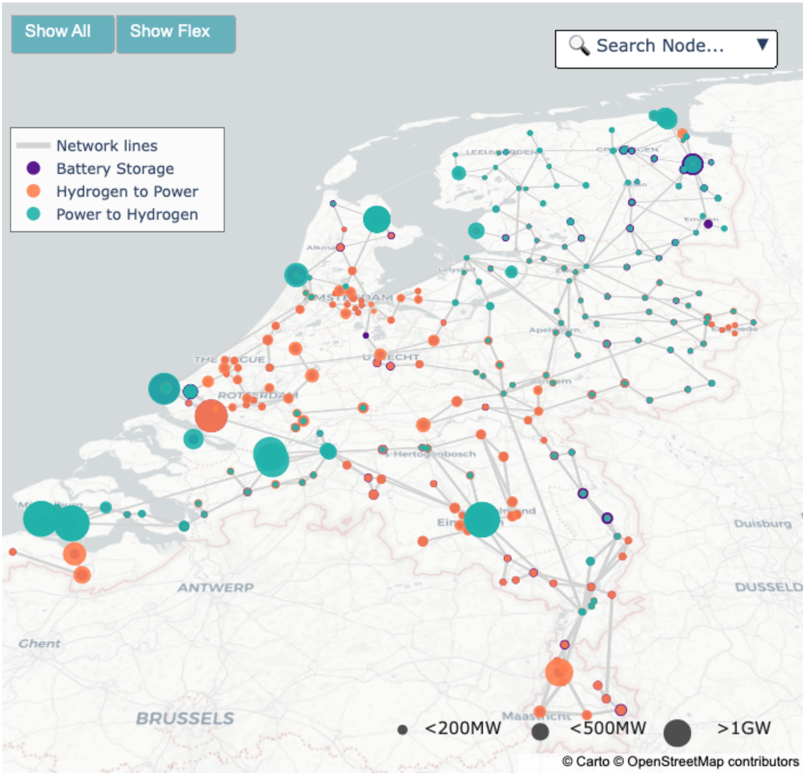


Figure 4.3: Spatial deployment of flexibility technologies in the cost-optimal configuration (Spore 0). Total installed capacity equals 137 GW.

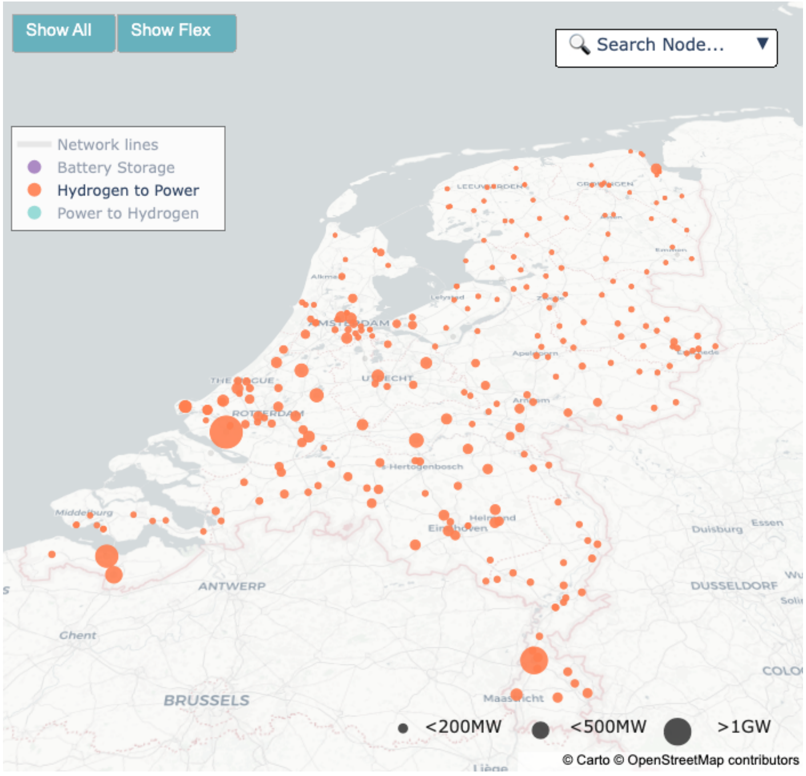


Figure 4.4: Spatial deployment of hydrogen to power in the cost-optimal configuration.

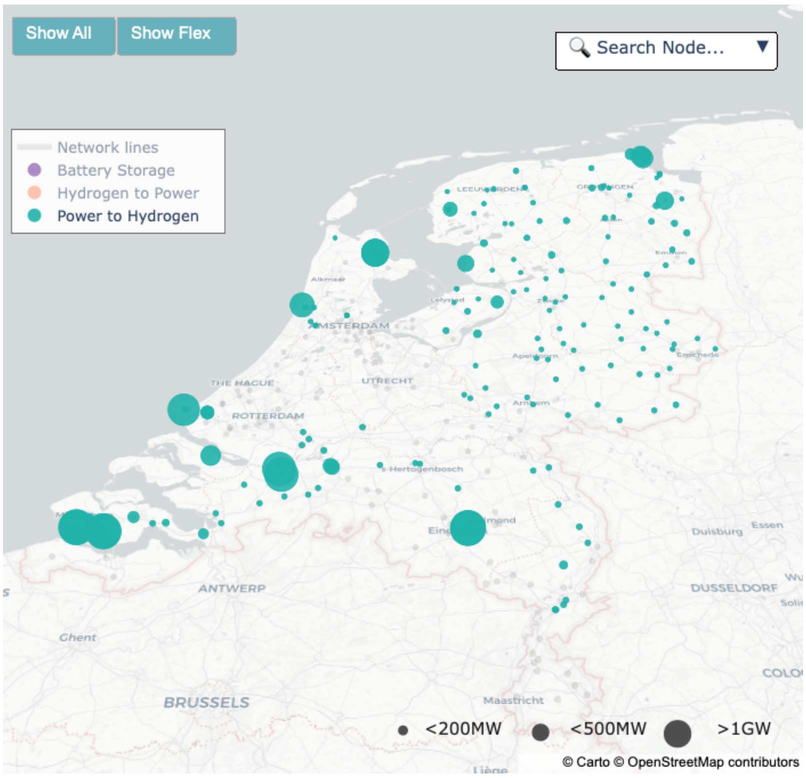


Figure 4.5: Spatial deployment of power to hydrogen in the cost-optimal configuration.

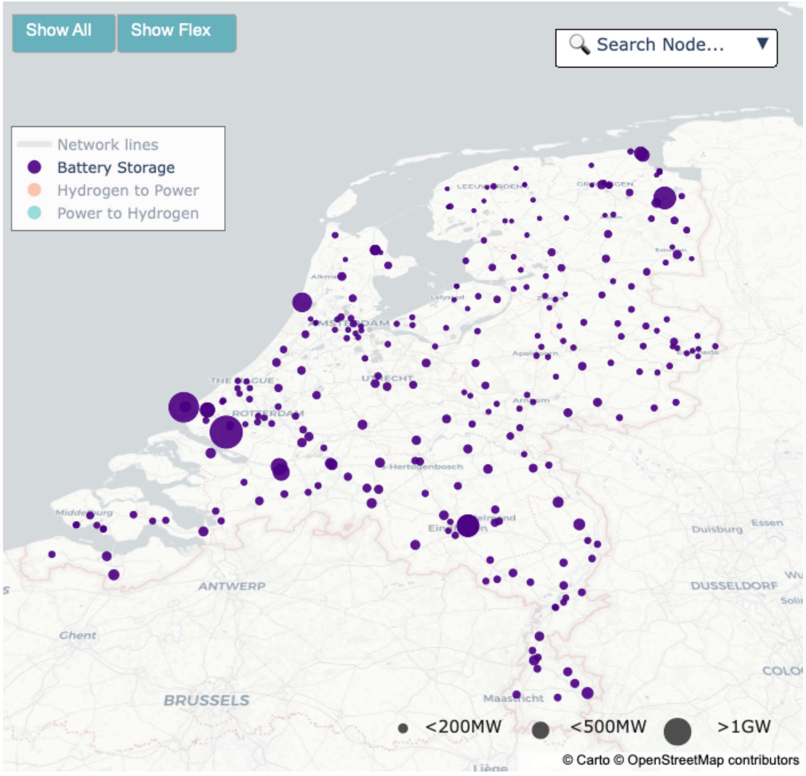
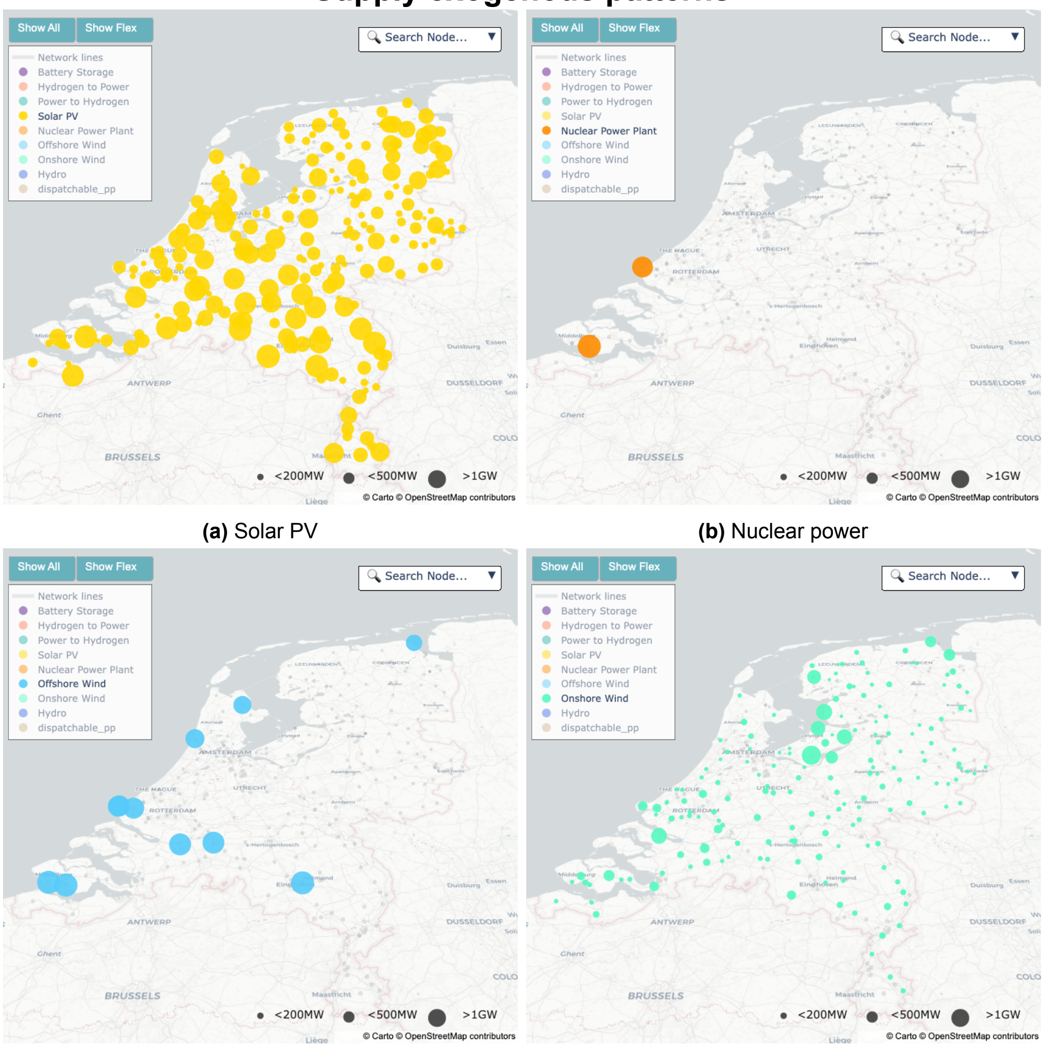


Figure 4.6: Spatial deployment of battery storage in the cost-optimal configuration.

Supply exogenous patterns



(a) Solar PV

(b) Nuclear power

(c) Offshore wind

(d) Onshore wind

Figure 4.7: Spatial distribution of the exogenous supply options used as model inputs

SPORES - II3050

Under the NAT2050 scenario reported in Figure 2.1, the II3050 projects 60 GW of battery storage, 45 GW of Power to Hydrogen, and 20 GW of Hydrogen to Power by 2050. Benefitting from the MGA application in this research, the exploration of the near-optimal space generated through the SPORES algorithm, does not reproduce a single configuration identical to these values but reveals several SPORES with comparable proportions and structural patterns. Table 4.8 lists the ten closest configurations to the II3050. However, it's interesting to consider how the model reshapes flexibility installations while sharing the same supply and demand input values.

Table 4.8: SPORE configurations closest to the II3050 NAT2050 scenario. The table reports the capacities of the main flexibility technologies, their combined battery deployment, and total flexible capacity.

SPORE	P2H2 (GW)	H2P (GW)	Total Batteries (GW)	Total (GW)
1	49.27	51.16	24.38	124.81
2	32.02	50.20	23.34	105.56
3	20.13	36.78	23.69	80.60
34	42.97	52.47	23.39	118.83
45	47.40	53.31	23.63	124.34
89	41.63	52.57	22.60	116.80
90	29.95	50.66	24.87	105.48
91	20.27	42.20	23.01	85.48
100	38.61	50.93	24.93	114.47
101	29.34	51.74	25.14	106.22

The optimisation implied in this research and grounded by the cost estimates presented in Section 3.1.3, to match the P2H2 and H2P shares simulated in the II3050, consistently converges towards systems with lower total battery deployment, see Table 4.8 column total batteries. Indeed previous results projected a more relevant role for batteries while here, there is more reliance on power to hydrogen and hydrogen to power installations. This deviation can be partially explained by the temporal resolution adopted in the model. The six hour timestep directly smooths the short-term fluctuations and it might be generally blind upon the visibility of intra day variability so, limiting the relative advantage of batteries. As a result, the model tends to attribute a larger share of flexibility to hydrogen technologies, which remains better visible.

4.2.1. Near-optimal alternatives RQ2

Each of the previous system analysis could be performed for a total of 115 systematic different flexible portfolios. Indeed, as introduced in Section 3.4.1 the visualisation environment offers the possibility to select a specific SPORES and, all the relevant supporting graphs change accordingly, picturing a different near optimal balanced portfolio representing the desired input configurations. This research fostered a total of 114 different near optimal spores designs, the cost optimal solution counts as the SPORES number 0. The methodology explained in section 3.3 was largely applied and therefore resulted in a wide set of near optimal alternatives. By maximising and minimising the deployment of the selected technologies, the near optimal area was covered and designs that differ in capacity deployments can be investigated, gaining similar in scope but systematically different conclusions.

Figure 4.8 displays the capacity distribution per technology while, Table 4.2.1 report their values. Again, each of these configurations is a different set up and, at the node - dispatch level, capacities are therefore different, and power exchanges within neighbouring nodes follow different patterns as well. This can be seen as the tangible output of the MGA theoretical workflow, it started with the cost optimal and it obtained 114 different solutions.

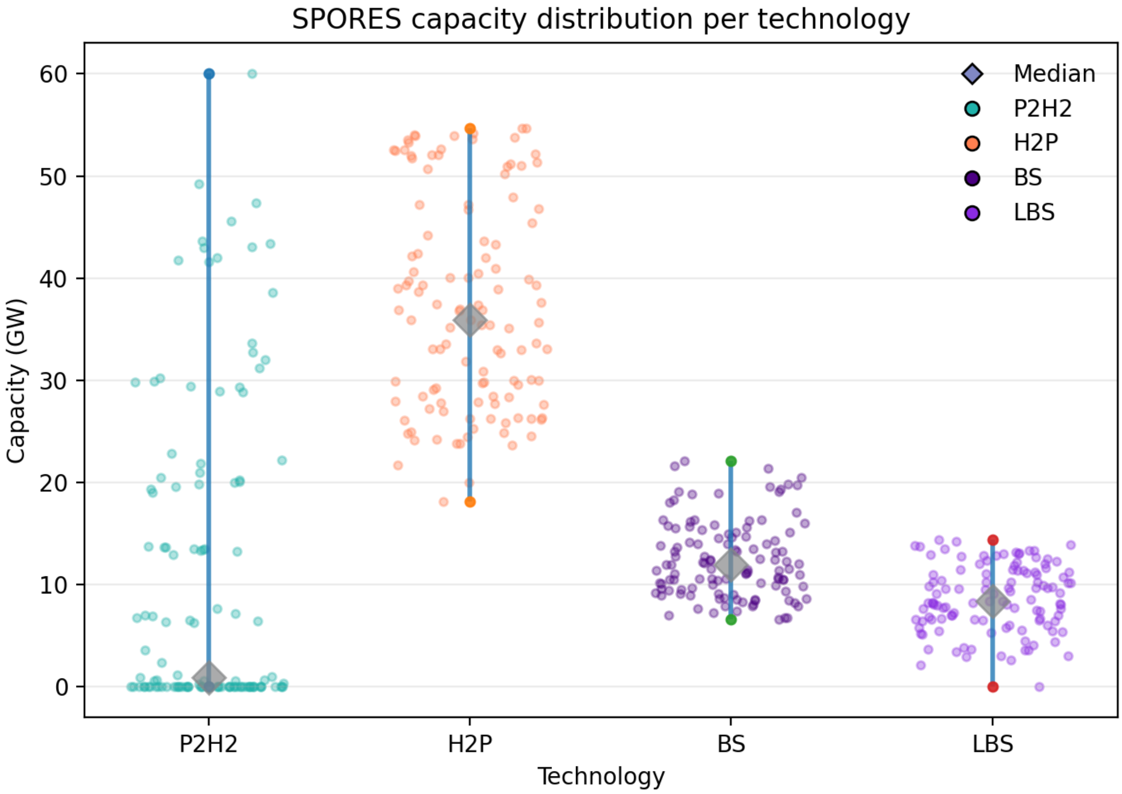


Figure 4.8: Distribution of flexible capacity across all SPORES configurations. Each dot represents a near-optimal solution, vertical lines indicate minimum–maximum ranges, and diamonds mark the median capacity for each technology. Abbreviations: P2H2 (Power to Hydrogen), H2P (Hydrogen to Power), BS (Battery System), LBS (Large Battery Storage)

To avoid unnecessary repetition and maintain readability, the abbreviations introduced in the caption of Figure 4.8 are used throughout the discussion. Figure 4.8 report the solution space with the distributions of the near-optimal points that reveal the boundaries and clustering areas of the deployed technologies. These expanded distributions, positively reveal a coherent and good initial configuration of the SPORES parallel batches presented in Section 3.3, indeed broader areas are covered by P2H2 and H2P while technologies that apparently tends to cluster more, such as BS and LBS, concentrate within narrow and numerically consistent ranges. On one hand, this result can be seen as a stable and recurring contribution of battery storage across many near-optimal settings, with deployment levels that vary little under P2H2 and H2P dispatches. On the other hand, the broader spread of hydrogen-related options shows a higher sensitivity, where their operation and installed capacity fluctuates the most.

In the entire set of solutions, P2H2 has a low median with a long upper cap (see Figure 4.8). Relative close to zero deployment levels of P2H2 push the model to import hydrogen streams to cope with the H2P needs to fulfil demand. The model finds more economic viable to buy it rather than in-house producing. Pointing to lower P2H2 installations, the system designs reported in Table 4.2.1 show that larger shares of battery capacity are dispatched to compensate for its reduced contribution. Approximately 60 SPORES solutions deploys close to zero P2H2 shares, therefore balancing the system with the remaining available H2P and batteries flexible technologies. This trend, which might be less evident in Figure 3.6, becomes clear when cross-referenced with Table 4.2.1.

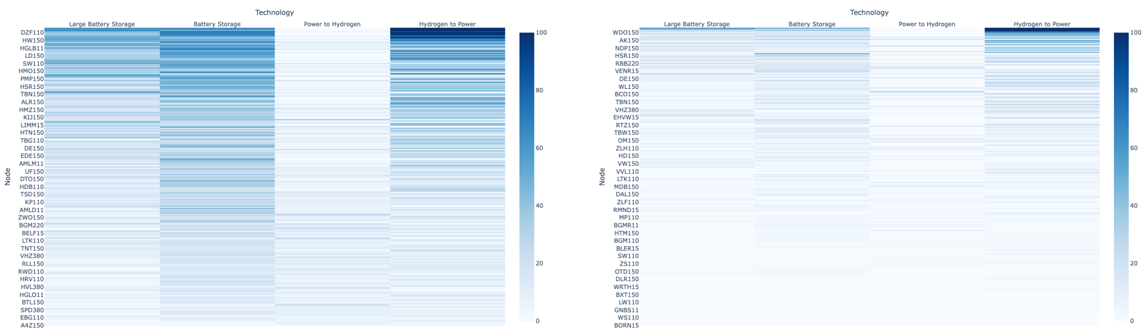
From a stakeholder perspective, this configuration represents a significant policy crossroads: whether to rely on domestic hydrogen production or to import it from external suppliers. Producing hydrogen locally could improve national energy autonomy but it would require substantial infrastructure. In the Netherlands, land availability is a recurrent topic and its limited spatial availability might push developers to lean towards different options. From the SPORES analysis, appear that importing hydrogen may reduce spatial pressure but, it would reinforce the dependency on external energy markets and long-distance transport routes. In both cases, the outcome deductible by the MGA implementation to the case study, points out the need for stronger hydrogen transmission infrastructure as well as better oriented siting strategies if the national system aims to pursue large scale hydrogen integration. This could be considered as an hypothetical low in-house hydrogen production scenarios from where stakeholders could develop future guidelines by also analysing the geographical patterns at the 283 substation level, available for those h2 scarce SPORES with the support of the near-optimal exploration page.

SPORE	P2H2	H2P	BS	LBS	Total
0	60.06	54.64	21.63	0.04	136.37
1	49.27	51.16	18.99	5.39	124.80
2	32.02	50.20	16.05	7.29	105.56
3	20.13	36.78	15.60	8.09	80.61
4	3.63	35.47	12.05	9.85	61.01
5	0.37	30.91	11.39	10.25	52.92
6	0.00	28.49	10.62	10.42	49.52
7	0.00	26.10	13.18	8.38	47.66
8	0.00	23.82	9.24	13.05	46.11
9	0.00	21.72	10.55	12.36	44.63
10	0.00	20.02	10.54	12.88	43.44
11	0.00	18.13	10.73	13.32	42.18
12	45.56	54.06	15.67	6.55	121.84
13	31.19	53.56	15.10	5.35	105.20
14	20.99	43.63	11.26	9.66	85.54
15	13.67	38.71	11.53	9.19	73.10
16	7.70	39.30	11.52	8.26	66.77
17	0.94	36.86	10.44	8.20	56.44
18	0.07	33.56	10.58	8.27	52.48
19	0.00	29.84	8.66	11.41	49.90
20	0.00	27.99	8.58	12.04	48.61
21	0.00	26.31	8.47	12.69	47.48
22	0.00	24.46	8.72	13.08	46.27
23	43.36	53.79	18.85	2.92	118.93
24	33.61	52.53	16.23	4.40	106.76
25	20.53	47.19	19.57	4.11	91.39
26	13.47	40.05	19.32	3.47	76.32
27	6.80	35.69	18.10	3.66	64.25
28	0.64	35.47	16.34	3.89	56.34
29	0.00	31.90	14.74	5.48	52.12
30	0.00	29.11	12.75	7.98	49.84
31	0.00	27.01	13.31	8.10	48.43
32	0.00	25.28	15.42	6.53	47.23
33	0.00	23.83	15.57	6.63	46.03
34	42.97	52.47	19.75	3.64	118.83
35	30.25	51.03	19.10	3.02	103.40
36	19.32	45.45	13.99	7.63	86.38
37	13.50	40.62	13.68	7.52	75.32
38	6.39	40.50	12.00	8.37	67.26
39	0.63	39.75	11.38	8.27	60.03
40	0.31	32.98	8.99	11.25	53.53
41	0.00	29.29	9.16	11.13	49.59
42	0.00	27.70	10.07	10.73	48.50
43	0.00	25.85	11.12	10.30	47.27
44	0.00	23.69	12.54	9.70	45.94
45	47.40	53.31	15.87	7.76	124.33
46	29.46	52.17	12.19	10.98	104.79
47	19.60	44.21	14.64	5.84	84.28
48	13.29	39.04	15.13	5.53	72.99
49	6.91	37.35	12.32	6.59	63.17
50	2.42	35.18	10.18	9.57	57.35
51	0.00	32.99	9.51	9.94	52.44
52	0.00	29.59	8.93	11.52	50.03
53	0.00	27.79	9.72	11.11	48.61
54	0.00	26.16	8.31	12.86	47.33
55	0.00	24.20	9.11	12.78	46.09
56	43.64	53.61	13.81	7.00	118.06
57	28.96	52.04	11.54	10.99	103.52
58	19.07	46.79	13.45	6.64	85.94
59	13.75	42.45	9.48	10.17	75.85
60	7.22	36.93	10.51	9.78	64.44
61	0.57	36.98	9.61	9.60	56.76
62	0.00	33.07	7.94	12.04	53.05
63	0.00	30.11	7.03	12.98	50.12
64	0.00	28.37	6.75	13.89	49.01
65	0.00	26.28	8.25	12.99	47.52
66	0.00	24.54	8.66	13.19	46.39
67	41.75	54.16	19.14	3.72	118.77
68	29.87	52.63	14.34	6.44	103.28
69	19.88	47.94	13.54	5.77	87.13
70	13.71	40.93	12.46	7.04	74.15
71	6.31	40.09	10.48	9.17	66.04
72	0.68	39.30	8.59	9.67	58.24
73	0.00	35.07	9.03	9.65	53.74
74	0.00	33.10	6.80	12.33	52.23
75	0.00	29.96	7.89	12.22	50.07
76	0.00	27.21	7.24	13.78	48.23
77	0.00	24.95	8.08	13.83	46.86
78	42.01	54.69	16.34	5.17	118.20
79	32.79	53.92	13.23	6.01	105.94
80	20.01	47.19	13.97	6.71	87.88
81	13.49	41.97	14.60	7.05	77.11
82	6.43	39.92	14.18	6.04	66.57
83	0.66	39.37	12.42	7.68	60.13
84	0.00	33.09	12.38	7.39	52.86
85	0.00	29.97	12.14	8.18	50.30
86	0.00	27.65	10.01	11.24	48.90
87	0.00	26.24	10.19	11.37	47.80
88	0.00	24.13	10.57	11.64	46.33
89	41.63	52.57	20.49	2.11	116.80
90	29.95	50.66	17.05	7.82	105.47
91	20.27	42.20	14.97	8.04	85.48
92	13.33	38.94	12.80	9.12	74.19
93	6.55	35.94	13.24	8.60	64.33
94	1.16	35.94	9.41	11.47	57.98
95	0.00	32.68	8.52	12.50	53.70
96	0.00	29.76	6.59	14.42	50.77
97	0.00	28.49	7.39	13.37	49.26
98	0.00	26.34	7.89	13.50	47.73
99	0.00	24.88	7.63	14.21	46.72
100	38.61	50.93	21.35	3.58	114.47
101	29.34	51.74	22.12	3.02	106.22
102	22.85	52.00	16.39	9.34	100.59
103	22.19	51.35	19.86	6.41	99.80
104	43.04	53.92	18.34	2.61	117.91
105	28.89	52.05	16.28	5.23	102.44
106	21.91	46.69	15.79	5.47	89.85
107	12.95	43.32	14.03	4.49	74.79
108	6.98	37.59	12.00	6.70	63.27
109	1.01	37.43	11.00	6.84	56.27
110	0.00	33.63	11.07	7.71	52.42
111	0.00	29.93	9.85	10.18	49.95
112	0.00	27.86	10.56	10.24	48.66
113	0.00	26.29	11.04	10.30	47.63
114	0.00	24.83	9.92	11.90	46.65

4.2.2. No-Regret Analysis

As reported in Section 3.4.2 and Section 1.3.3, this section extends the exploratory work conducted under RQ3 by applying the visualisation platform to the identification of No-Regret Investments. The aim is to recognise flexibility options that consistently appear across near-optimal configurations and, therefore, represent confident system components that consistently appear in the set of alternatives reported in Table 4.2.1. To explore its full functionalities, two complementary cases are presented. The first analyses the full near-optimal space without any capacity threshold. The second applies an indicative 200 MW threshold, therefore removing from the presence matrix logic (see section 3.4.2), less relevant deployments while isolating the most recurrent and system nodes. Strategic locations more in line with real system sizes can therefore be inspected.

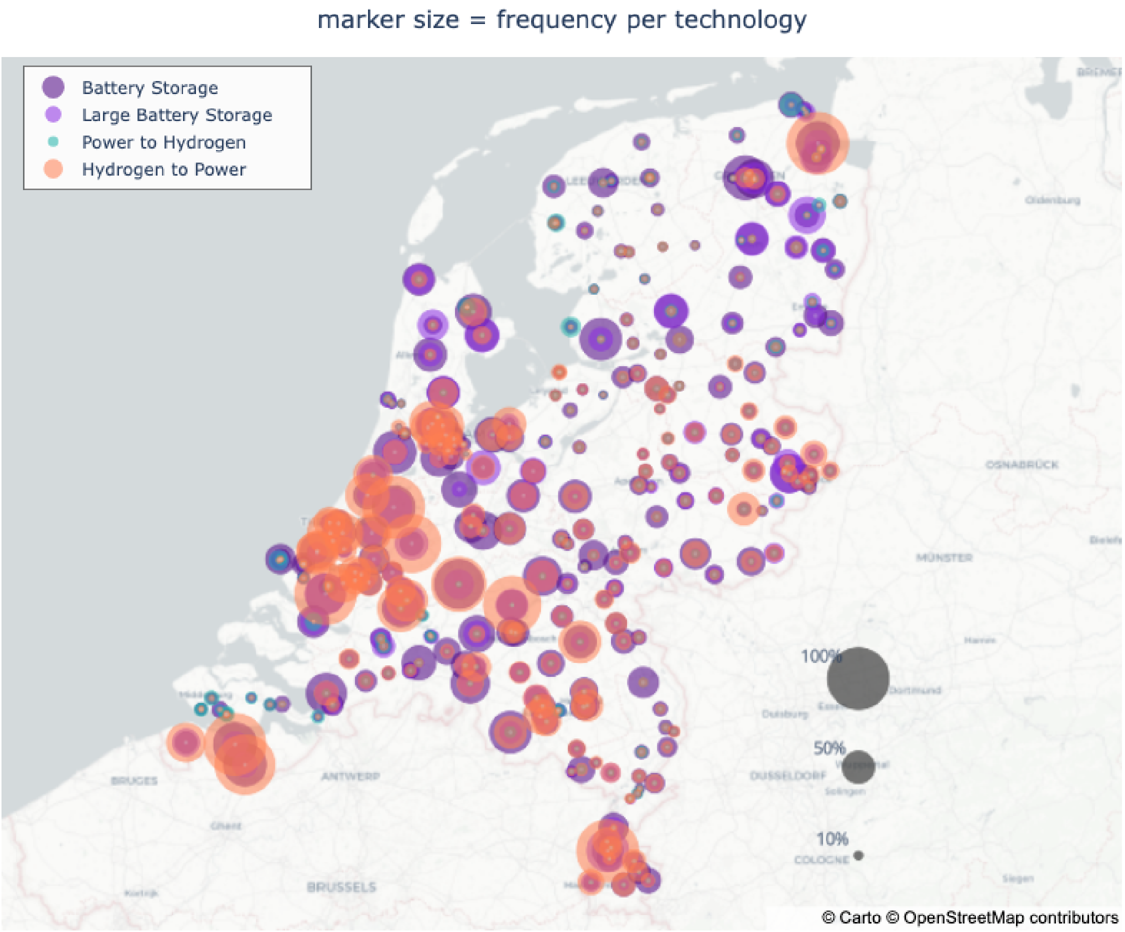
Figure 4.9 compares side by side the frequencies of appearances from the presence matrix. It is indeed evident the important functionality of the presence threshold. By increasing the deployed capacity of the set under analysis, the focus narrows towards fewer nodes that display clearer geographical patterns and more consistent physical meaning see Figure 4.11 for reference. Figure 4.10 compares the full set of unfiltered nodes with the one threshold applied. The high-voltage substations that remain active even at higher capacity levels are reported in Figure 4.9b. From Figure 4.11 (a) and (b) H2P capacity patterns analysed for the Spore 0 configurations are confirmed trough the lens of their consistent presence in the many solutions. It clusters in the Randstad area, Zeeland and south Limburg region; moreover, its solid presence is remarked by Figure 4.11(b) where larger installations (>200MW) are again prominent in the most industrialised areas. While more spread throughout the national tissue, BA and LBS confirms their peak presences in similar location than H2P (see Figures 4.11(f) and 4.11(h). The model is therefore complementary deploying H2P and batteries to jointly support those area of the Netherlands. P2H2 even if it comes with generally lower absolute values (bubble sized) it is mainly deployed in the similar location of Wind Offshore supply (See Figure 4.6c).



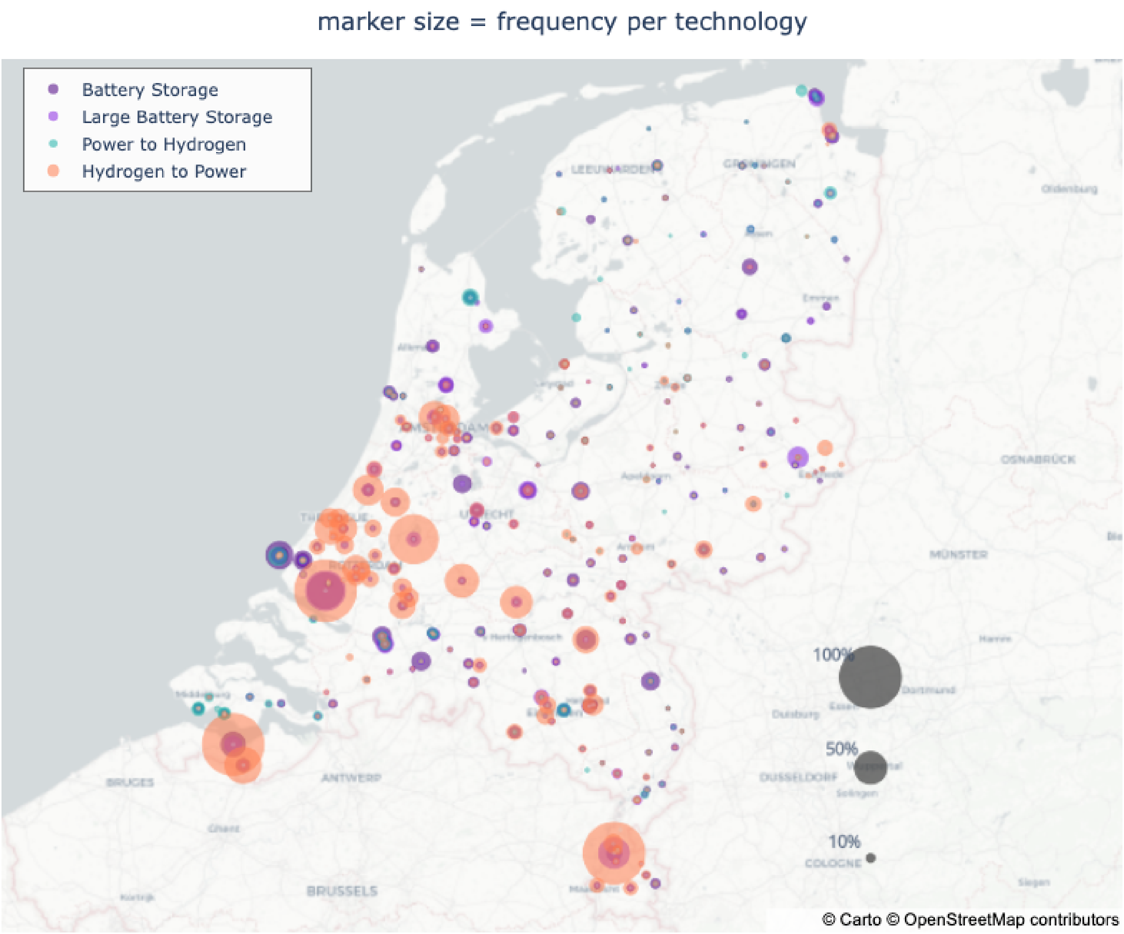
(a) Heatmap, baseline (no threshold).

(b) Heatmap, threshold $\geq$ 200 MW.

Figure 4.9: Frequency of appearance per node and technology. Darker tones indicate higher presence across SPOREs.

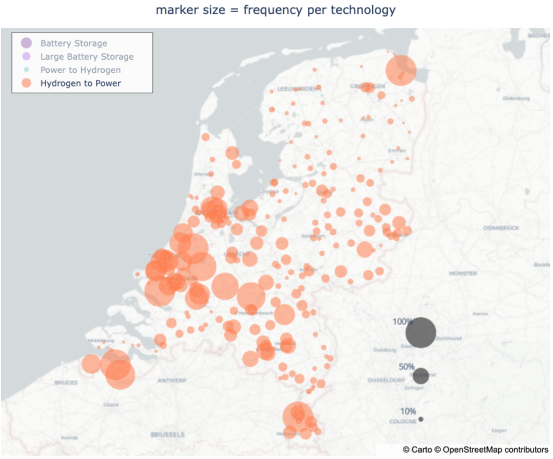


(a) Presence intensity map, baseline (all technologies).

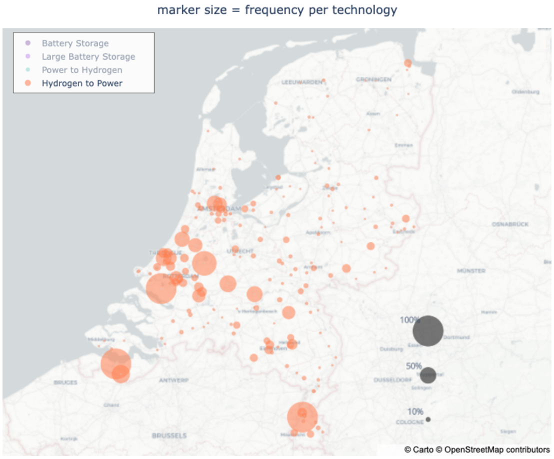


(b) Presence intensity map, threshold $\geq$ 200 MW (all technologies).

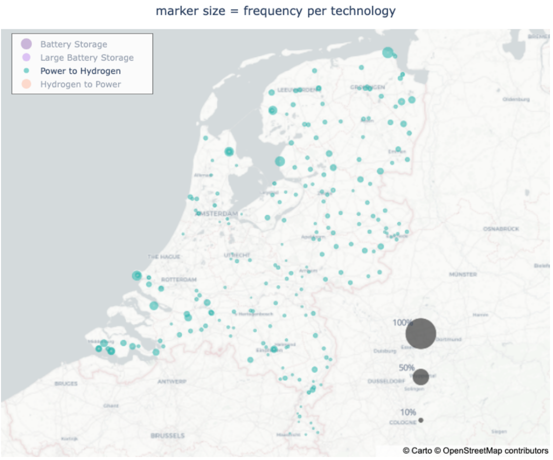
Figure 4.10: System-wide presence. Marker size denotes frequency across SPOREs.



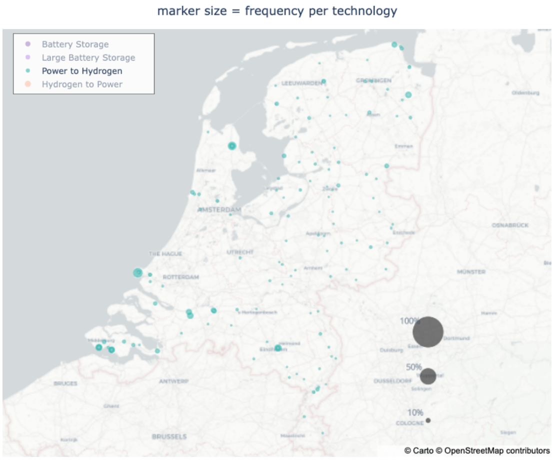
(a) H2P, baseline.



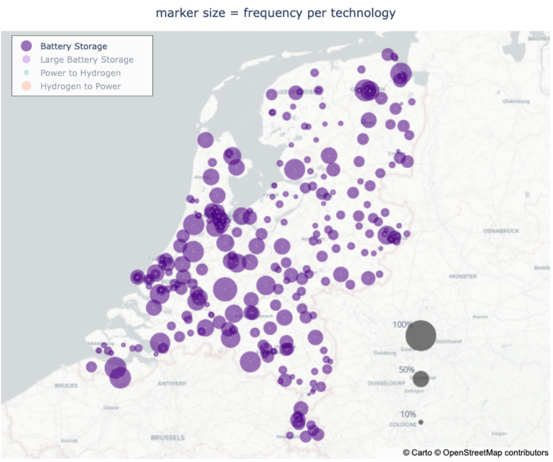
(b) H2P, threshold $\geq$ 200 MW.



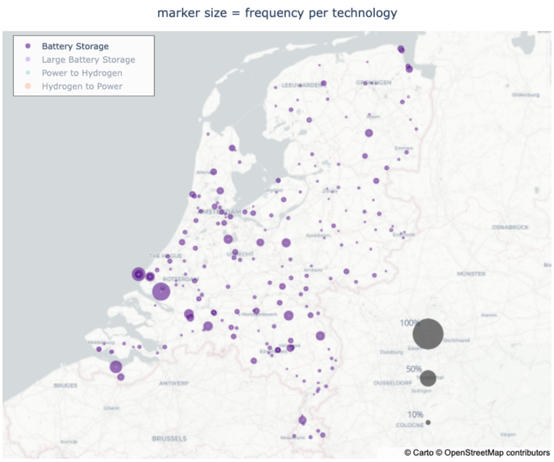
(c) P2H2, baseline.



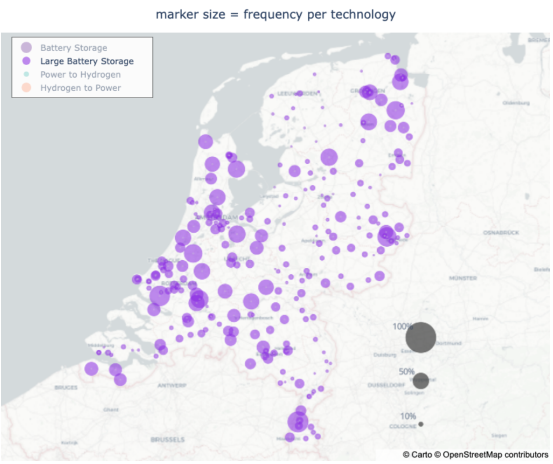
(d) P2H2, threshold $\geq$ 200 MW.



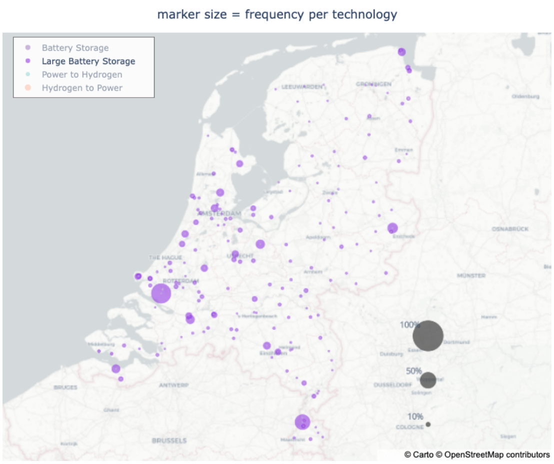
(e) Battery Storage, baseline.



(f) Battery Storage, threshold $\geq$ 200 MW.



(g) Large Battery Storage, baseline.



(h) Large Battery Storage, threshold $\geq$ 200 MW.

Looking at the confidence class distribution, the 200 MW threshold reduces the amount of No-Regret and Robust options, those with appearances above 90% and between 50% and 90%. However looking at the comparison proposed in Figure 4.10, the 200MW threshold filters out the more widespread installations keeping those that are structurally more relevant, indeed local or generally less dispatched units are excluded. Recurrent patterns highlighted above still confirms their dominance at a higher MW threshold. In terms of numbers, H2P shows the greatest stability even with the higher MW filter threshold, 13 nodes remain 'no-regret- and 24 'robust', this can be confirmed while visually comparing Figures 4.11 (a) and (b) with reference to their bubble sizes. P2H2 on the other hand has low appearances values, yet this might be due to the model preference to import h2, highlighted in Section 4.2.1 as a response to many SPORES alternatives not deploying it. However, from a geographic comparison P2H2 appears in those wind-intensive sites. Battery Storage (BS and LBS) lose almost all of their more robust no-regret nodes. Batteries remain widespread but rarely reach capacities that would make investments above 200 MW no-regret. This suggests that their role remains local and complementary while the model it confirms more inclined to deploy hydrogen supporting technologies. From a planning and policy perspective, these results do not suggest to install less flexibility, but to install it better in more accurate locations, see Figures 4.11 (b) (d) (f) (h).

Technology	No-Regret (>90%)	Robust (50–90%)	Considerable (<50%)	Total Nodes
Battery Storage	60	112	98	270
Large Battery Storage	26	70	169	265
Power to Hydrogen	0	8	219	227
Hydrogen to Power	46	69	154	269

Table 4.9: Distribution of confidence classes by technology in the baseline case. Without the threshold, most nodes remain active, indicating widespread flexibility presence but less concentration around dominant large-scale sites.

Technology	No-Regret (>90%)	Robust (50–90%)	Considerable (<50%)	Total Nodes
Battery Storage	2	13	193	208
Large Battery Storage	2	8	168	178
Power to Hydrogen	0	2	133	135
Hydrogen to Power	13	24	165	202

Table 4.10: Distribution of confidence classes by technology for the 200 MW threshold case. The higher capacity filter reduces the total number of active nodes, revealing only the most recurrent large-scale deployments.

Top 20 scoring stations

Applying another dynamic filter it is possible to display the no regret tools for the higher IRI as introduced in Section 3.4.2. This allows to directly identify, between the many, the high-voltage substations that have a better predisposition to host the four flexible assets. Once removed the 200MW threshold and applied the Top20 nodes, new system figures are available to support the findings. Table 4.11 reports the list of substations. The provincial distribution in Tables 4.12, retrieved from the presence tools in the No-Regret page, reveals how flexibility is distributed in terms or presences at the provinces scales; this could be seen as another strong indicator to facilitate DSOs and TSO policy making. Limburg, Zeeland, and Zuid-Holland stand out for their higher recurrence of hydrogen to power and batteries. These regions host some of the most energy intensive and industrialised areas of the Netherlands. There, flexibility is more about securing stability for heavy industry and port infrastructures. In the northern and eastern provinces, such as Groningen and Gelderland, flexibility appears in a more hybrid form. Further south, Noord-Brabant and Overijssel maintain good battery deployment but with the support of Figure 4.10 flexibility is more at the local level.

Table 4.11: Nodes with highest frequency of flexible technology presence, indicating strong potential for hosting flexibility assets.

Code	Name	Voltage (kV)
SMH380	Simonshaven 380	380
AP150	Alphen a/d Rijn 150	150
KRH150	StratioDSM-2 Kerensheide	150
AK150	Arkel 150	150
DZF110	Delfzijl Farmsum 110	110
TNZ150	Terneuze 150	150
WDO150	Westdorpe 150	150
ZBM150	Zaltbommel 150	150
DDZ150	Dordrecht Zuid 150	150
GD150	Gouda 150	150
DDM150	Dordrecht Merwedehaven 150	150
HW150	Amsterdam Hemweg 150	150
TL150	Tiel 150	150
HPT150	Hapert 150	150
SS150	Sassenheim 150	150
WYW150	Wijdewormer 150	150
GNBH11	Groningen Bornholmstraat 110	110
UD150	Uden 150	150
HGLB110	Hengelo Boldershoek 110	110
GNHK110	Groningen Van Heemskerckstraat 110	110

Table 4.12: Provincial distribution of flexibility technologies across the top 20 high-IRI nodes. The table shows the percentage of nodes within each Dutch province retrieved from the No-Regret page.

Province	Nodes	Battery	Large Battery	P2H2	H2P	Avg Presence
Limburg	1	47.8%	66.1%	0.0%	100.0%	**53.5%**
Zeeland	2	68.2%	37.8%	0.0%	98.2%	**51.1%**
Zuid-Holland	8	54.1%	52.5%	3.0%	84.3%	**48.5%**
Groningen	3	65.8%	41.4%	7.5%	52.8%	**41.9%**
Gelderland	1	60.9%	47.0%	6.1%	47.0%	**40.2%**
Noord-Holland	2	48.3%	49.6%	3.5%	57.8%	**39.8%**
Noord-Brabant	2	57.8%	28.2%	10.0%	57.8%	**38.5%**
Overijssel	1	59.1%	60.0%	3.5%	23.5%	**36.5%**
Netherlands Total	20	38.5%	31.9%	2.8%	43.5%	**29.2%**

5 Discussion

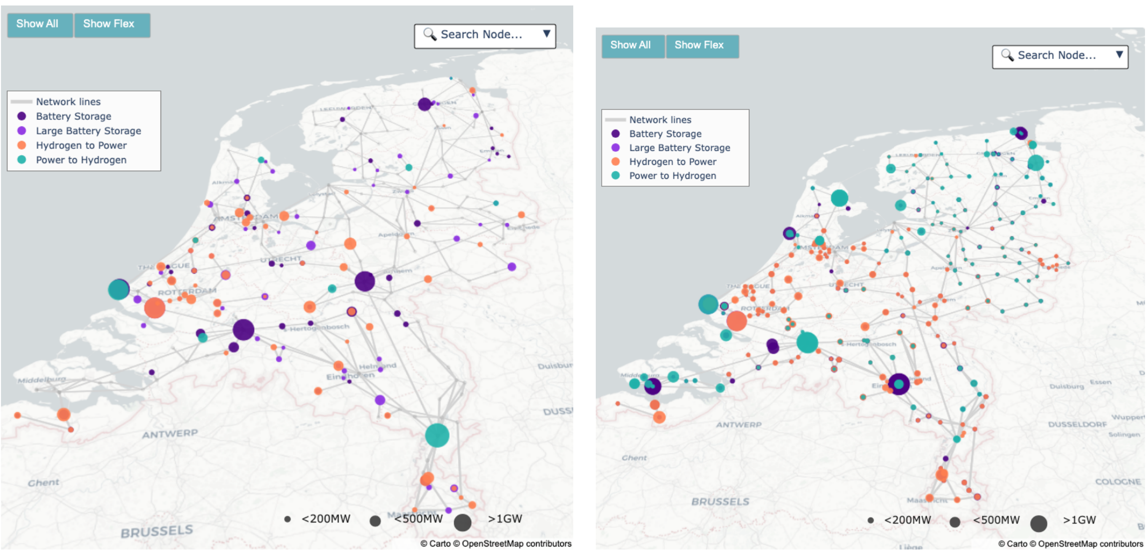
5.1. Interpretation of Results

The cost optimal SPORE 0 solution mainly deploys power to hydrogen (60GW) and hydrogen to power (55GW). A rather less relevant role is covered by the battery storage system (22GW), both at the smaller and the larger scale. However, relying too heavily on a single technology (hydrogen in this case) may expose the system to higher vulnerability and reduce its overall resilience, thus leading to suboptimal system performance. However, expanding the exploration, thus, benefitting from the MGA applied to flexibility deployment in the high-voltage grid in the Netherlands, Section 4.2.1 highlighted that approximately 60 SPORES solutions deploys close to zero P2H2 shares. Therefore, balancing the system with the remaining available H2P and batteries flexible technologies while relaying on the imports to fulfil internal h2 needs. From a stakeholder perspective, this configuration brings a critical strategic choice, deciding between building upon domestic hydrogen production capacity or depending on imported supplies from abroad. Producing hydrogen domestically could indeed improve national energy resilience, but it would also demand extensive new infrastructure in a country where land scarcity is a concern. This considerations might steer developers towards alternative strategies.

In energy modelling, it usually a good practice to not firmly rely on the system designs situated at the extremes points. Instead, attention should be given to more balanced configurations. A diversified mix of flexibility options is therefore important to overcome limitations of traditional cost-optimal approaches previously discussed in Section 1.3.2. To this extent, this thesis was developed in parallel to address such cases, where solutions may be cost optimal but not necessarily balanced in terms of spatial distribution, operational viability or social acceptability. Identifying and accounting for the near-optimal alternatives together with tailored insights as the one presented in Section 4.4.2, provides a way to explore configurations that offer both economic efficiency and improved structural and social acceptability, adding greater interpretive value to the overall validity of the results. With the SPORES framework implemented in this research, the available solution space has been expanded, and it has therefore become possible to identify, analyse, and evaluate alternative configurations. Table 5.1 reports some of the most balanced SPORES configurations identified by the newly introduced model. SPORE 3 emerges as a good balance with proportional rates of H2 production (in house resilience) and H2 consumption together with batteries . SPORE 91, 15, 92, 14, and 48 maintain a good balance with slight variations. Compared to the other balanced configurations, SPORE 100 has an increase in hydrogen related capacity while keeping batteries at similar levels. Looking at Table 3.6, SPORE 100 is obtained with a different scoring method (iterative penalities, see Section 3.3). Substantially, looking at Figure 5.1 the integer method seems to deploy larger shares of P2H2 and H2P with more dissimilarity but a higher widespread capacity when compared to SPORE 3. Indeed, SPORE 3 concentrates resources in less geographical points.

Table 5.1: Highlighted balanced SPORE configurations, representing diversified mixes of flexibility options.

SPORE	P2H2 (GW)	H2P (GW)	Batteries (GW)	Total (GW)
3	20.13	36.78	23.69	80.60
91	20.27	42.20	23.01	85.48
15	13.67	38.71	20.72	73.10
100	38.61	50.93	24.93	114.47
92	13.33	38.94	21.92	74.19
14	20.99	43.63	20.92	85.54
48	13.29	39.04	20.66	72.99



(a) SPORE 3 — Random method

(b) SPORE 100 — Integer method

Figure 5.1: Comparison of the spatial deployment of flexibility assets between the random (SPORE 3) and integer (SPORE 100) weighting methods. The random configuration shows a more distributed and exploratory pattern resulting in higher shares of H2 related technologies, while the integer one concentrates clusters in a few structurally favourable nodes.

Spatially, consistent patterns across the 0-114 systematically different SPORES suggest hydrogen to power technologies appears well distributed among the Randstad area, particularly in the densely populated and industrial neighbourhoods of Amsterdam, Den Haag and Rotterdam, see Figure 4.4. Peaks also appear in Zeeland, the southern part of Limburg province (Maastricht), Eindhoven and are present as well in the northern regions of the Netherlands. Cost optimal and near optimal solutions together, therefore deploy power to hydrogen in industrialised areas as well as strategic connection points with neighbouring countries (south Limburg - Cologne). From a stakeholder perspective, it might be worth considering the concentration of hydrogen production in these areas, where deployment could strengthen the currently limited supply side and improve the hydrogen management chains. Moreover, this concentration could drive investments and operations towards the development of a dedicated hydrogen transmission network, efficiently designed to serve these 'robust' regions.

Battery systems remain widely spread in the inland regions. However, even if less deployed in the cost optimal solution (spore 0), their relevance becomes evident when expanding the dataset to include the near optimal configurations. With the support of the no regret tools which results have been presented in Section 4.2.2 and Table 4.9, battery storage emerges as a clear 'no-regret' investment option with a consistent presence above 90% across 60 of the 271 nodes. Even more remarkable is that it appears in 112 nodes with a presence frequency between 50% and 90%. Furthermore, it is present in all the remaining nodes, even if below 50%. Geographically, the presence intensity map (Figure 4.10) also displays a large presence of battery systems in approximately the same locations where hydrogen to power is mostly needed. This indeed reflects the lack in these regions of sufficient supporting technologies to cope with high demand needs. However, their presence is not limited to these areas alone. In Figure 4.6 batteries also represent the preferred flexibility option across less energy intensive regions, such as Noord-Brabant, Utrecht, Flevoland, Drenthe, Overijssel. Hydrogen production trough electrolysis, even if largely deployed in terms of capacity by the cost optimal solution (60GW), its presence is evenly spread across the national tissue (see Figure 4.5). Friesland and Zeeland sees the largest deployment in frequency of appearances. However, a good interpretation is offered when considering the cost optimal solution alone, see Figures 4.4 4.5 in the Noord-Holland, Zuid-Holland and Zeeland provinces, p2h and h2p are clearly complementary distributed. Separation of production and utilisation is evident again, with the peak in hydrogen demand used to produce electricity, being in the Randstad. Due to an intensive wind deployment see Figure 4.6c, the north Zeeland is seen as the ideal and most strategic location to massively deploy hydrogen production hubs to support the Randstad needs. It is straightforward to conclude that the h2 transmission assets, flowing between south Zeeland up to Noord Hooland, require careful and forward looking evaluation.

From a power network perspective, while examining the IRI index for evaluation purposes, an interesting pattern emerges among the top 100 nodes with the highest IRI values. IRI simultaneously indicates both readiness to host flexibility support and, conversely, depicts an actual need for systematic reinforcement. However, as a result of a internal post processing, it appears among the top 100 nodes with the highest IRI, that 81 of those belong to the 150kV network, while 16 to the 110kV and only three to the higher voltage levels. High voltage topology, see the 150kV network, mainly deployed in the southern Netherlands provinces, the north east is covered by the 110kV and 220kV instead. This reflects a call for action by the Dutch high voltage system operator TenneT, to canalise investments and improve coordination with regional DSOs (such as Stedin), responsible for the medium/low voltage infrastructure branching from those high-voltage connections. It's worth acknowledging that the availability of multiple near-optimal configurations has proven again valuable to offer a broader perspective, resulting in generating this system-level perspective.

5.2. Research highlights

The main highlights of this research are summarised below, presented as concise responses to the research questions introduced in Chapter 1. Each section summarises the key findings and methodological contributions obtained with its respective question.

RQ1 – Data and model: what data are needed and how to build the required energy system model?

- This research produced a high resolution model based on the Dutch high-voltage grid with 283 substations, their interconnections, and a portfolio of four flexible technologies, namely, battery storage, large battery storage, power to hydrogen and hydrogen to power to distribute flexibility with foresight at 2050.
- Calliope is an open-source optimisation framework developed to support the design and analysis of complex energy systems. It provides a reproducible architecture for modelling generation, demand, and transmission across multiple spatial and temporal dimensions.
- The optimisation run over a six-month horizon with a six-hour temporal resolution, so the model could capture an entire seasonal cycle while keeping the computational efforts feasible.
- Previous methods introduced in the II3050 report, based on simulation techniques, have been reinforced by using Calliope, therefore, introducing optimisation as the mathematical foundation to build the new energy system model.
- The network novelty allows nodes to be considered as part of an interconnected system of different voltage layers. Intra node relations have been considered as well.
- Once made available, the complete high voltage network dataset developed in this research will be open for further academic and operational use both within Stedin and Academia boundaries.

- The workflow adopted (data collection, preprocessing of demand and supply, technology parameters, YAML model assembly) provides a reproducible framework.
- The technology datasets and the Calliope optimisation tool used in this research are fully open and reusable. They can be directly implemented by others, and this study could be used as a reference for the methodological choices and assumptions applied.

RQ2 - Cost optimal, near optimal and no regret tools: how to explore alternatives efficiently and turn them into recommendations?

- The cost-optimal solution concentrates on power to hydrogen 60 GW and hydrogen to power 55 GW, with 22 GW of battery contribution; near optimal exploration can help to match stakeholder preferences and investigate different system designs.
- The comparison with the II3050 scenario in Section 4.2 reveals that, while sharing the same input assumptions, the optimisation introduced in this research leads to a structurally different balance between flexibility technologies. The system converge to configurations with higher hydrogen capacities and lower battery deployment. This can be influenced by the six-hour temporal resolution adopted in the model, which smooths short-term fluctuations and limits the operational 'visibility' of batteries. The importance of exploring near-optimal alternatives to understand the robustness and interpretive depth of system configurations stays.
- The near-optimal analysis trough the tailored input SPORES assumptions, resulted in a well distributed set of flexibility technologies across the 114 generated SPORES. The dispersion of values in Figure 4.8 reveals a good exploration of the alternatives such as a coherent clustering of battery technologies around consistent numerical ranges. P2H2 and H2P exhibit broader variability.
- Around 60/114 SPORES converge towards configurations with very low Power-to-Hydrogen (P2H2). This is facilitated by the model's capability to buy and import hydrogen; in these cases, external hydrogen supply becomes economically favourable compared to local production. From a stakeholder perspective, this configuration represents a significant policy crossroads: whether to rely on domestic hydrogen production or to import it from external suppliers.
- In the No-regret analysis with 0MW threshold proposed in Table 4.9 and all nodes included, Battery storage emerges as a solid no regretoption:

present in 60 nodes in more than 90% of solutions, in 112 nodes within 50–90%, and with less than 50% presence in the remaining nodes. Hydrogen to power emerges as another solid no regret option: present in 46 nodes in more than 90% of solutions, in 69 nodes within 50–90%, and with less than 50% presence in the remaining nodes.

- In the No-regret analysis in Table 4.10 , the 200MW threshold narrows the set and it highlights those options with grater structural relevance by filtering out the more widespread installations. Recurrent patterns still confirm their dominance at a higher MW threshold; H2P shows the greatest stability even with the higher MW filter threshold, 13 nodes remain 'no-regret- and 24 'robust'. P2H2 on the other hand has low appearances values, yet this might be due to the model preference to import h2. Battery Storage (BS and LBS) lose almost all of their more robust no-regret nodes. Batteries remain widespread but rarely reach capacities that would make investments above 200 MW no-regret.
- The spatial overlap in the presence intensity map (see Figures 4.6 and 4.4), between hydrogen to power and battery systems reflects a complementary relationship, as both technologies tend to cluster in areas with high demand.
- Hydrogen to power, see Figure 4.11 (a) (b) is mainly concentrated in the Randstad and other industrial areas such as Amsterdam, Den Haag, and Rotterdam, with additional peaks in Zeeland, Zuid-Limburg such as the cities of Maastricht and Eindhoven.
- Power to hydrogen through electrolysis, see Figures 4.11 (c) (d) is widely distributed, with more recurrence in Friesland and Zeeland; the cost-optimal layout shows spatial complementarity between P2H siting (for example north Zeeland with strong wind) and H2P utilisation (Randstad).
- The highlighted spatial complementarity between production (power to hydrogen) and utilisation nodes calls for dedicated hydrogen transport infrastructure. Strengthening the hydrogen transmission system along the Zeeland–Randstad corridor should therefore become a policy priority.
- From a power network perspective, 81 of the 100 most suitable high-voltage substations for hosting flexible technologies, belong to the 150 kV network, 16 to the 110 kV, and only three to the extra high-voltage levels. This calls for stronger coordination between TenneT and regional DSOs to reinforce medium and low voltage connections to then strengthen future flexibility deployment.

RQ3 – Interactive visualisation: how to make results intuitive and actionable for stakeholders?

- The interactive platform developed in this research provides full access to all the model outputs through a single environment accessible with one click.
- The first page, near optimal designs, provides capacity and system insights with a complete overview of each system configuration. It displays the national map of flexibility deployment and the dispatch of the selected individual nodes, as well as their installed capacity. Every spore is accounted for, and each represents a distinct system configuration.
- The second page, no regrets analysis, aggregates the results from all configurations to identify consistent flexibility patterns across the cost and near optimal alternatives. It uses interactive and supporting tools to assess where each technology repeatedly appears in the whole solution set.
- The presence threshold slider manages all no regret analytical tools displayed by filtering nodes above a defined minimum capacity; all the tools are dynamically updated.
- The presence intensity map visualises the frequency of technology deployment across all nodes, where marker size reflects how often each technology appears in the solution space. The filtering options isolate individual technologies or combinations, helping to show spatial complementarities.
- The infrastructure readiness index (IRI) aggregates presence frequencies per node.
- The provincial deployment table exposes regional clusters and supports province level strategies. It additionally helps DSOs to investigate their area of interest.

5.3. Limitations and Future Research

This thesis developed an energy optimisation framework tailored to the largest dataset yet employed to represent the Dutch network. By delivering tangible results, it demonstrated their validity and created an interactive environment where complex outputs are translated into intuitive figures.

However, several limitations and research trajectories remain open. For example:

- The research objective is at the high voltage transmission level. Nevertheless, insights into local flexibility dynamics remain limited. Future research should extend the analysis to the DSO level to reflect local grid conditions and analyse potential investment at smaller scales.
- Current model results do not incorporate capacity line expansions scenarios. Model runs with x2 and x3 line expansions have been tested but resulted in non optimal configurations. This would required a new extensive SPORES and technical parameters adjusting procedures to test and find input settings what will results in feasible solutions.
- Recent work introduced by authors in [17] describes five progressive stages for applying MGA in energy planning, with each level adding more depth and value to the analysis. It serves as a guiding framework to move beyond conventional optimisation approaches for those interested in doing so. Level 1 calls for recognising that cost based optimisation may miss other valid solutions. Following, level 2 suggests that testing key model assumptions could be simply validated with smaller MGA checks on those specific hypotheses. Level 3 suggests the use of MGA to identify and acknowledge that there are many different options to achieve the shared objectives, meaning, to look for those different technology mixes and locations that can meet the same goals (e.g balance the energy system). Level 4 pushes the analysis to interpret the entire map of the near optimal plausible alternatives to understand and draw conclusions on their interdependencies. Even though not addressed directly, the methodology applied in this research naturally incorporated these steps: MGA was considered valuable from the beginning, while near optimal portfolios and supporting mechanisms to interpret the spores interdependencies were introduced and evaluated. However, level 5 pushes the analysis even further, introducing collaboration with policymakers, DSOs, and industry to translate results into shared and realistic planning strategies. Future developments of this research should aim toward this direction.
- The model depends on exogenous supply data from the ETM scenario, where generation capacities and profiles are fixed. Developing new supply datasets would reduce such dependencies.
- The model, implemented in Calliope v0.7.0, becomes computationally demanding when solving for an extended time frame. Newer versions allow technologies to be fixed as constants rather than variables in the objective function, reducing the problem size and therefore improving computational efficiency.

- The platform could be extended to automatically export numerical and graphical deliverables for each configuration. A third page 'export scenario' could be added where system choices carried out in the previous pages, will result in the print of supporting material such as, text file, csv, graphs.
- The current formulation focuses solely on cost objectives. Non economic factors such as social acceptance, environmental externalities, and network reinforcement costs should be incorporated, given the MGA capabilities to do so.
- Future realistic operational developments should initially focus on regional hydrogen transmission analyses, starting from areas where the network appears more centralised according to the present results. Starting smaller, for example, would foster a more pondering assessment before scaling up to the entire national system.
- In energy planning, it is common practice to represent transmission capacity through simplified power transfer limits rather than detailed power flow equations. This allows to still capture the intra-node synergies while keeping the model computationally feasible. However, power flow studies could improve the operational-level analysis. Future developments could extend this framework by integrating OPF-based methodologies as well as validation tools like pandapower. Previous work analysed in Chapter 2 might come particularly valuable to this extent.
- The six hour six months timestep adopted in this model, smooths short-term fluctuations and might be generally blind to the intra day variability, thus limiting the relative advantage of batteries. Under such conditions, the model shifts flexibility adoption to hydrogen technologies. Future work should run new systematic optimal end near optimal designs at higher resolution. In doing this, the newer Calliope capabilities might facilitate the computational solve by parametrising the exogenous inputs thus leaving more computational space to run at a finer temporal windows.

6 Conclusion

Finding an answer to the initial research questions made it possible to build and represent an entire energy modelling system.

This research project introduced a systematic and mathematically different method to inspect deployment strategies of flexible technologies in the Dutch high voltage power grid. Stemming from a completely new and more accurate network dataset, purposely developed for this thesis, as well as tailored pre processing procedures, it resulted in an enjoyable energy modelling tool with a dedicated environment to explore its results.

It fully embraces the rapidly expanding field of modelling to generate alternatives. Indeed, the key innovation introduced was the expansion of the focus to look beyond the traditional cost optimal solution. The shared goal was to understand how flexibility can be distributed in different ways than from the ii3050. In the course of this thesis, it has been reached, together with all the fundamental steps to obtain a system capable of creating these solutions and then making them visually accessible.

With this master's thesis, a small but meaningful step toward a good way of approaching energy system modelling, by looking beyond the optimal and valuing exploration, transparency, and creative ways of understanding complex systems, has been made.

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A
Energy planning platform

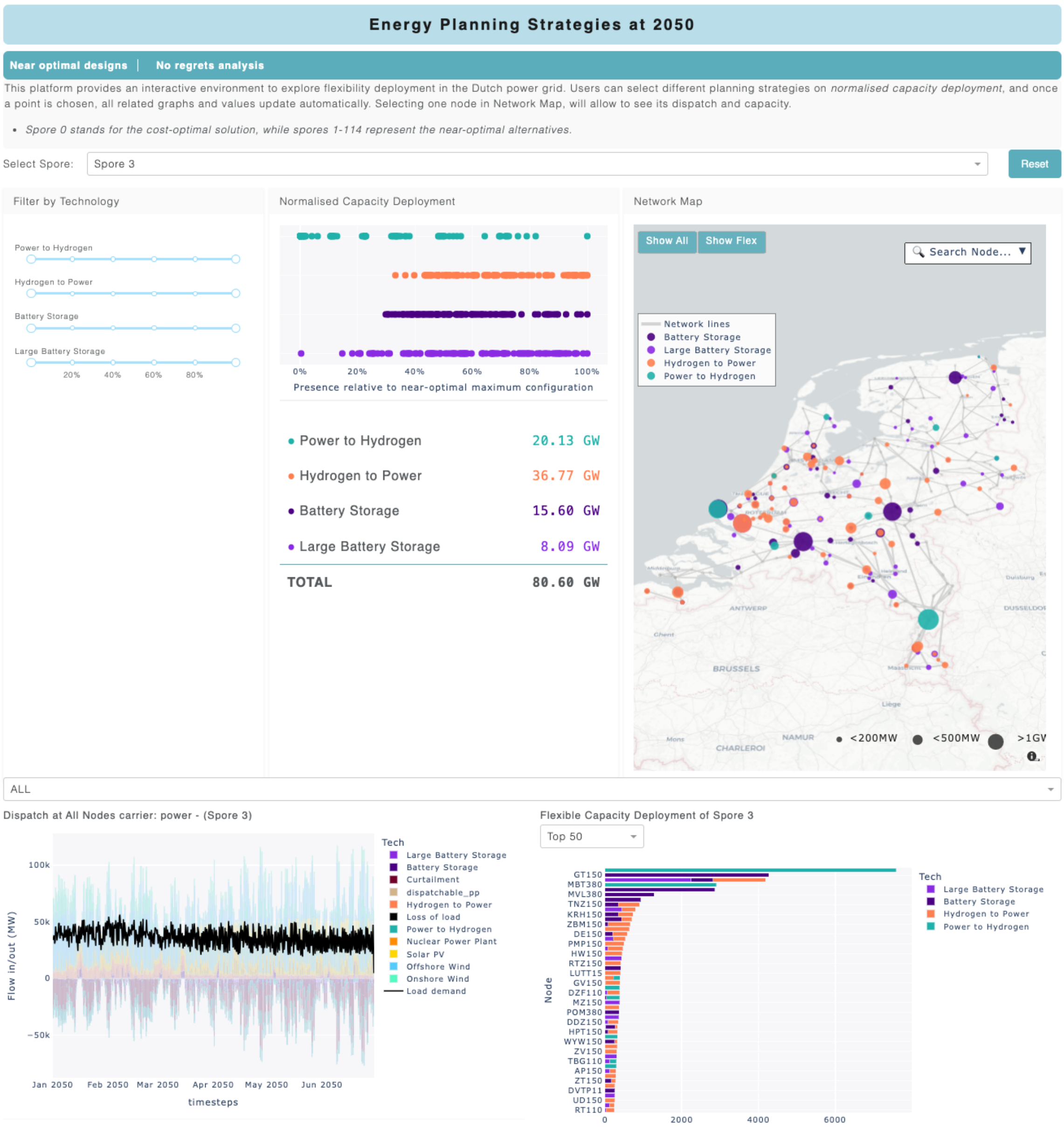


Figure A.1: Interactive platform developed to explore flexibility deployment and near optimal alternatives in the Dutch power grid at 2050.

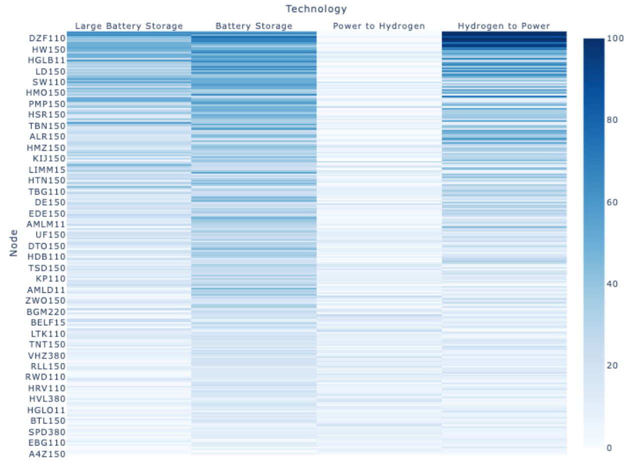
Energy Planning Strategies at 2050

Near optimal designs | **No regrets analysis**

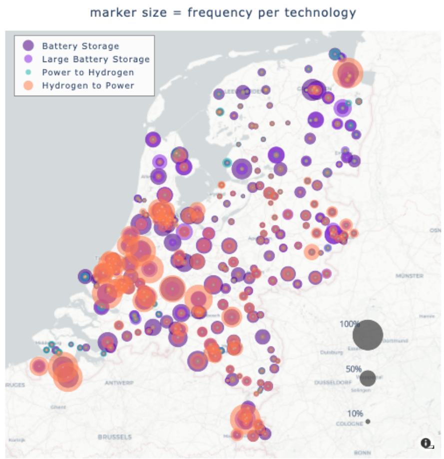
This section explores No Regrets Investments. The objective is to identify flexibility solutions that consistently appear across different system designs, highlighting robust regional deployment patterns. Technologies that recur with high frequency can be interpreted as 'no regrets' options for long-term planning.Heatmaps, geographic maps, and dynamic charts reveal patterns, helping to understand where flexibility is most needed and how solutions perform across the network.

SPORE set: ALL (0-114) | Presence threshold (MW): 0 – 500 | Top-N nodes: All | Reset

Frequency of appearance – heatmap

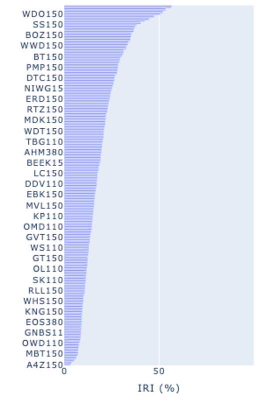


Presence intensity Map

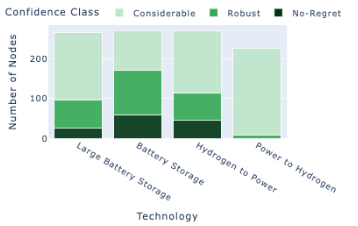


Investment Readiness Index (IRI)

271 nodes shown (Top-N: ALL out of 271).
Threshold = 0 MW.



Confidence Class Distribution



TECHNOLOGY	NO-REGRET (>90%)	ROBUST (50-90%)	CONSIDERABLE (<50%)	TOT NOI
Battery Storage	60	112	98	270
Large Battery Storage	26	70	169	265
Power to Hydrogen	0	8	219	227

Regional Technology Mix

PROVINCIAL TECHNOLOGY PRESENCE OVERVIEW

Average presence frequency of flexibility technologies aggregated by province

PROVINCE	NODES	BATTERY	LARGE BATTERY	P2H2	H2P	AVG PRESENCE
Zuid-Holland	42	37.1%	26.9%	4.3%	**42.5%**	**27.7%**
Flevoland	8	**32.2%**	26.9%	3.1%	31.3%	**23.4%**
Noord-Brabant	43	**31.8%**	19.2%	7.5%	25.1%	**20.9%**
Zeeland	11	24.4%	16.0%	11.9%	**26.3%**	**19.7%**
Groningen	17	**31.3%**	22.4%	10.3%	14.4%	**19.6%**
Gelderland	17	**30.4%**	17.3%	7.1%	22.3%	**19.3%**
Noord-Holland	27	**27.3%**	17.6%	3.1%	23.8%	**18.0%**
Drenthe	15	**29.4%**	22.7%	10.6%	7.7%	**17.6%**
Utrecht	4	**30.8%**	10.2%	4.5%	23.9%	**17.4%**
Limburg	21	**25.1%**	14.0%	5.1%	22.6%	**16.7%**