Implementing high-resolution grid modeling to find decentralized system designs

A use case of the Dutch power system

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Picture from: Freepik Power System Image

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Preface

This thesis is the product of my final period as a student here at TPM. The past 6 months I have challenged myself by taking a deep dive into energy system modeling.

My thanks goes to Stefan and Giacomo for providing valuable feedback during the kick-off, mid-term, and the Green Light meeting. Special thanks goes out to the ETS team at TNO and especially Sebastiaan and Floris for their help in shaping the path towards this final document. Lastly, I would like to thank Francesco, with whom I spent many hours discussing obstacles and potential applications for my model.

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Summary

The Paris Agreement has intensified international efforts to reduce greenhouse gas emissions. Electrification and the adoption of renewables like wind and solar power are central to achieving this goal. However, the ongoing electrification of energy demand, e.g. the growing share of EVs in the car fleet (RvO, 2024), and the increasing integration of renewable generation technologies in the Dutch energy system (CBS, 2023) have put the high-voltage grid under considerable pressure. The growing demand for and supply of electricity leads to grid congestion. Grid congestion occurs when the requested amount of transported electricity cannot be facilitated by the grid, which means that the capacity of the transmission lines is not large enough. This limits the uptake of renewables and the electrification of energy use. Thus, to keep the energy transition moving, it is essential to tackle grid congestion.

The most straightforward method for reducing grid congestion is to expand the capacity of the transmission lines. However, the growth in electricity demand and renewable supply is currently outpacing the growth of grid capacity (Ministerie van Algemene Zaken, 2023). This underlines the need for a different type of solution. Battery Energy Storage Systems (BESS) could prove to be an efficient alternative. TenneT, the Dutch Transmission System Operator, the organization responsible for maintaining a stable grid, confirms the need for BESS on the high voltage grid in a design that allocates BESS to Dutch provinces by 2030 (TenneT, 2024). BESS can be distributed in many ways, both geographically i.e. at different locations and in terms of size i.e. large versus small amounts of storage capacity at locations. Thus, there are many different decentralized system designs with BESS to consider, each with relative strengths and weaknesses.

Policymakers use large electricity system optimization models to build grounded arguments for infrastructure planning and policy. A high spatial resolution in this type of model is critical to capture regional variation in energy generation and consumption. This level of detail allows for a more precise identification of areas prone to grid congestion, as well as the design of localized solutions for storage and generation capacity. The goal of this research is to identify the trade-offs for future designs of decentralized electricity systems to support decision-making in infrastructure planning. Thus, this research proposes a multi-node model of the Dutch power system on the NUTS2 level i.e. the province level.

Available literature provides many examples of how to build a model with renewable generation (Tröndle, 2020) and electricity demand (Launer, 2024) on the NUTS2 level, but the most effective approach for high resolution grid modeling is not yet known. The issue here is twofold.

First, it remains unclear how to integrate physical constraints into Net Transfer Capacity (NTC) calculations to estimate realistic transmission line capacities that account for voltages and resistances. Although more advanced, methods exist (flow-based alternatives), they tend to be computationally intensive and may not be easily integrated into large-scale optimization frameworks that co-optimize generation and transmission capacity.

Secondly, while there are datasets from power-flow based models that include specific electrical parameters, such as in PyPSA-EUR (Xiong, Fioriti, Neumann, Riepin, & Brown, 2024), the potential benefit of using these parameters in NTC based models is not proven. Furthermore, most NTC based models are not capable of handling such specific parameters and as most energy system models are based on NTC grid modeling methods, developing reliable estimates of NTCs out of electrical grid data would open up the use of high-resolution grid data, which are increasingly available. This research attempts to bridge these gaps by identifying the most accurate method to calculate NTCs and by evaluating the benefit of exploiting electrical data from power-flow based models in a NTC based model.

With such a model, it is then possible to identify the trade-offs in decentralized system designs and make grounded recommendations for storage and generation infrastructure. Using three demand scenarios, the model builds least-cost system designs based on the BESS capacity projections by TenneT (TenneT, 2024) and also based on flexible allocations of BESS capacity based on a system wide cost optimization to highlight important trade-offs for decentralized system designs with a focus on the application of BESS, reducing congestion and reaching climate goals.

To begin with, this study identifies the most accurate method for calculating NTCs using line specific

data from the Static Grid model (TenneT, 2023) to validate the accuracy of NTC calculation methods found in literature. The research evaluates three different methods for calculating NTCs: simple-transport model, efficiency per kilometer and the St. Clair approximation. An efficiency per kilometer is found to be the most accurate method to estimate key physical constraints in NTC calculations. This method provides a straightforward way to prevent overly optimistic capacity estimates and its abstract formulation makes it easy to incorporate into both existing and newly developed NTC-based models, thereby enhancing the realism of NTC based models.

Then, after establishing the most accurate method for calculating NTCs, the study dives deeper into the using the to NUTS2 level clustered grid data from PyPSA-EUR in NTC calculations. The goal is to assess the usability of such data sets, by comparing the data to the data in the Static Grid model. The inherent simplifications of the clustered dataset, such as universal voltages, resistances, and maximum currents, result in substantial inaccuracies. Additionally, there is an asymmetry between the PyPSA-EUR data and the SGM in the number of lines between different sets of regions, further emphasizing the negative impact of the clustering on the accuracy of the NTCs. This inconsistency leads to overestimation in one case and underestimation in the other, highlighting the effect of using simplified and clustered data compared to more detailed line-specific parameters. Moving forward, the multi-node model thus utilizes data from the Static Grid model and an efficiency per kilometer to estimate NTCs.

Next, the model is used to identify important trade-offs for designing decentralized system designs. The results show that grid expansion can cut down congestion significantly, especially on the lines that connect Zuid-Holland and Noord-Holland to Noord-Brabant and Flevoland respectively. Unfortunately, efforts to expand the grid are currently outpaced by the growth in demand for electricity transport. Storage proves to be an alternative, with estimates for required capacities in 2030 ranging from 7.45 GW to 13.02 GW. A significant contribution to minimize congestion can be made by deploying BESS in the South and West, especially in the regions where most of the projected offshore wind is connected to the shore and Utrecht. Although storage in these areas can offset some of the need for extra transmission capacity (and vice versa), both are necessary elements of a balanced grid in the near future. This underlines that TenneT should coordinate the BESS deployment based on the efforts to expand the transmission together with battery operators to identify the most efficient locations for BESS.

However, focusing solely on the deployment of BESS in these key areas results in a large dependence on gas generation and imports and exports to balance the grid, especially in the northeast region, where demand is relatively small. During hours with large renewable output, the excess electricity from these small demand areas cannot be fed into the grid to supply high demand areas, because the grid in these areas is also heavily loaded during these hours. By storing excess renewable power in small demand areas, more of the generated power can be used locally or for supplying high-demand areas, rather than being exported or wasted. This reduces uncertainty in terms of costs related to dependence on gas power plants and imports to provide flexibility. This also enables the import and storage of cheap foreign electricity for later usage. Thus, it is recommended to complement renewable generation in small demand areas with storage options.

Overall, the projected BESS capacities require a significant increase in collaborative efforts of TenneT, DSOs, ACM, and battery operators, starting with the implementation of a tariff structure that facilitates flexible loading and unloading of BESS to strengthen the business case of BESS while also accounting for TenneT's and the DSO's business model and balancing requirements.

In addition, large amounts of solar PV are consistently installed across scenarios in the large demand areas such as Noord-Holland, Zuid-Holland, Noord-Brabant, and Gelderland. This emphasizes the benefit of local solar generation and the need for support schemes for solar generation that incentivize smart self-consumption to account for the spatial and temporal value of electricity while also incentivizing consumers and businesses to invest in solar PV. However, the uptake of solar PV in areas with high demand increases the pressure on land availability in these regions, especially in Zuid-Holland. Placing large amounts of BESS and solar to meet local demand might not always be feasible within these regions. Infrastructure planning should thus also consider the trade-off between system-wide cost and additional land use in less demand intensive areas compared to the land use of regions with large annual demand. The results indicate that there is a limit to the benefit of local rooftop PV capacity. At a certain point, the addition of local generation capacity results in only marginal improvements in overall system costs and might even results in higher levels of congestion. TenneT and battery operators should therefore work together with DSOs and local governments to smoothen permitting processes and identify precise locations that integrate BESS in public space, the distribution system, and the transmission system to ensure smooth distribution of the storage systems.

These findings show that although local storage and renewable generation in high-demand regions can help match supply closer to consumption, it is also possible to shift renewable generation and storage to smaller-demand areas in close proximity to these areas at slightly higher costs. This complements earlier statements on the potential benefits of storing surplus power in small demand areas for later usage during low renewable hours to reduce reliance on gas or imports during peak times. This approach alleviates land-use pressure in densely populated areas and ultimately creates a more balanced and resilient electricity system that maximizes existing transmission infrastructure.

Substantial investments in renewable generation and storage infrastructure are necessary across all scenarios, with large deployments of rooftop photovoltaic systems, offshore wind, and high storage capacities. However, time is short, and if additional renewable capacity and storage do not materialize, this study suggests continued reliance on fossil fuels and the potential need to keep coal plants operational for a longer time. The development of Carbon Capture and Storage (CCS) can mitigate some climate-related concerns related to gas-fired power, highlighting the need for continued investment incentives for innovative projects to support the development of carbon capture technologies.

Although challenges remain in determining the most optimal locations for storage infrastructure that reduce congestion and facilitate the integration of renewables in the Dutch power system, this work presents a stepping stone toward more realistic high-resolution grid modeling, enabling informed decision making in decentralized power system design.

Acronyms

- **BESS**: Battery Energy Storage Systems
- **HVAC**: High Voltage Alternating Current
- **HVDC**: High Voltage Direct Current
- **NTC**: Net Transfer Capacity
- **PV**: Photovoltaics
- **SGM**: Static Grid Model
- **CSGM**: Clustered Static Grid Model
- **NUTS**: Nomenclature of territorial units for statistics
- **PTB**: Power Triangle Based

Province	NUTS2 Code
Groningen	NL11
Friesland	NL12
Drenthe	NL13
Overijssel	NL21
Gelderland	NL22
Flevoland	NL23
Utrecht	NL31
Noord-Holland	NL32
Zuid-Holland	NL33
Zeeland	NL34
Noord-Brabant	NL41
Limburg	NL42

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1

Introduction

1.1. Problem introduction

The Paris Agreement seeks to limit global temperature rise to well below 2 ° C, pushing nations around the world to accelerate their energy transitions. In the Netherlands, this has resulted in a rapid increase in renewable energy deployment, with the share of wind energy doubling and solar energy tripling in the past four years (CBS, 2023). However, implementing renewable energy sources in our electrical systems is not without obstacles. To enable a transition to clean energy sources, different challenges must be overcome. First, solar and wind are intermittent sources, which means that they cannot be turned on and off as needed. This makes it more difficult for transmission system operators, TenneT in the Netherlands, to balance the supply and demand for power. For example, when solar generation exceeds the demand for power shares of the solar energy must be exported to other regions or countries, stored, or, if storage is not feasible, curtailed. Curtailed means that excess power is wasted. Also, relying on intermittent energy sources causes problems for the reliability of supply in times when these sources have hardly any output, emphasizing the need for sufficient flexible generation capacity. The intermittency of renewables thus challenges the uptake of these sources. Second, the electricity demand, or load, has experienced a large growth in recent years due to electrification of the energy demand. With increasing demand, more transfer capacity is required to deliver electricity. Data shows that there has been an increase of roughly six times the number of electric vehicles (EVs) in the past six years (RvO, 2024). This is an example of electrification that intensifies the demand for electricity. In the future, with electric mobility and electric heating being used more frequently, the demand for electricity is expected to grow even further. An assessment of the impact of this load growth is needed to identify what type of infrastructure is needed in what locations to maintain a stable grid.

The electrification of energy demand and the additional renewable capacity are in some areas causing grid congestion. Grid congestion occurs when the requested transported amount of electricity is larger than the capacity of the grid connection. This emphasizes that the challenges of the energy transition must be addressed not only on a national scale but also on a more regional scale to account for local grid constraints that limit further electrification and integration of renewable resources. Figure 1.1 illustrates the congested areas for consumer requests. Here red means that there is no transport capacity available and congestion management is not possible, orange means that there is no transport capacity at this point in time, yellow areas have limited capacity available, and transparent areas still have available capacity. Looking at the congestion map for feeding and consuming electricity in the Netherlands, it can be noticed that in large areas of the country congestion is already a major issue. Consequently, businesses cannot start or expand their operations and new renewable energy plants cannot be connected to the grid due to capacity restrictions.

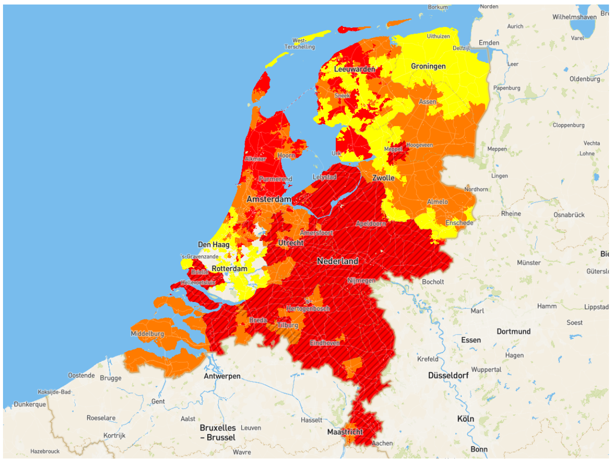


Figure 1.1: Congestion map (Netbeheer Nederland, 2024)

Additional transport infrastructure can help relieve the stress caused by congestion was it not that expanding the grid infrastructure requires a significant amount of time and funds. Currently, the growth of demand and electricity supply is outpacing the growth of transfer capacity (Ministerie van Algemene Zaken, 2023). According to (TenneT, 2024), Battery Energy Storage Systems (BESS) will have an important role in balancing the Dutch power system in the coming years. BESS can provide the necessary flexibility through supplying and consuming power during hours with low and peak renewable output, respectively. TenneT (2024) shared a vision for the BESS which the system requires by 2030. However, there are many potential system designs with different amounts of generation and storage capacity that could work around local grid constraints, making the distribution of the capacity complex in terms of capacity and geographical placement.

To inform decision makers in this complex process of grid infrastructure planning, large electricity system optimization models are used to find cost-optimal future system designs. High spatial resolution is essential for accurately modeling the grid, renewable generation, and load because it captures regional variations in electricity demand, flexibility, and availability of renewable resources. This granularity allows for a more precise analysis of localized grid congestion and the effectiveness of additional generation and BESS capacity.

The literature describes many examples of methods to enhance spatial resolution in energy system optimization models. Although we already have established methods for integrating generation capacity, renewable generation, and demand on a high spatial resolution, such as those employed in the Euro-Calliope model (Tröndle, 2020), there remains a critical gap in understanding. Specifically, we lack knowledge of the most effective methods for modeling the grid constraints, i.e. calculating Net Transfer Capacities (NTCs) between areas in a model with a high spatial resolution. More precisely, while there are good-quality datasets to model grids at a high resolution (Xiong et al., 2024), these datasets are based on electrical grid parameters (such as voltage, impedance, resistance, reactance and susceptance) conceived for use in power-flow-optimizing models. However, flow-based alternatives are often computationally heavy and not easily integrated into large-scale optimization frameworks that co-optimize generation and transmission capacity on the long-term. The majority of energy system optimization models, instead, bypass the need for power-flow balance constraints by adopting simpler power capacity constraints, namely NTCs, which are often available for pre-defined resolutions (Pickering, Lombardi, & Pfenninger, 2022). As a drawback, NTC based models cannot benefit from high-resolution grid data based on electrical parameters that they cannot handle. Developing robust techniques to incorporate grid constraints in NTCs using electrical grid data would facilitate the use of high-resolution grid data, which is becoming increasingly accessible.

Using high-resolution electrical grid data in NTC based models thus requires methods to circumvent the lack of power-flow balances in such models while still retaining information on the underlying physical constraints in such a way as to avoid overly optimistic NTC estimations. For example, NTC correction factors that account for resistance and voltage differences across regions. Although some attempts have been made to formulate correction factors in recent work (Wiese, Bökenkamp, Wingenbach, & Hohmeyer, 2014; Van Ouwerkerk et al., 2022; Martin et al., 2017), the relative merits of each approach are not yet well understood or validated. This research aims to address these gaps by exploring the methodologies for calculating NTCs and incorporating adjustments for physical grid characteristics. The first step of this research is therefore to dive deeper into the literature to identify the available approaches for calculating NTCs and correction factors for voltages and resistances. This led to the formulation of the first sub-question, where the goal is to find methods for calculating NTCs while also accounting for resistances and voltages into the formulation of these NTCs.

Ultimately, the most accurate approach will be used to build an optimization model within the framework of the Calliope model (Pfenninger & Pickering, 2018). Calliope is used in different studies on national-scale power system analysis. Additionally, Calliope allows for mixed-integer problems and easy customization and integration. The basis for the model used in this research already exists at TNO in the form of the single-node model. The model is first enhanced with known methods for implementing high spatial resolution demand and renewable generation. Thereafter, the most promising method for calculating NTCs is implemented. High-resolution electrical grid data from PyPSA-EUR (Brown et al., 2024) using the OSM data (Xiong et al., 2024) is applied to evaluate to what extent NTC based models can potentially benefit from using high-resolution electrical data from power-flow-optimization models. High spatial resolution is critical in this research to capture regional disparities in energy generation and consumption. This level of detail allows for a more precise identification of areas prone to grid congestion, as well as the design of localized solutions for storage and generation capacity. So far, literature does not provide studies that apply high spatial resolution grid modeling to assess the trade-offs between (de)centralized design options while optimizing for both costs and line loading. The research will thus add to existing literature by providing deep insights to the trade-offs for (de)centralized designs of the network. This gives a new perspective and a better understanding of the discussion of BESS as a solution for grid congestion. Therefor, the contents of this research will also prove to be useful for decision makers to enhance the robustness of the network.

1.1.1. Main research question

The main research question is: 'What are the trade-offs for future decentralized Dutch electricity system designs in the face of future load growth?'

To divide the main research question into different sub-questions an approach must be defined. The research question focuses on three key areas: First, it aims to compare and identify the most effective methods for calculating NTCs and accounting for voltages and resistances within regions. This involves different methods that are assessed for their performance by comparing the resulting NTCs to reference NTCs. Then, the goal is to assess the potential of using grid data from a power-flow-optimization model in an NTC based model. The last focus point is to select the most "promising" method from this analysis and integrate it into the TNO single-node model using accurate grid data. The enhanced multi-node model is then used to explore potential decentralized system designs, specifically designed to address grid congestion under various load scenarios for 2030.

- How can we calculate Net Transfer Capacities and how can we integrate correction factors for resistances and voltages and transferring it to a Net Transfer Capacity?
- How well does the model reflect the real electricity system's operation?
- What are potential decentralized design options for relieving congestion in the Dutch electricity system considering different scenarios for future load development?

1.1.2. Link with MSc program

The research will not only contribute to finding the most optimal method for calculating NTCs in high spatial resolution electricity system optimization models and the benefits of using high spatial resolution electrical parameters from power-flow-optimization models. It also aims at designing different effective measures for policy and infrastructure in the network to deal with grid congestion. Through assessing the impact of potential interventions and showing the trade-offs for different design options, the research will help decision makers make informed decisions with respect to power infrastructure. The Dutch power system is a system with many different technical components, but also with many different stakeholders in business and policy. Insights into the relative merits of each design can help stakeholders reach a consensus. The energy transition problems discussed are analyzed using an electricity system optimization model, which is closely related to different courses in the Energy and Industry domain.

2 Methodology

This part of the study provides an overview of the methods employed to answer each sub-question, starting with an introduction to the literature research and the methods used to identify the most accurate methods for calculating NTCs. Subsequently, a description is given of the steps taken to assess the use of data from a flow-based model in the NTC based model. Thereafter, the modeling approach is discussed, starting with an introduction to Calliope and the TNO single-node model. Different aspects of the single-node model are highlighted, such as the context and the technologies. Next, the process of enhancing the spatial resolution of the single-node into the multi-node model is discussed, showing the disaggregation of demand, the input data, and the constraints that are used in different steps of the research. Lastly, the section describes the methods that are used to validate the resulting multi-node model, and lastly a description is given of how the model uses different scenarios and objective functions to find decentralized system designs.

2.1. Methods for calculating NTCs

The first sub-question is addressed by reviewing state-of-the-art literature and examining examples of how researchers calculate NTCs in high spatial resolution electricity system models. The primary source for identifying the available methods is Scopus. The result is a list of potential methods for calculating NTCs, found in Section 3, including an explanation of the method, characteristics, applications, and related study. To determine the most accurate NTC method, the methods are applied to real-world data. Twice a year, in accordance with Article 25(2)(f) of the Day-ahead capacity calculation methodology for the Core capacity calculation region, the TSOs publish the Core SGM. This model takes the form of an Excel file and provides a list of the transmission system elements along with their properties such as lengths, resistances, and voltages. This part of the research concludes by comparing the resulting NTCs of individual lines from the SGM using each method to the actual NTCs in Section 4.1.1. This comparison is based on graphs that show the ratio of the Power Triangle Based (PTB) NTCs (see Section 3.2, which serve as a reference, and the NTC calculated with each estimation method. A ratio close to 1 indicates a high accuracy. In addition, Pearson correlation coefficients are calculated to measure the linear correlation between the NTCs calculated with the PTB and each method.

Thereafter, the grid data from PyPSA-EUR is evaluated as a potential source for high-resolution grid data. PyPSA-EUR is a publicly accessible dataset that models Europe's energy system comprising the demand, supply, and transmission networks for the entire ENTSO-E region. Currently, it is the only openly available tool that can generate clustered grid representations at any desired resolution. Although detailed grid data, such as that provided by TenneT in the Static Grid Model (SGM) (TenneT, 2023), is available for the Netherlands, similar datasets may not be accessible for other regions. This makes it valuable to assess whether the adaptable workflow of PyPSA-EUR is sufficiently robust for broader applications. Moreover, even for the Netherlands, there are instances where clustering the grid at a lower resolution than TenneT's is beneficial. In these cases, having a customizable grid generation workflow like that offered by PyPSA-EUR could be particularly useful. In this phase, the NTCs are again calculated with each method, but now using clustered NUTS2 line data from PyPSA-EUR. The resulting intterregional NTCs are compared to the sum of interregional NTCs as per the Clustered Static Grid Model (CSGM). The clustering of both PyPSA-EUR and the CSGM are explained in Section 2.2.3. Different aspects of the data are discussed, including the number of lines that connect two regions, voltages, maximum current and resistances to make a complete assessment of the usability of the PyPSA-EUR grid data as input for the multi-node model.

2.2. Modeling approach

2.2.1. Calliope

Calliope is an open-source tool for energy system analysis that uses a least-cost optimization approach. In this framework, various technologies are configured to supply energy, convert one carrier into another, transport energy, store it, or consume it. In the Calliope framework, it is possible to assign technologies many different characteristics, such as ramp rates, emissions, operational expenditures (OPEX) and capital expenditures (CAPEX).

The model operates by seeking the least-cost design to meet energy demand in all locations and time steps, within a set of constraints defined by the modeler. The constraints ensure that the amount of energy produced at any location and time is consumed, stored, or exported. When no solution satisfies these constraints, the model is infeasible. Unmet demand and supply are added to ensure feasibility. However, this is linked to high costs, so the model will try to avoid unmet demand and supply.

Cost can be represented in different ways. However, in this study, the cost is measured in millions of euros (MEUR). Meanwhile, the model is also able to separately track emissions associated with fossil fuel use and line load, but does not incorporate these into its cost-minimizing objective. This opens the door to adding emission constraints or minimizing for line load within a certain cost range.

To arrive at the optimal solution, the model must address two key aspects: system design and system operation. System design is about the choice of how much capacity to install for each technology at each allowed location. The model uses technology characteristics such as OPEX and CAPEX to find the least-cost solution. The user can pose constraints as to what technologies can be deployed at which location, including a minimum or maximum capacity. Once design choices are set, the model operates each technology by controlling its input and output at each time step.

Calliope represents energy systems using a node-link topology. The nodes house supply, conversion, storage, and demand technologies, anchored to a specific geographic location based on coordinates. Links connect pairs of nodes to define transmission lines, and their distance is derived from the nodes' positions. This distance, in turn, can be used to influence the cost of building and operating transmission technologies.

2.2.2. The single-node model

The starting point of this research is the Dutch single-node model, which is provided by TNO. The goal is to develop a high spatial resolution model of the Dutch energy system. Currently, the Netherlands is modeled as a single node and this node hosts all the technologies described in Section 2.2.2.

Context of the single-node model

The single-node model approaches the Dutch energy system as a single node within the North-West of Europe (Figure 2.1). This structure includes transmission lines for import and export, but neglects internal transmission bottlenecks.

Figure 2.1: Single-node model network

North-West Europe includes the United Kingdom, Belgium, Germany, Denmark, and Norway. These countries are also represented by one node to simulate import and export with historic day-ahead prices for which the price duration curves are presented in Appendix C.3. These countries host two technologies each, an electricity import interconnector, to model Dutch imports, and an electricity export interconnector to model Dutch exports. The other countries are connected to the Dutch node with HVAC and HVDC lines.

Technologies
The model includes renewable generation technologies, storage, gas, coal, nuclear, waste, biomass, and hydrogen infrastructure. A complete overview is found in Table D.1. The cost data are retrieved from the existing TNO database and completed using additional sources on the Internet. Appendix D lists the cost data and other characteristics of the different technologies. The table includes carrier in, carrier out, CAPEX, OPEX, variable OPEX, efficiency, interest rate, dispatch and flexibility rules.

Table D.3 highlights a notable assumption. Unlike Utility PV and onshore wind, rooftop PV does not have an interest rate. This zero-interest assumption makes rooftop PV the most cost-efficient technology of the three in terms of the levelized cost of electricity (LCOE). Including an interest rate, the LCOE of rooftop PV would be more than twice that of the non-interest rate LCOE of rooftop PV. The LCOE of onshore wind is 75% higher than the LCOE of rooftop PV without interest, but including interest rooftop PV has a 35% higher LCOE than onshore wind. At the same time, the LCOE of rooftop PV without interest is also lower than the LCOE of utility PV. This is not the case when interest is also applied to rooftop PV. The zero interest assumption strongly impacts the LCOE of the different technologies, given that the other cost assumptions remain the same. Given an average weather year, this zero-interest assumption will cause the model to favor rooftop PV over utility PV and onshore wind. Also, comparing LCOE in Table D.3 to the LCOE in Euro-Calliope (Table D.6, it is expected that the zero-interest assumption results in a relatively large share of Rooftop PV in the future generation capacity.

The single-node model is an NTC based optimization model that defines three technologies for transmission: HVAC, HVDC and free transmission. The technologies differ in terms of the efficiency per kilometer that is used to calculate the NTC for each link. In the single-node model, internal transmission is neglected (free transmission).

2.2.3. The multi-node model

The following section describes how the single-node model is transformed into the multi-node model. (Section 2.3). For the purpose of this research, the spatial resolution of the single-node model is enhanced to the NUTS2 i.e. province level, using technologies and their techno-economical characteristics. That means that the multi-node model has 12 nodes for the Netherlands. Each node is assigned a set of technologies, from the list in Table D.1, and a capacity based on historic capacities. The nodes are connected with links (HVAC, HVDC and gas pipelines). High-resolution electrical grid data is retrieved from a power flow optimization model (Xiong et al., 2024), based on OpenStreetMap data (Open Infrastructure Map) or on the CSGM.

Context of the multi-node model
In the multi-node model, other countries are represented with one node (the same as in the single-node model), including the import interconnector and the export interconnector. However, where the single-node model has a single transmission line between the Netherlands and the connected countries, the multi-node model contains the interconnecting lines from each individual region to the neighboring countries. Export prices are based on historic 2023 day-ahead prices. Future day-ahead prices might be different in terms of volatility or an increase in hours where renewables set the price. However, forecasts are based on many assumptions, such as future capacities, regulations and fuel prices, whereas historical values capture actual price patterns. The import price is constant and higher than the costs of the most expensive generation technology. This means that the model only uses imports from neighboring countries as a last resort to balance the grid.

Another aspect of imports that is important to highlight is that imports do not result in additional CO_2 output. The model can thus use imports as a non-emitting flexible resource during low renewable hours, when ETS credits are scarce or high in costs.

Capacities on NUTS2 level
The historic capacity is the capacity in 2023 and for each technology at each node the capacity is given by a source listed in Table E.1. For the sake of this research, gas infrastructure is included as a copperplate.

This means that there is one node that contains all the existing gas supply infrastructure (LNG terminals and gas production fields) with unlimited pipeline capacity to the other nodes in the system.

Hydrogen infrastructure is left out of the scope of this study and the forecasted electricity demand for hydrogen production is also filtered from the total demand to align with this assumption. Nevertheless, hydrogen could serve as a form of long-duration storage in comparison to lithium-ion batteries, which have high round trip efficiencies. This might make hydrogen relatively appealing for balancing seasonal or inter-day fluctuations, whereas BESS may target more frequent, shorter-term shifts in supply and demand. As a result, both technologies can coexist, addressing different segments of the market. In combination with filtering out the demand related to power to hydrogen demand, this reduces the impact of leaving the hydrogen infrastructure out of scope.

The weather data consists of the capacity factors at NUTS2 level for the year 2019 from renewables.ninja (Pfenninger & Staffell, 2016). The model uses weather time series based on the year 2019 to determine the output from renewable sources. According to KNMI, 2019 was the year with the third most sun hours since 1999 (KNMI, 2020). Thus, the dispatch runs could results a relatively large output of solar PV technologies.

Demand

The hourly demand data from 2023 from the single-node model is disaggregated to NUTS2 level using Gregor (Launer, 2024). Based on a population proxy, the total load of the Netherlands is first disaggregated to a square kilometer raster for each time-step. In this study, the population density data (people/km^2) is retrieved from WorldPop and is based on the Dutch population in the year 2020 (WorldPop, 2020). From the raster level the load is aggregated to NUTS2 level to be applied in the model.

Alternative disaggregation methods could involve the use of separate industrial demand data alongside the population proxy to capture both residential and industrial loads. Another option is to rely on historical demand distributions, which capture observed spatial distributions of demand, or to use economic indicators, such as GDP, to reflect regional activity levels.

The strength of the population-based method lies in its practicality, because it is straightforward and applicable even when high-resolution historical or industrial demand data are not available. However, its weakness is that it may not accurately capture variations in industrial demand or regional economic activity, potentially leading to imprecise estimates. The resulting 2023 demand distribution is visualized and compared to historical demand in Section 4.2.

Transmission

The single-node model is currently unable to handle high-resolution electrical grid data. The goal is to use the most promising methods for calculating NTCs in the model using high-resolution electrical grid data from a power flow optimization model. Xiong et al. (2024) proposes such a multi-node model of the European power system that can be clustered to NUTS2 level. The output of this model will serve as input for the NTC calculations in the multi-node model to make up for the lack of power-flow balances in the model while retaining information on the underlying physical constraints in such a way as to avoid overly optimistic NTC estimations. By validating the model, we can then assess to what extent NTC based models can benefit from the use of high-resolution grid data from PyPSA-EUR (Xiong et al., 2024).

PyPSA-EUR uses k-means clustering based on the geographical centers of the NUTS2 areas. In addition, a weight is assigned based on the load and demand in the area. Thus, the aggregated grid data is based not only on the geographical center but also on an electrical center. Unfortunately, the PyPSA-EUR cluster drops certain physical and electrical parameters for the transmission lines when clustering to NUTS2. PyPSA-EUR clusters the Netherlands to a NUTS2 level by simplifying to a 380kV system with a standard line type (Al/St 240 4 cable bundles) thus neglecting the differences in voltages and other line characteristics. As a reference, this research proposes the use of the SGM as a means of validation for using the PyPSA-EUR data. The SGM, on the other hand, contains physical and electrical line specific values of all the HVAC lines in the Netherlands and the interconnectors with Belgium, Denmark, Norway, the UK and Germany. For the sake of evaluating the benefit of using the data of the PyPSA-EUR clustered grid in interregional NTC calculations, the SGM data is clustered to NUTS2 level by filtering for interregional lines based on the strategy in Figure 2.2. The result is the CSGM, that uses the sum of NTCs of the individual interregional lines per set of neighboring NUTS 2 regions to define the total interregional NTCs per set of regions. The CSGM is based on individual line characteristics, such as real-world cable length, resistance, reactance, maximum current and voltage.

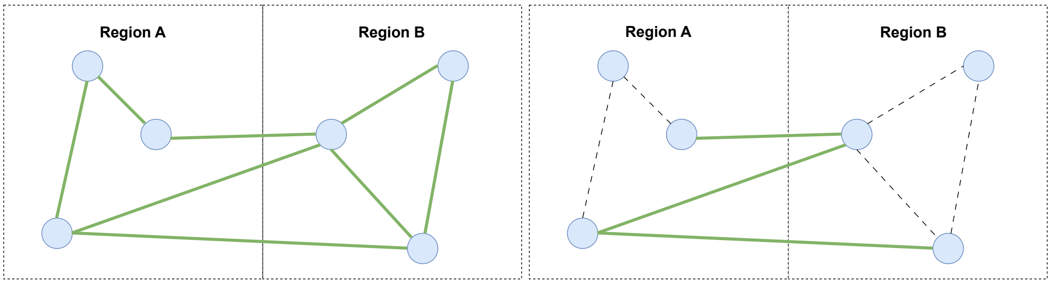


Figure 2.2: Illustration of the selection of interregional lines from the Static Grid model.

The CSGM does not consider transmission between substations within regions and neglects internal transmission bottlenecks. Moreover, the model does not consider the capacity of transformer and converter stations. The underlying assumption is that the planning of building converter and transformer stations is integrated with the planning of additional transmission capacity. The model thus assumes that internal transmission, converter and transformer capacity is always sufficient. Also, the model is based on existing lines and does not account for transmission projects that are already in the pipeline (under planning, permitting or construction).

Emissions

The multi-node model does initially not impose an emission limit on the system's operation in terms of annual emissions. The ETS price is equal to €83 / ton CO_2 according to the average price in 2023 (Agency, 2024).

2.3. Model validation

Having outlined the modeling approach, attention now turns to the validation of the model. The validation is based on the multi-node model and historic capacities, demand and weather data as explained in Section 2.2.3. This step focuses on comparing the model's performance to the actual operation of the Dutch power system to answer the second sub-question. This step involves a comparison of the PyPSA-EUR and the CSGM grid data. First, the most promising methods for calculating NTCs are applied to the PyPSA-EUR data. To assess whether the methods are also applicable to clustered data, the resulting NTCs are compared to the NTCs using the PTB approach. Next, the line characteristics, such as voltages, current, line crossings and eventually the resulting NTCs of the PyPSA-EUR cluster are compared to the CSGM. Interregional NTC is the sum of all the lines that cross the border between a set of neighboring NUTS2 regions. The number of line crossings is defined as the number of lines that connect two regions. This will provide insights into the usability of the clustered grid data from PyPSA-EUR in the multi-node model.

After the grid data and the resulting NTCs from PyPSA-EUR and the CSGM are compared, both data sources are implemented into the multi-node model. The multi-node model is then validated in three steps according to methods found in Open Data Based Model of the Dutch High-Voltage Power System (Zomerdijk, Gusain, Palensky, & Cvetkovic, 2022) for which the 220kV and 380kV data also comes from the SGM.

1. Conceptual validation: Are the assumptions and theories for the conceptual model correct?
2. Operational verification. Does the model operate as intended?
3. Operational validation: comparing performance metrics against the Open Data Based Model of the Dutch High-Voltage Power System and available real world data for one year (Zomerdijk et al., 2022)

After building the multi-node model, two dispatch runs are performed using historic demand, weather and capacity data. The results from the CSGM and PyPSA-EUR based grid models are then compared to one another and to historic data to compare the operation of the model the actual system's operation, while also testing the impact of using PyPSA-EUR as a source for grid data. The historic data includes monthly generation per production type.

2.4. Scenario analysis

In contrast to the model used in the validation, which is based on historic data for generation capacities, this section describes how the model is used to find optimal capacities based on future demand profiles. This section further describes the methodology for the scenario analysis, starting with the input data for demand, renewable capacities, storage, power plants, transmission and emissions. The section then presents the formulation of the model objectives and the sensitivity analysis before giving a detailed overview of the flow of the research and the tested cases.

2.4.1. Input data

The following section gives an overview of the data that is used in the scenario analysis, starting with the demand forecasts for 2030. Subsequently, the renewable capacity factors and the input and constraints of the storage, generation, emission, and transmission technologies are discussed.

Demand

The hourly load data for 2030 are based on the three scenarios of the Investment Plan 2024 (IP2024), published by Netbeheer Nederland (2023). The IP2024 serves as a strategic guide for the development of the Dutch electricity and gas infrastructure. It employs a scenario-based approach to ensure that the energy network can adapt to emerging trends, such as growing electrification and the integration of renewable energy. By examining possible futures through three scenarios, IP2024 offers a view of how policy, market dynamics, and technology could shape electricity demand patterns in the Dutch energy system through 2030. The three scenarios are Internationale Ambitie, Nationale Drijfveren and Klimaat Ambitie. Figure 2.3 shows the demand scenarios and their relation to future demand scenarios as per (Netbeheer Nederland, 2023).

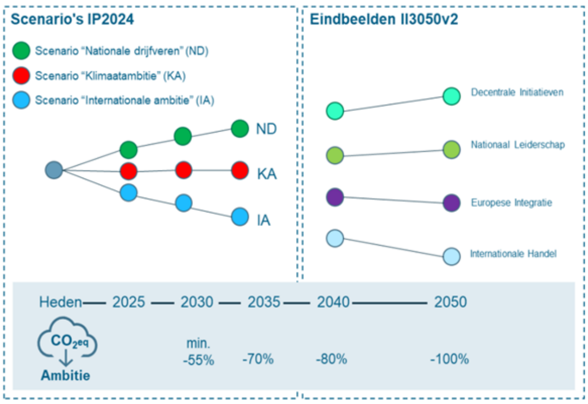


Figure 2.3: Demand scenarios IP2024 Netbeheer Nederland (2023)

In short, the storyline of each scenario is as follows:

1. **Klimaat Ambitie (KA)**: Reflects current and proposed climate policies, aiming for a 55% reduction in CO_2 by 2030. This scenario emphasizes a balanced transition that features electrification, sustainable gases, and energy efficiency. The annual load in this scenario is equal to 159.49 TWh.
2. **Nationale Drijfveren (ND)**: Focuses on self-sufficiency and widespread adoption of domestic wind and solar resources. This scenario assumes a rapid move toward electrification in transport, industry, and buildings, supported by decentralized generation. In this scenario, the annual load is equal to 181.33 TWh.
3. **Internationale Ambitie (IA)**: Describes extensive global cooperation and cross-border energy trading. Large-scale renewable projects, hydrogen imports/exports, and carbon capture and storage play an important role, positioning the Netherlands as a central energy hub. This scenario has an annual load of 146.39 TWh.

For this study, the demand scenarios are derived from these IP2024 scenarios as provided by The Energy Transition Model (Quintel, 2023). Each scenario provides electricity demand under different policies and technology pathways enabling robust analysis of potential system designs. To align the demand scenarios with the scope and purpose of this research, the demand related to future power-to-hydrogen applications is filtered from the time series. The resulting load-duration curves can be found in Appendix C. This approach supports more resilient decision making, as infrastructure investments can be informed by a range of plausible futures.

Renewables

The generation capacities of wind on land and solar PV are determined by the optimization model. In the scenario runs, rooftop PV is allowed to increase up to a maximum of 5.15 GW per region, which is equal to 10% of the maximum installed capacity in the IP2024 scenarios. Utility PV per region is constraint according to the same logic. Each region can host up to 10% of the maximum estimated systemwide Utility PV capacity. These constrainst are added to force the model to divide the generation capacity more equally over the regions. Onshore wind is only constraint by a systemwide maximum capacity of 12GW. The offshore wind capacity scenario is based on the Routekaart wind op zee (Rijksoverheid, 2022). This document provides an overview of offshore windparks that are operational, under construction, and planned. The total offshore capacity in this scenario is 21 GW. The capacity is allocated to NUTS2 regions based on information on the preferred connections (RVO, 2023).

Similar to the model used in the validation, weather data in the scenarios consists of capacity factors at NUTS2 level for the year 2019 from renewables.ninja (Pfenninger & Staffell, 2016). Since 2019 was a relatively favorable year for solar generation, it is important to consider the impact of the weather year when interpreting the resulting generation capacities, especially because of the relative LCOE of the renewable generation technologies in the multi-node model. In scenarios with weather conditions that favor solar generation, the model may allocate a relatively large amount of solar capacity compared to runs with less favorable conditions. As a result, the additional solar capacity might partially reduce the deployment of other generation technologies, such as onshore wind.

Storage

The first scenario for storage (Centralized) is based on the document published by TenneT, showing minimum and maximum battery storage capacities needed per NUTS2 region to maintain a stable grid in 2030 (TenneT, 2024). The Centalized scenario assumes the maximum capacity per region presented in the TenneT estimates, which sums to a total of 13 GW.[1] The second scenario (Flexible) for storage allows Calliope to estimate the optimal BESS allocation without any systemwide capacity constraints. In terms of costs, current estimates for OPEX, CAPEX and round-trip efficiency are used, even though there are indications of potential future cost reductions. However, the impact of increased demand for lithium, potential trade restrictions, and technological innovation is uncertain. Consequently, using current cost parameters provides a foundation for modeling based on available data rather than speculative future pricing. Implementing learning curves and cost reductions could be an interesting topic for future studies focussed on the business case of BESS.

Power plants

The TenneT BESS estimates assume that by 2030 Dutch hard coal plants are closed. To align with the storage scenario, the generation capacity of the coal plants is equal to zero in all the 2030 scenarios. Gas power plants remain open at minimum of the existing capacity, and the same applies to biomass and nuclear power plants. However, since nuclear plant planning and construction is not considered feasible by 2030[2], capacity expansion is not allowed. The potential of small modular reactors could be included in future research. The model allows expansion of the capacity for gas CCGT plants, while keeping Carbon Capture Storage (CCS) out of the equation. CCGT in combination with CCS could be an alternative for BESS for flexible generation while also cutting CO_2 emissions. Although Porthos, a CCS project for the industry at the Port of Rotterdam, is already under construction, and Aramis is under development, the potential availability for storage of CO_2 for suppliers with CCGT plants remains uncertain. The model also allows investments in biomass capacity.

[1]As there is no indication of the assumed storage capacity in the TenneT scenario, for the Centralized scenarios in this research the storage capacity is assumed to be four times larger than the installed GW.

[2]History learns that only construction of nuclear power plants is very time consuming. According to Shykinov, Rulko, and Mroz (2016) the construction of a nuclear power plant consumes 7 years on average, with the process from planning to commissioning taking approximately 11 to 12 years in total.

Transmission
For the transmission system, the current estimated interregional capacities are used as fixed NTCs. The methods for calculating these NTCs are explored in Section 3 and validated in section 4.1. The most accurate method is implemented in the multi-node model to calculate the current intterregional capacities that are used in the scenario analysis (Section 4.4). Later, in the sensitivity analysis (Section 4.6), the model has the possibility to invest in additional transmission capacity according to the constraints laid out in Section 2.4.3. The idea is to find the impact of not expanding the grid, identifying bottlenecks in a decentralized system and comparing the relative merits of (de)centralized system designs to limit congestion. Congestion is defined as a line operating above 99% of it's capacity and the number of congested line hours on an annual basis is equal to the the number of lines being congested per hour summed over a full year. The model does not contain line specific parameters for lines that are not built yet. Thus, in the case of expansion of transmission capacity, the model uses the areal distance between the nodes in the optimization to determine CAPEX and tranmission losses. Moreover, when optimizing the transmission capacity, the model does not consider the need for transformer and converter stations. The underlying assumption is that the planning of building converter and transformer stations is integrated with the planning of additional transmission capacity. This idea is not represented in the cost assumptions, which is an important note when comparing the system costs of system designs with and without transmission capacity expansion. The model thus assumes that transmission, converter and transformer capacity is always sufficient.

Emissions
The amount of emissions allowed through the ETS is determined by the emissions target, which for 2030 is equal to a reduction of 55% compared to 1990. In 1990 the emissions of the power sector were equal to 39.6 Mton CO_2 (Centraal Bureau voor de Statistiek, 2024). A 55% reduction means that in 2030 the equivalent to 17.82 Mton CO_2 is emitted though power generation. In all scenarios, the model operates within the limit of the 55% reduction. The ETS price is equal to the average 2023 ETS price that is used in the model validation.

2.4.2. Optimization formulation
The research uses the methodology of modeling to generate alternatives (MGA) to find energy system designs that limit the load of the lines within a solution space that is nearly cost-optimal. First, the model will look for the cost-optimal solution for each of the scenarios. Then, for each scenario, the focus will shift to minimizing congestion in terms of the average line loading. In this step, the costs of the cost-optimal solution for each demand scenario are used as input for a new constraint. For each scenario, the total system costs are constraint to be equal or less than 101% of the system costs in the cost-optimal solution, allowing the model to look for designs that limit the line load in the system within the near-cost-optimal solution space. The implementation of this strategy in the model is visualized in Appendix F. The hourly line loading for each line is equal to the flow divided by the line's NTC.

$$\text{Line load}_{t,i} = \frac{\text{Net flow}_{t,i}}{\text{NTC}_i} \tag{2.1}$$

where t is the time step, i is the line, Net flow and NTC are both given in GW. The net flow in the model is calculated by:

$$\text{Net flow}_{t,i} = \text{carrier\_prod}_{t,i} - \text{carrier\_con}_{t,i}. \tag{2.2}$$

2.4.3. Sensitivity analysis
The sensitivity analysis's goal is to highlight the potential of different system designs by making changes to the model's input. For each of the previous scenarios, two changes are proposed: A smaller limit to solar PV per region, to prevent high concentrations of renewables, and allowing the model to expand the transmission capacity.

Loose solar PV
In this case, the max allowed capacity for solar rooftop PV is increased. The max capacity of rooftop solar is equal to 7.725 GW per region, this is equal to 15% of the maximum installed capacity as per the IP2024 scenarios for 2030. As described in Section 2.4.1, in the original scenario runs, rooftop solar was allowed to increase up to a maximum of 5.15 GW per region. In this analysis, the model has more

freedom to allocate rooftop PV in the most cost-efficient way. Key aspects that are compared are the costs, emissions, congested hours, BESS capacity (factor) and the land use in each region.

Transmission expansion
In this case, the study tries to find the impact of not expanding transmission capacity on system costs and allocation of generation and storage capacity. Key aspects that are highlighted involve costs, emissions, congested hours and BESS capacity (factor). To this end, expansion of the capacity of the transmission lines is possible within a margin per line, where the current NTC of the line determines what this margin is. The line with the smallest NTC can increase by the maximum amount of addition allowed: 50%. For the other lines, the size of their NTC relative to the smallest NTC determines the allowed expansion, where the allowed expansion is equal to 50% over the relative size. The relative size is equal to a line's NTC over the minimum NTC.

2.4.4. Overview of the tested cases

This section provides an overview of the tested cases in this research. Figure 2.4 gives an example of the cases per demand scenario.

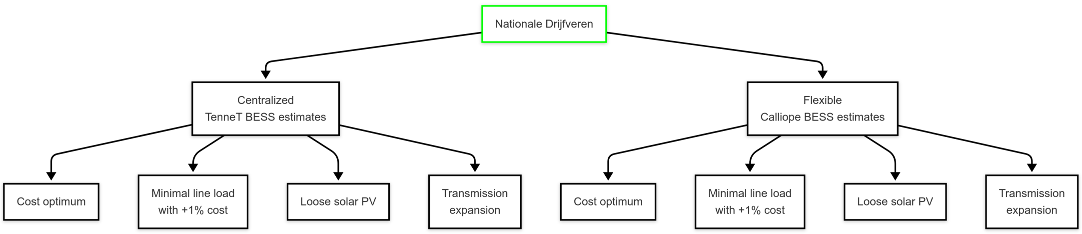


Figure 2.4: Scenario overview Nationale Drijfveren.

The first distinction between scenarios lies in the allocation of BESS, which is addressed through two approaches (Section 2.4.1):

- **Centralized**: In this approach the battery capacity per region is fixed based on the **BESS estimates by TenneT**. Under these constraints, Calliope determines the cost-optimal allocation of generation capacities and dispatch, using the existing capacities as a minimum baselin, except that coal plants are assumed to be decommissioned. Furthermore, transmission capacity is maintained at historic levels and the offshore capacity is fixed in accordance with the Routekaart Wind op Zee.
- **Flexible**: In this approach, **Calliope determines the BESS capacity** to find the least-cost system design. The other constraints are the same as in the Centralized scenarios.

Combining these approaches with the demand scenarios in Section 2.4.1, the optimization of both the cost and line load and the sensitivity analysis results in a total of 8 cases per demand scenario. A complete overview of the tested cases is listed in Table 2.1.

Technology	**Model Validation**	**Cost Opt. Centralized**	**Cost Opt. Flexible**	**Minimal Line Load**	**Loose PV**	**Transmission Expansion**
Generation						
Offshore wind	Historic capacity	Routekaart wind op zee	Routekaart wind op zee	Routekaart wind op zee	Routekaart wind op zee	Routekaart wind op zee
Onshore wind	Historic capacity	Calliope	Calliope	Calliope	Calliope	Calliope
Rooftop PV	Historic capacity	Calliope	Calliope	Calliope	Calliope **(max 7.725GW/region)**	Calliope
Utility PV	Historic capacity	Calliope	Calliope	Calliope	Calliope	Calliope
Nuclear	Historic capacity	Historic capacity	Historic capacity	Historic capacity	Historic capacity	Historic capacity
Gas CCGT	Historic capacity	Calliope	Calliope	Calliope	Calliope	Calliope
Coal	Historic capacity	-	-	-	-	-
Biomass	Historic capacity	Calliope	Calliope	Calliope	Calliope	Calliope
Import	Calliope	Calliope	Calliope	Calliope	Calliope	Calliope
Storage						
BESS	Historic capacity	TenneT estimates	Calliope	TenneT estimates/Calliope	TenneT estimates/Calliope	TenneT estimates/Calliope
Grid						
Transmission	PyPSA-EUR / CSGM based Historic capacity	Historic capacity	Historic capacity	Historic capacity	Historic capacity	**Calliope**
Rationale	The model uses historical grid and generation capacities in an economic dispatch to meet historical demand.	Minimizes system costs and optimizes generation investments to meet future electricity demand using historical grid capacities.	Minimizes system costs and optimizes generation and **storage** investments to meet future electricity demand using historical grid capacities.	Reduces transmission usage while maintaining near-optimal costs by minimizing line load within 1% of cost optimum as explained in Section 2.4.2 using historical grid capacities.	Minimizes system costs and optimizes generation and storage investments. Tests impact of the regional PV constraints and the potential benefit of increased PV adoption by applying less strict PV constraints as explained in Section 2.4.3. Uses historical grid capacities	Minimizes system costs and optimizes generation, transmission and storage investments. Evaluates system behavior with expanded transmission and gives insights into the trade-offs for (de)centralized system design. Transmission expansion is allowed as explained in Section 2.4.3.

Table 2.1: Overview of how technologies are modeled in the validation, optimization, minimal line load, and sensitivity scenarios. *Note: In the table "Calliope" refers to the model's optimization of capacity within constraints laid out in Section 2.4, using historical capacity as a minimum.*

Figure 2.5 provides a schematic overview of the research workflow, outlines the sequential application of the methods employed in this study, and highlights how the steps relate to the sub-questions.

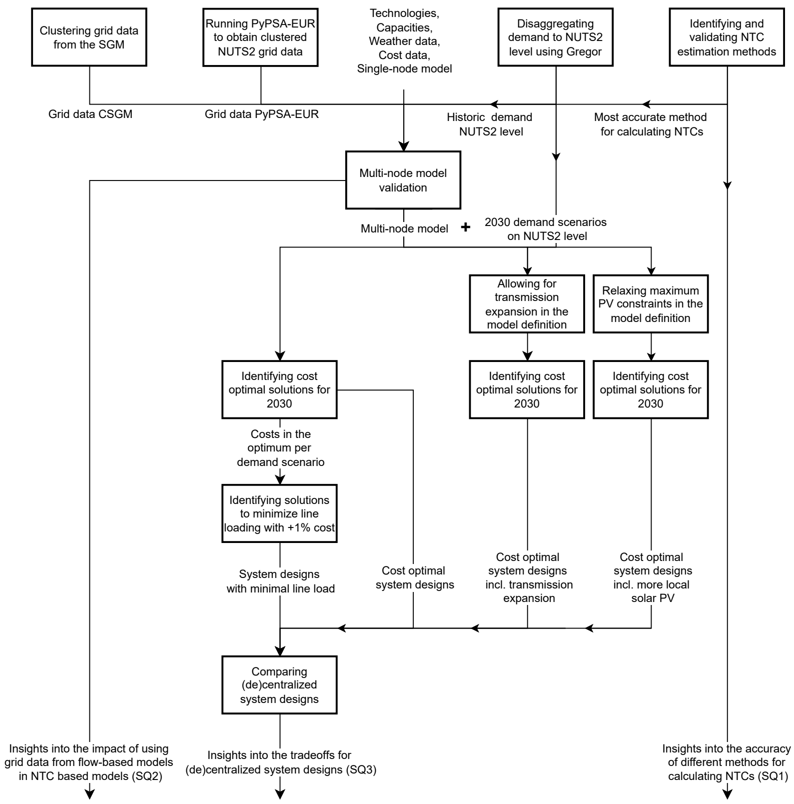


Figure 2.5: The research flow diagram.

3 Literature

This section presents the findings of the literature and desk research to give an overview of the different methods for calculating NTCs. This includes a brief description of what TSOs call NTCs and the PRB method, that is used as a reference NTC to validate the methods in Section 4.1. The section concludes with a discussion on existing knowledge and a link to the contribution of the work to answer the first sub-question:

"How can we calculate Net Transfer Capacities and how can we integrate correction factors for resistances and voltages and transferring it to a net power cap?"

3.1. NTCs according to the TSO

TSOs calculate NTCs based on total transfer capacity (TTC) and transmission reliability margins (TRM) ((ETSO), 2000). TRMs are used to account for imperfect information from market players and unexpected real-time events. Information from market players is imperfect at the time the transfer capacities have to be communicated. This comes in addition to the uncertainty on some power system parameters, as well as the uncertainty of tie-line flows due to unexpected real-time events, which are always possible. The TRM represents the capacity that is needed to ensure the security of the system in such unexpected events. The TSO accounts for ambient temperatures impacting the capacity of the transmission lines in load flow based calculations. TTC is based on thermal and voltage limits as well as stability limits.

Additionally, the n-1 criteria is used, all line capacities are multiplied by 0.7. The n-1 criteria states that the system should be able to continue operation when one of the lines fails for whatever reason. This rationale is also applied in the multi-node model.

3.2. Power Triangle Based

The Power Triangle Based (PTB) approach is based on the relation between the true power, reactive power and the apparent power. The PTB approach is used as a reference to validate the other methods for calculating NTCs. The actual power consumed in a circuit is known as true power and is measured in watts (P) (Circuits, 2014). Reactive power influences voltage and current levels, but does not directly dissipate power as heat or work. When true power and reactive power are combined, the result is apparent power, which corresponds to the product of voltage and current magnitudes without considering their phase relationship.

True power is calculated using a circuit's resistance (R), while reactive power depends on the circuit's reactance (X). Apparent power, on the other hand, is related to the total impedance (Z). The equations describing these relations are:

$$P = I^2 R \quad \text{(true power)}$$

$$Q = I^2 X \quad \text{(reactive power)}$$

$$S = I^2 Z \quad \text{(apparent power)}$$

True power, reactive power, and apparent power can be described using the Power Triangle in Figure 3.1 (Circuits, 2014). Using the figure, it is possible to determine all the different powers using either the impedance (Z) and the size of one side or the length of the two known sides. This method is used as the "real" NTC and serves as a reference NTC to validate the approximation methods found in the literature.

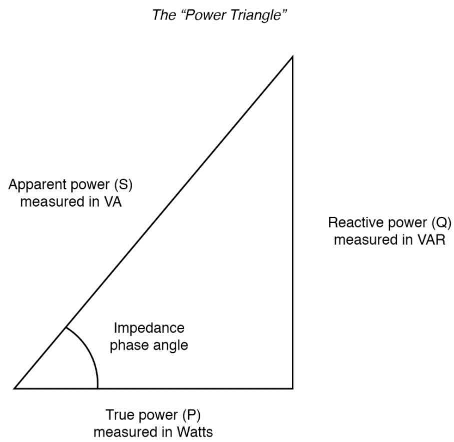


Figure 3.1: The Power Triangle

The literature does not provide applications of the PTB approach in energy system optimization models, potentially due to the impossibility of using line-specific parameters when dealing with grid expansion or the general unavailability of such specific parameters. So far, no examples are found that demonstrate a method to apply the PTB in the absence of the line-specific parameters. In this study, expansion of transmission capacity is an important part of identifying trade-offs for the design of future electricity systems.

The literature mentions roughly two types of models: NTC based, and power-flow-optimization models or flow-based. Although, power-flow optimization models results in a representation of grid dynamics that closely aligns with physical constraints and real-time operations by adhering to Kirchhoff's voltage law and the use of detailed line-specific parameters (Gunkel, Koduvere, Kirkerud, Fausto, & Ravn, 2020), this complexity increases computational requirements, which can slow down simulations in large, multi-node systems and render flow-based models less suitable for overarching investment analysis. Thus the focus of this research is to compare methods for calculating NTCs and assessing the benefit of using the high-resolution electrical data from power-flow-optimization models in NTC based models to avoid overly optimistic NTC calculations.

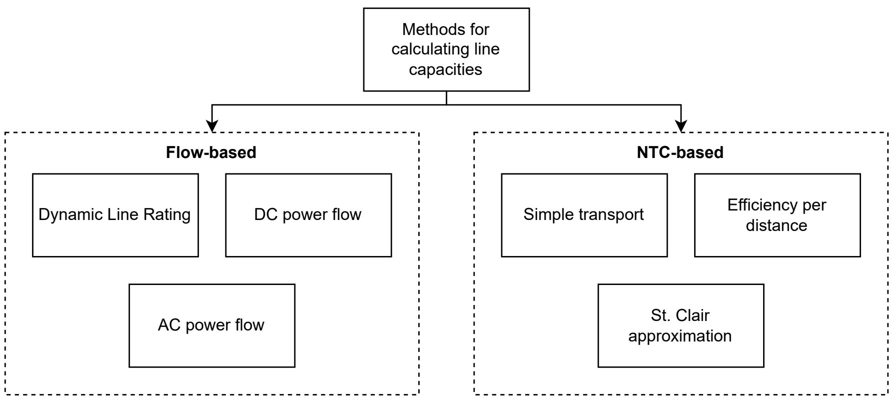


Figure 3.2: Methods for calculating line capacities from the literature

The next subsection will give a brief description of three methods used in NTC based models, the models that we are interested in, and the section thereafter describes examples of flow-based models.

3.3. NTC based models

3.3.1. Simple transport model

There are models that do not take into account physical constraints. These simple transport models apply fixed capacities, equal to the nominal capacities. PyPSA is an open source framework that includes an option for using simple transport models (Brown et al., 2017). PyPSA offers two approaches for modeling inter-regional power transfers: one is a simple transport model, and the other incorporates constraints based on Kirchhoff's current and voltage laws in linear optimal power flow (LOPF) based on AC or DC power flow. In large scale optimization models with large time-horizons, the simple transport model can help to reduce the computational burden. In the transport model, PyPSA calculates line limits using the maximum current and the voltage with the following formula:

$$NTC_{\text{PyPSA}} = \sqrt{3} \cdot U_i \cdot I_i \cdot 0.7 \tag{3.1}$$

where U_i is the voltage of line i (in volts), I_i is the maximum current of line i (in amperes), and 0.7 is a factor that serves as an $n-1$ approximation.

Models of this type do not account for resistances, such as in DIETER (Zerrahn, Gaete-Morales, Kittel, Roth, & Schill, 2021). The question remains why PyPSA would not use the method explained in section 3.2 in the transport model as PyPSA has the necessary parameters in the standard line types. A potential explanation could be that using one standard line type, ignores other characteristics such as the different voltage levels across regions. Implementing exact line types per region might not be feasible, for example when the line type is not publicly available. In section 4.1 the simple transport method is compared to the actual NTC to validate the method.

3.3.2. Efficiency per distance

TNO is looking to enhance the spatial resolution of their current Dutch single-node model, which is currently using the nominal grid capacity (in MW), length and efficiency per distance parameters for HVAC and HVDC to calculate NTCs between regions (HVDC at 0,99965%/km and HVAC at 0,999967%/km).

The same method is found in renpass (Wiese et al., 2014). renpass is an open-source energy system optimization model designed to be fully transparent and capable of representing both entirely renewable energy systems and current systems at a high spatial and temporal resolution. In renpass NTCs, are based on nominal capacity, efficiency per kilometer per line type and distance. Another option in renpass is to reduce the nominal capacity of each line with a percentage that is the same for each line regardless of the voltage or line type.

Van Ouwerkerk et al. (2022) mentions a slightly different approach, which they implement in GENESYS-2 (G2), based on capacities of all lines between regions, combined into a single link. G2 uses length of the line and an efficiency parameter for overhead and submarine lines to calculate NTCs between regions. In the essence, G2, renpass and the TNO single-node model apply the same theory, which is expressed in this formula:

$$NTC = \sqrt{3} \cdot U_i \cdot I_i \cdot eff^{km} \cdot 0.7 \tag{3.2}$$

where U_i is the voltage of line i (in volts), I_i is the maximum current of line i (in amperes), eff^{km} is the efficiency per kilometer of the line, and 0.7 is a factor that serves as an $n-1$ approximation.

3.3.3. St Clair approximation

The last method proposes three regions for line limits based on the length of a line. The first region is the region of thermal limitation, the second region is the region of voltage drop limitation and the last region is the region of small-signal stability limitation as shown in Figure 3.3. The method is based on based on Surge Impedance Loading and St. Clair curves that reduce the rating of a line based on line impedance, shunt susceptance, and length for stability and voltage considerations.

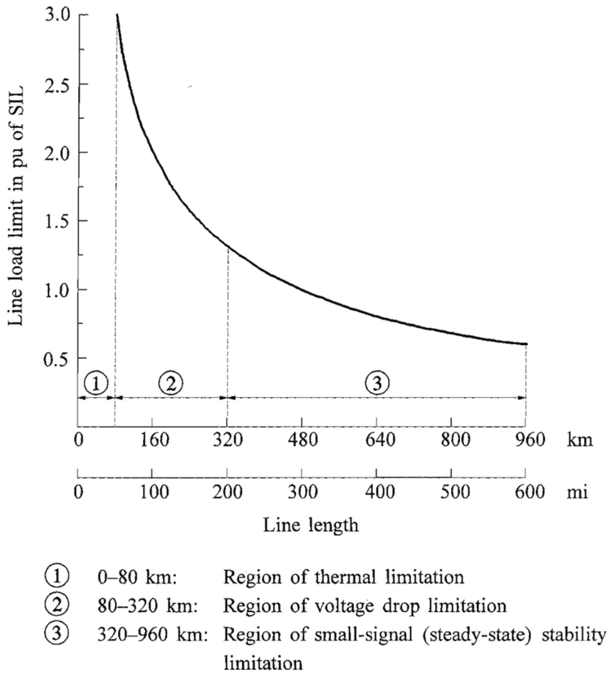


Figure 3.3: An example of a St. Clair curve Martin et al. (2017)

In their study on the Texan high-voltage grid, Martin et al. (2017) demonstrate that while the St. Clair method can be effective for estimating the overall magnitude of transmission interconnections between regions, their level of inaccuracy may be excessive for direct use in unit commitment and dispatch models. A key challenge lies in the absence of a systematic bias such as a consistent tendency to over- or underestimate transmission capacity, which makes it difficult to interpret the results as definitive bounds. The authors suggest that part of the error arises from how the length of the equivalent transmission line is estimated, noting that smaller regions in the western part of their case study led to overestimates of capacity, whereas larger regions in the east resulted in underestimates.

For future applications of the St. Clair curve in transmission approximation, the authors propose designing regions of uniform size to foster a predictable pattern of over- or underestimation. They also recommend delineating regions in a way that aligns approximated lines with actual transmission corridors, a step that would allow for more thorough validation against known capacities. Although the St. Clair curve offers a promising foundation for transmission approximation, Martin et al. (2017) conclude that additional refinements are necessary before it can be confidently employed in unit commitment and dispatch models for renewable capacity planning.

The St Clair approximation is also found in a version of a PyPSA model made for South Africa (PyPSA-RSA) (Economics, 2024). This method proposes a different approach than PyPSA-EUR and PyPSA simple transport, based on Surge Impedance Loading and St Clair curves. The NTC of HVAC lines equals the total of line capacities between two regions. A 30% reduction is applied as an n-1 approximation. If there is more than one line connecting two regions, the capacity of the largest line is deducted to approximate the n-1 criterion. The authors use the St. Clair approximation because PyPSA-EUR overestimates NTCs in the case of long lines. According to the documentation, the model is currently under development and only validated for the 1-supply spatial resolution i.e. the single-node version, meaning that the model including the transmission network at high spatial resolutions is not yet validated. In the high spatial resolution, NTCs are calculated using the St. Clair approximation using the following formula:

$$NTC_{\text{St.Clair}} = \min\left(\text{Thermal limit}, \ SIL_i \cdot 53.736 \cdot l_i^{-0.65} \cdot 0.7\right) \tag{3.3}$$

Here, l_i is the length of the line in kilometers, and SIL is the surge impedance loading in megawatts (MW) and 0.7 serves as an $n-1$ approximation. The thermal limit is given by:

$$\text{Thermal limit} = \sqrt{3} \cdot U_i \cdot I_i \cdot 0.7 \tag{3.4}$$

where U_i is the line voltage in volts, and I_i is the maximum current in amperes and 0.7 serves as an $n-1$ approximation. The Surge Impedance Loading, or SIL, is calculated using the following equation:

$$SIL_i = \frac{U_i^2}{Z_{0,i}} \tag{3.5}$$

where U_i is the line voltage in kilovolts, and $Z_{0,i}$ is the characteristic impedance of a line. The characteristic impedance of a line is calculated with the following formula:

$$Z_{0,i} = \sqrt{\frac{L_i}{C_i}} \tag{3.6}$$

In this formula, L_i is the inductance and C_i is the capacitance of the lines. Appendix G illustrates how L_i and C_i can be calculated. Unfortunately, the SGM does not provide the specific characteristics to calculate C_i. Thus, the capacitance from PyPSA-EUR is used.[1].

For the lines in the thermal limitation region, according to the St. Clair approximation, the thermal limit applies. For HVDC, there is no such thing as a voltage drop and thus the thermal limit determines the NTC. N-1 also does not apply to DC lines.

3.4. Flow-based models

Alternatively to NTCs, one can choose to use flow-based models, for which two example models are given in the next section.

3.4.1. Dynamic Line Rating

In PyPSA-EUR, physical parameters are used to calculate line ratings in an optimal-power flow balance that accounts for power flow constraints. It calculates dynamic line ratings based on thermal limits and heat exchange (Brown et al., 2024). This includes resistance-based loss, radiation from the transmission line and natural/wind-based convection. A heat balance that incorporates each line's maximum temperature threshold is employed to calculate the highest feasible capacity factor, or NTC, for every transmission line at each time step. This approach ensures that the line operates within its thermal limits, thereby providing a more accurate measure of its real-time capacity.

3.4.2. AC load flow

In LOPF in PyPSA for AC networks, the series reactance together with the deviations in voltage angle are used to compute the load flow. Voltage angles are calculated using a linear set of equations. This includes the incidence matrix, which describes how buses are connected by branches and a diagonal matrix that contains the inverse of the series reactances for each branch. Once the voltage angles are computed, the active power flows in the network branches can be determined by multiplying the voltage angles with the transpose of the incidence matrix with the diagonal matrix of inverse series reactances. This approach is useful because it simplifies the analysis by reducing the number of variables and focusing on the key parameters that affect active power flow in an AC transmission system.

3.4.3. DC load flow

In DC networks, PyPSA, applies the same AC LOPF formulas, but instead of the differences in voltage angle, the deviation in the magnitude of the voltage is used as well as the series resistance instead of the reactance. In another paper, Gunkel et al. (2020) compare flow-based (FB) with Power Transfer Distribution Factors to the NTC representation when using optimization models for investment. FB uses Kyrchoff's circuit law to generate so called thermal limits and DC approximation resulting in a DC load flow model. This approach makes many assumptions to linearize AC line characteristics. This approach uses a PTDF matrix that shows how the power generated in the nodes relates to the line flows. At the same time, it assumes lossless transmission lines. In this paper the authors use PyPSA-EUR for grid data, which is interesting as this study proposes to validate the use of this data source for high-resolution grid models.

[1] PyPSA-EUR leverages the capacitance per unit length from the standard line types provided in PyPSA: 13.8 nF/km and 12.5 nF/km for 220kV and 380kV lines respectively

Flow-based models offer improved realism by adhering to Kirchhoff's voltage law and using detailed line-specific parameters, leading to a representation of grid dynamics that closely aligns with physical constraints and real-time operations (Gunkel et al., 2020).

However, this complexity increases computational requirements, which can slow down simulations in large, multi-node systems and render flow-based models less suitable for overarching investment analysis (Gunkel et al., 2020). Furthermore, the authors indicate that flow-based models might overestimate capacity, potentially leading to unforeseen congestion or stress under actual operational conditions. So, NTC proves to be conservative while FB might overestimate.

3.5. Discussion

Many multi-node optimization models in energy systems do not fully capture the physical constraints of transmission lines, relying instead on simplified Net Transfer Capacity (NTC) assumptions. This can lead to mismatches between the actual physics of power flows and the capacity limits used in high-level planning or investment models. Since the goal of this research is to look for potential system configurations that help solve grid congestion, more accurate estimates of NTCs help to assess the need for additional local generation, transport or flexibility needs to relieve the stress of the grid. Although more advanced, methods exist (e.g., in PyPSA-EUR and other flow-based alternatives), they tend to be computationally intensive and may not be easily integrated into large-scale optimization frameworks that co-optimize generation and transmission capacity. Moreover, as most energy system models are based on NTC grid modeling methods, developing reliable estimates of NTCs out of electrical grid data would open up the use of high-resolution grid data, which are increasingly available.

Currently, most NTC models apply nominal capacities or an efficiency per distance per line type. The St. Clair curve offers another relatively straightforward method to account for physical constraints when estimating NTCs. However, as Martin et al. (2017) highlights, its application can produce significant inaccuracies, particularly when the regions or line lengths vary substantially. The method has yet to be comprehensively validated in unit commitment or capacity expansion contexts. Its use in PyPSA-RSA has also not been accompanied by extensive documentation or peer-reviewed studies that demonstrate its effectiveness in practical, multi-node optimization models because it is still in development. Martin et al. (2017), highlight in the Texan case significant inaccuracies and unpredictable bias, potentially caused by the large size difference of the regions and the significant difference in line lengths. In the Dutch case, the line lengths and the size of the NUTS2 regions vary less than in the Texan case. By implementing the St. Clair approximation alongside other, more established NTC assessment methods, and validating the model operation for a present-day Dutch power system configuration against real-world data, the research will provide valuable insights to the boundaries of the application of the St. Clair approximation.

The St. Clair approximation is highly dependent on the line lengths and the voltages of approximated transmission lines. The authors recommend delineating regions in a way that aligns approximated lines with actual transmission corridors. In this work, regions and line lengths from PyPSA-EUR as well as from the SGM are used as a basis for the St. Clair approximations. This way, an assessment of the accuracy of the St. Clair approximation is made with the clustered data from a validated flow-based model such as PyPSA-EUR as well as actual transmission line data. This could point out whether it is interesting to use the grid data from such models in models that initially do not consider physical constraints when calculating NTCs.

This research aims to bridge this gap by testing the St. Clair curve in a high spatial resolution model of the Dutch power system considering the improvements suggested by Martin et al. (2017). This is an environment fundamentally different from the Texas system in both scale and geographical layout. By leveraging the detailed grid data from PyPSA-EUR and the SGM, the model will optimize generation and storage to address grid congestion issues, examining how the St. Clair-based NTC estimates perform. Because the Netherlands comprises smaller, more densely interconnected regions than Texas, the method's validity in this context is not assured; nonetheless, if it proves effective, the St. Clair curve could offer a middle ground between abstract capacity assumptions and the computationally heavy flow-based approach. This work thus aims to evaluate whether incorporating physical parameters with the St. Clair approach into multi-node models can yield more accurate, system configuration solutions for grid congestion than the other NTC methods that use the nominal capacity or an efficiency per distance to account for losses.

4 Results

The Results section shows the results from the methods as explained in the Methodology section. The section starts with the validation of the methods for calculating NTCs, concluding with the most accurate method to be used in the model. Following the method validation, the PyPSA-EUR grid data is evaluated by comparing the data and the resulting NTCs to the clustered SGM (CSGM). After that, the demand distribution is illustrated before diving deeper into the model validation and the scenario analysis. Finally, a sensitivity analysis is performed to test the robustness of the results.

4.1. Validating NTC methods

This subsection describes the results of the analysis that is used to validate and compare the different methods for calculating NTCs, starting with the validation of each method. The approximated NTCs according to each of the methods are compared to the NTC using the method found in Section 3.2. The methods are first applied to all the individual lines, as per the SGM. The NTC methods are then applied to the PyPSA-EUR and CSGM data to calculate the interregional NTCs for each network representation. Finally, the grid data of both PyPSA-EUR and the CSGM and the resulting NTCS are compared to validate the usage of clustered grid data from a flow-based model such as PyPSA-EUR in NTC based models. Table 4.1 gives an overview of the different abbreviations and names used for the NTC methods and the grid data sources.

ID	Explanation
Data Sources	
SGM	Static Grid Model by TenneT, including line-specific parameters, used to approximate line-specific NTCs.
CSGM	Clustered SGM, which aggregates the NTCs from the SGM into a single NTC per set of neighboring regions. The CSGM is used to validate the PyPSA-EUR data.
PyPSA-EUR	Clustered grid data on the NUTS 2 level from PyPSA-EUR, based on OpenStreetMap data and standard line types.
Approximation Methods	
Simple Transport	A Simple Transport-Based approximation using the PyPSA simple transport approach.
Efficiency per Distance	Estimates transmission losses based on an efficiency factor per kilometer.
St. Clair	Uses the St. Clair approximation to compute line NTCs.
PTB	Power Triangle Based approach, serving as the reference NTC for validating the approximation methods.

Table 4.1: Overview of data sources and approximation methods used in this study.

4.1.1. Method validation

In this analysis, the PTB NTC values for all the individual lines from the SGM are compared with the three approximation methods: the St. Clair approximation (Figure 4.1), the Simple Transport from PyPSA (Figure 4.3) and an efficiency-per-kilometer-based approach (Figure 4.2). In the method validation, parameters provided by the SGM serve as input to estimate the NTC values. The resulting NTCs are thus based on individual line characteristics from the SGM.

Validation of individual line NTCs

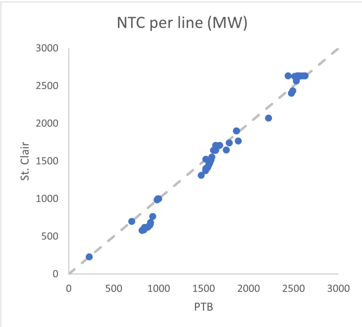


Figure 4.1: Validation of the NTC per line using the St. Clair approximation.

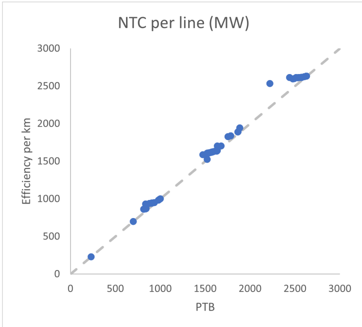


Figure 4.2: Validation of the NTC per line using an efficiency per kilometer.

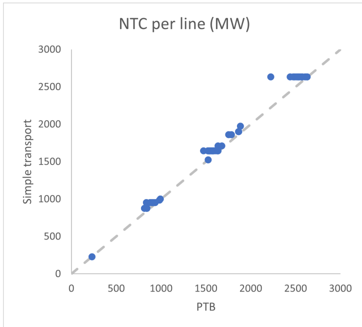


Figure 4.3: Validation of the NTC per line using Simple Transport.

Each point in the plots represents a specific transmission line, and the diagonal dashed line indicates perfect agreement between the estimated and PTB NTC values. A strong alignment of the points along the diagonal suggests a high degree of accuracy in the approximation methods. The Pearson correlation coefficients quantify this relationship, with values of **0.991** for the St. Clair approximation, **0,995** for the Simple Transport and **0.997** for the efficiency-per-kilometer method. These high correlation values indicate that all the methods closely replicate the NTC values from the PTB approximation, with the efficiency-per-kilometer method showing the highest alignment.

Figure 4.1 illustrates that, for certain transmission lines, the St. Clair approximation yields a lower NTC than the PTB NTC, whereas Figure 4.2 does not show this behavior. The St. Clair approximation is used to account for losses, specifically in systems with long transmission lines. In such cases, the Simple Transport calculation is said to overestimate NTCs. However, in this case, there are lines for which the St. Clair method actually underestimates the PTB NTCs. Several lines demonstrate an underestimation by the St. Clair method, especially when the lines tend to be relatively long.

Figure 4.4 further highlights this trend by plotting the difference between the PTB NTC and the St. Clair-based NTC against the line length. The difference is calculated by subtracting the St. Clair NTCs from the PTB NTCs. For shorter lines, the bias of the St. Clair approximation seems more unpredictable in terms of underestimation and overestimation.

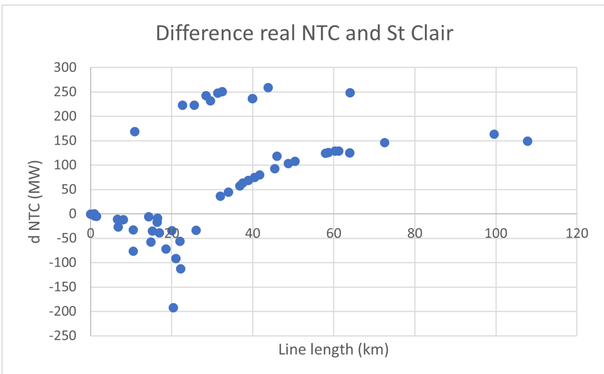


Figure 4.4: NTC estimation error using the St. Clair approximation.

Nonetheless, these results validate the reliability of the approximation method using the efficiency per kilometer in capturing the transmission capacity of the grid.[1] This comparison provides confidence in using the approximation for scenarios where the full SGM parameters might not be readily available. It also confirms the findings of Martin et al. (2017) indicating an unpredictable bias in the approximation results using the St. Clair curve. The results further suggest that additional refinements to the St. Clair approximation may be required to not become overly conservative when calculating the NTC of long individual transmission lines, to prevent underestimation.

Validation of the cluster

The following analysis will provide information on the accuracy of the clustered grid data from PyPSA-EUR and the potential benefit of using such data to approximate NTCs. First, by applying the different methods for NTC approximation to the PyPSA-EU and then by comparing the PyPSA-EUR data and the resulting NTCs to the CSMG. After clustering the SGM data to the NUTS2 level CSGM[2], the methods for calculating NTCs are applied to both the PyPSA-EUR data and the CSGM. The resulting NTCs and the underlying network characteristics are then compared.

Appendix B.2 shows the NTCs of interregional lines using the different methods with the PyPSA-EUR grid data as input in Figure B.1 and Figure B.2. No strange behavior is observed, and the approximated NTCs seem to align with the PTB NTCs quite closely.

Figure B.3 in Appendix B.2 confirms this, indicating that all the NTC methods closely resemble the PTB NTCs using PyPSA-EUR as input. Based on the PyPSA-EUR data, the St. Clair method shows a strong correlation (Pearson’s r = 0.9915) with the PTB NTCs, while the per kilometer approach shows an even higher correlation (Pearson’s r = 0.9988). Thus, both methods closely track the PTB NTCs, although the per-km approach appears to provide a marginally better fit. The methods are thus also applicable to clustered data.

To test the accuracy of the PyPSA-EUR grid data, the NTCs are compared to the interregional NTCs derived from the CSGM in Figure 4.5. Interregional NTC is the sum of all the lines that cross the border between a set of neighboring NUTS2 regions. Additionally, the number of line crossings at each border is analyzed for both data sources, where line crossings are defined as the number of lines connecting two regions. Figure 4.6 shows the alignment of the number of line crossings per set of regions, represented by a data point. The dotted line indicates perfect alignment, where the number of line crossings according to the PyPSA-EUR cluster is equal to the number of line crossings as per the CSGM data. Figure 4.5

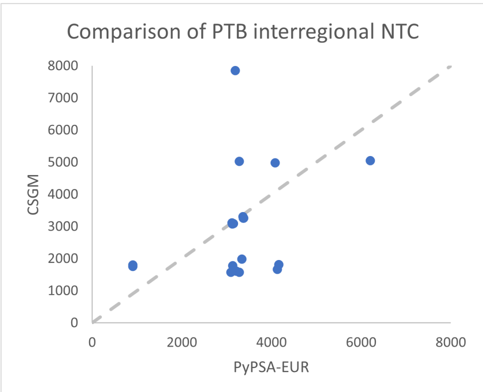


Figure 4.5: Comparison of interregional NTC using the PTB with PyPSA-EUR and CSGM data.

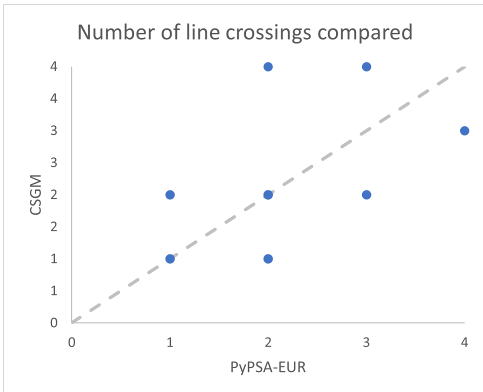


Figure 4.6: Comparison of line crossings between CSGM and PyPSA-EUR.

compares the interregional NTCs based on the CSGM with the PyPSA-EUR PTB NTCs, revealing a moderate spread around the diagonal: some points lie close to a 1:1 relationship, while others deviate more substantially. Figure 4.6, which contrasts the number of line crossings recorded by the CSGM versus the PyPSA-EUR approach, likewise shows a scattered relationship. Looking at the correlation statistics, the PyPSA-EUR PTB NTCs achieve a moderate Pearson coefficient of 0.5237, compared to the PTBs NTCs using the CSGM. Although these results indicate some linear alignment, they also highlight that neither method fully captures the interregional capacities observed using the CSGM.

[1] The kilometers in the SGM are real-world cable lengths.

[2] The SGM is clustered to the CSGM according to the method laid out in Section 2.2.3

Comparing estimates for interregional NTC using both the CSGM data and the data from PyPSA-EUR indicates that systemwide interregional capacity estimates are relatively similar with PyPSA-EUR and the CSGM, 68GW and 63GW, respectively (without the n-1 criteria). However, the CSGM clusters the NTCs from the SGM, which incorporates detailed line parameters (maximum current, voltage, resistance, and reactance), while the PyPSA-EUR data uses uniform line characteristics. This simplification, along with the clustering strategy, inevitably affects the accuracy of capacity calculations for individual connections. Furthermore, the differences in line crossings between the grid data sources reflect how the clustering alters both the line characteristics and the resulting capacity estimates. Figure B.4 gives an overview of the difference per individual line. Although many of the capacities line up reasonably well, certain interconnections deviate substantially such as NL32:NL33 and NL11:NL13. Moreover, some lines show CSGM estimates exceeding the calculation based on PyPSA-EUR, while others show the opposite trend. These discrepancies underscore the impact of simplified assumptions and clustered line characteristics in the PyPSA -EUR data, as opposed to the more detailed, line-specific parameters using the CSGM. In the model validation, the model's operation is compared to the actual system's behavior to help decide on what input data to use for further analysis of the Dutch power system.

4.2. Demand distribution

The demand distribution is computed according to the method described in Section 2.2.3. Each demand scenario follows the same process. Figure 4.7 illustrates the process of distributing the demand in the different regions using the historical demand for 2023. The figure shows that the demand is allocated based on the density of the population. Noord-Holland, Zuid-Holland, Noord-Brabant, and Gelderland have the largest annual load, while Zeeland and the regions in the North-East have relatively small loads. According to Klimaatmonitor (Klimaatmonitor, 2025), the electricity consumption in 2023 in Noord-

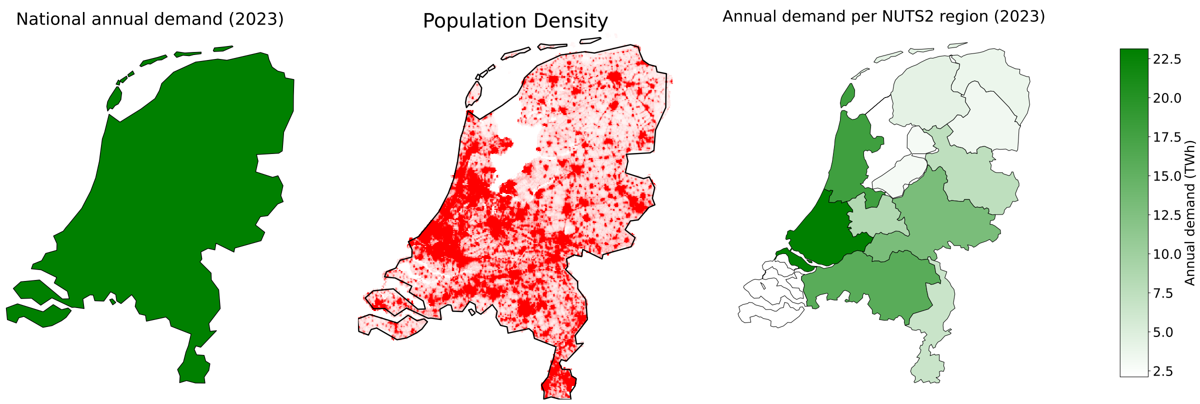


Figure 4.7: National annual demand, population density and demand distribtuion map.

Holland is equal to 18.59 TWh. The demand disaggregation proposed in this research estimates the electricity demand in 2023 to be equal to 17.95 TWh. For Groningen Klimaatmonitor shows an electricity consumption of 4.80 TWh and the disaggregation in this research results in 3.74 TWh. Thus, it can be concluded that a population-based proxy offers a reasonable approximation of regional electricity consumption.

4.3. Model validation

The multi-node model is validated in three steps according to methods found in Open Data Based Model of the Dutch High-Voltage Power System (Zomerdijk et al., 2022) for which the 220kV and 380kV data comes from the SGM.

1. Conceptual validation: Are the assumptions and theories for the conceptual model correct?
2. Operational verification. Does the model operate as intended?
3. Operational validation: comparing performance metrics against the Open Data Based Model of the Dutch High-Voltage Power System and available real world data for one year (Zomerdijk et al.,

2022)

4.3.1. Conceptual validation

In this subsection, the underlying theories and concepts of the multi-node model will be validated using the TenneT model Infrastructure Outlook. Looking at the underlying theories, (Zomerdijk et al., 2022) identifies the following points of interest:

1. A linear programming framework determines the optimal network flow pattern.
2. Hourly demand and supply profiles are derived from historical weather data.
3. The national supply and demand data are allocated regionally to identify local grid constraints.
4. Cross-border electricity flows serve as a last-resort mechanism for balancing the system.
5. Each transmission line is assigned a maximum bidirectional flow limit in megawatts (MW).

Calliope uses a linear programming framework to determine optimal energy flow patterns across a network. By defining nodes as locations with energy demand, supply, or storage, and edges as transmission links connecting them, the model ensures energy balance at every node while minimizing system costs or achieving other objectives. The multi-node model considers hourly profiles to determine the generation of sources that rely on weather conditions, such as solar and wind. The demand is based on historical hourly demand, which is determined by historical weather and other factors. In the multi-node model the national supply and demand are indeed allocated across the different provinces of the Netherlands with the goal of identifying bottlenecks in the Dutch high-voltage grid. The assignment of a high price to imports causes the model to use cross-border electricity flows only as a last resort to balance the system. In the multi-node model, each transmission line is assigned a NTC in megawatts, which is a maximum bidirectional flow limit.

4.3.2. Operational verification

To verify the model's operation, from the model results, the electricity demand at different nodes is first compared to the demand input. Secondly, the maximum generation capacity of renewable sources is tracked for a subset of time and compared to the product of the installed capacity and the capacity factor at each node for the same subset of time. The results showed that the capacity factors in the model results are slightly different compared to the capacity factors in the input data. The difference is caused by the small amount of curtailment that can be observed in the model results. When forcing resource utilization of the renewables to it's fullest, the difference in the capacity factor is no longer present. The third part of the operational verification looks at the merit order and the cost assumptions of each generation technology. Finally, the model's compliance with some important constraints is tested. The first constraint is the balance of supply and demand of electricity. For each node, the system balance for a subset of time is analyzed. For the system to be balanced, the sum of generated electricity equals the sum of consumed electricity and the import and export balance at each node. Additionally, the line loading for each line is computed to check the results for overloaded lines. The line loading is defined as the flow on a line at a certain time divided by the NTC of that line. A line loading value larger than 1 would mean that the model does not operate within the given constraints. The results show no signs of overloaded lines. Moreover, no irregularities are observed in the other variables and the model operates within the system balance constraint. Thus, the operation of the model is verified. This is as expected because Calliope is a reliable, long-established modeling framework.

4.3.3. Operational validation

In terms of the grid, it is observed that the NTC estimates based on the PyPSA-EUR network do not align with the estimated NTCs in the CSGM in all cases, because of differences in underlying characteristics such as voltages and number of line crossings. To uncover the impact of these inaccuracies, the output of the multi-node model using both network representation is compared. However, the input for the calculations proved to be crucial for calculating accurate NTCs. Thus, in the operational validation, instead of looking at one model, two models are compared. The difference between the models lies in the input data that is used to calculate the NTCs. The first model uses the PyPSA-EUR clustered data, whereas the second model will use the aggregated interregional line capacity as calculated per the CSGM.

To validate the operation of the models, a separate dispatch run is performed with both the grid data sources. A dispatch runs means that all capacities are fixed and no additional investment is allowed. Using the output data of these dispatch runs, a comparison can be made with real world data. The first interesting model output is the average monthly generation per technology, which is compared to the actual generation per type in 2023 (CBS Statline, 2025) in Figures H.1, H.2 and H.3. There are deviations in the model generation, first of all in the renewable generation. This can be explained by the fact that the multi-node model uses the installed capacities of renewables (or opgesteld vermogen) of 2024 instead of the operational capacity of 2023. Moreover, the model uses weather time series based on the year 2019, which was a year with a relatively large amount of sun hours.

In another effort to validate the operation of both models, the daily average line loading is computed as in Figure 4.8. Both models show the same pattern, with the CSGM based model showing a slightly higher average and higher peaks.

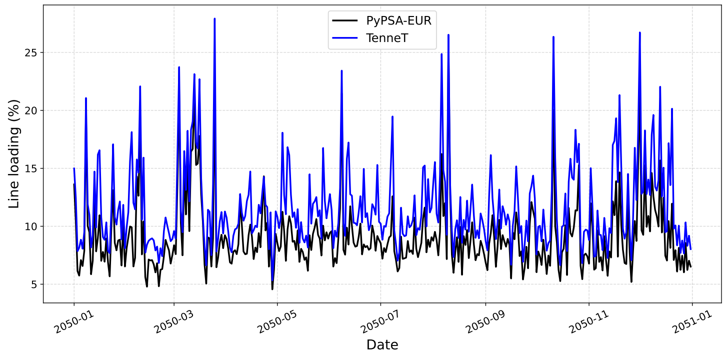
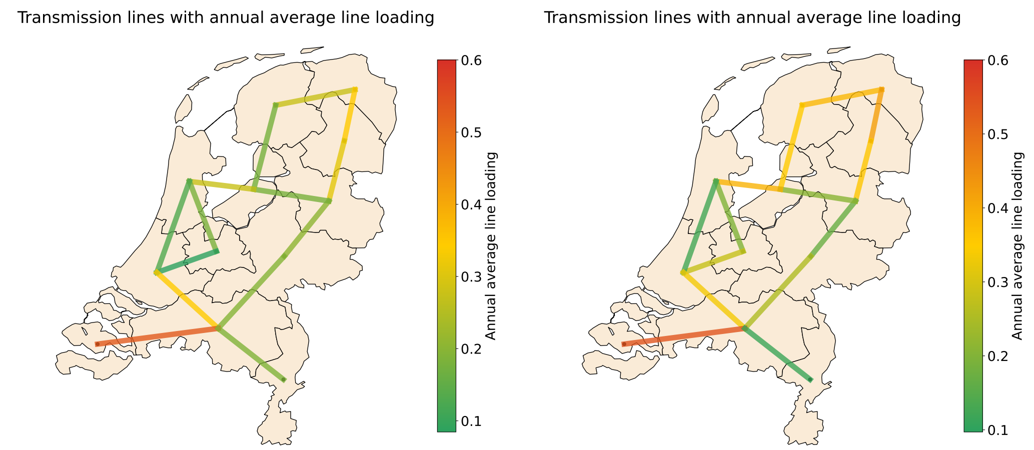


Figure 4.8: Comparison of line loading per PyPSA-EUR and CSGM network.

In terms of the average annual line load, both models again show similar patterns. However, the lines connecting the north to the rest of the country, experience higher line loading in the CSGM network representation. The same applies to the line connecting Flevoland and Noord-Holland.



(a) Average line loading using the PyPSA-EUR grid data. (b) Average line loading using the CSGM grid data.

Figure 4.9: Average line loading using PyPSA-EUR and CSGM data.

Taking another perspective, when optimizing the distribution of power infrastructure over the NUTS regions, it is not only the line loading that is interesting. Being dependent on the NTC, the line loading might not give a full view of the impact of the different grid data sources on the required infrastructure at at each location. The absolute amount of power being transported from one node to another might result

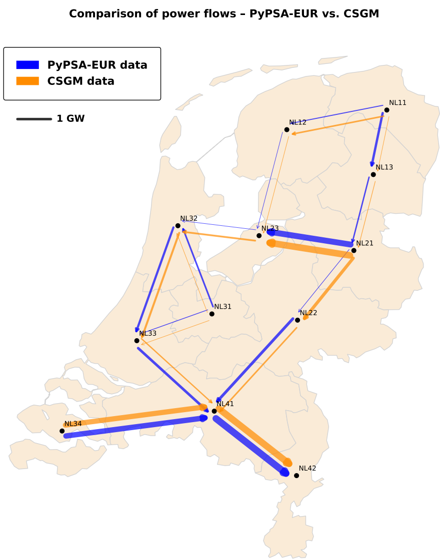


Figure 4.10: Power flows during maximal renewable output using both grid data sources.

in different conclusions in terms of flexibility needs for example. Therefor, this last validation step dives deeper into the power flow during critical hours such as the hour with the largest load and the hour with the largest renewable production. Figure 4.10 shows the size and direction of flows during the hour with the highest renewable output, where the thickness of the line indicates the size of the flow relative to the maximum flow.[3]

It can be observed that the magnitude of power transported across certain lines varies between the model that uses the CSGM and PyPSA-EUR grid data. Again, the lines connecting the north to the rest of the country are showing different patterns in the CSGM network representation compared to the PyPSA-EUR network. In the PyPSA-EUR network, large amounts of power are transported from Groningen to Drenthe and from Drenthe to Overijssel, whereas this power transfer is limited to smaller amounts in the CSGM network. This affects the required generation in the individual regions, which is confirmed in Appendix H in Figure H.4 showing the gas generation during the largest load hour. The figure shows larger gas output in Groningen (NL11) in the PyPSA-EUR based model.

The analysis in this section points out that even though the annual generation per technology is similar for both models, the aggregated daily line loading and the hourly line loading per individual line, plus the different utilization of gas generation, show that the underlying grid not only impacts the power flow in the optimization, but also the need for different types of infrastructure. Bearing in mind that the goal of this research is to look for potential decentralized system designs and identify the tradeoffs for designing these systems, moving forward, the NTCs of the lines are based on data from the CSGM.

4.4. Scenario analysis

In the scenario analysis, the multi-node model is employed to determine cost-optimal designs for each scenario. Section 4.4.1 presents these designs. First, the the allocation of capacity among various technologies is presented and then the line loading for each scenario is discussed. Next the section gives an overview of the emissions, capacity factors of BESS, the number of congested hours, the generation mix and costs for each of the scenarios. Following, the research explores the near cost-optimal solution space with the objective to minimize line loading. Different metrics are highlighted to compare the line-load-optimal solutions to their cost-optimal counterparts. Finally, in Section 4.6, the designs are compared with designs of the that allow for larger amounts of Rooftop PV or transmission capacity expansion. The goal is to test the robustness of the results and highlight more potential trade-offs in decentralized energy system design.

[3]The maximum flow is equal to the maximum flow of the two models combined to enable direct comparison of the flows in both models.

4.4.1. Cost-optimal results

Capacity allocation

The following analysis examines the cost-optimal allocation of generation and storage capacities. Figures 4.11, 4.12, 4.13, 4.14, 4.15 and 4.16 depict the optimized distribution of onshore wind, rooftop and utility-scale PV, and BESS. In addition, these figures illustrate the offshore capacity assigned directly to regions connected to offshore wind parks. A comprehensive summary of the total generation capacity by technology is presented in Table I.1.

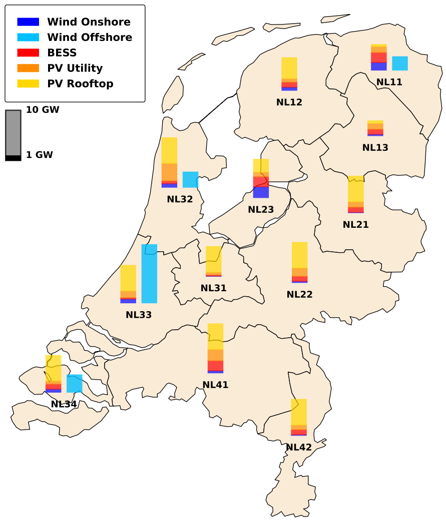


Figure 4.11: Installed renewable and BESS capacity for Central ND scenario.

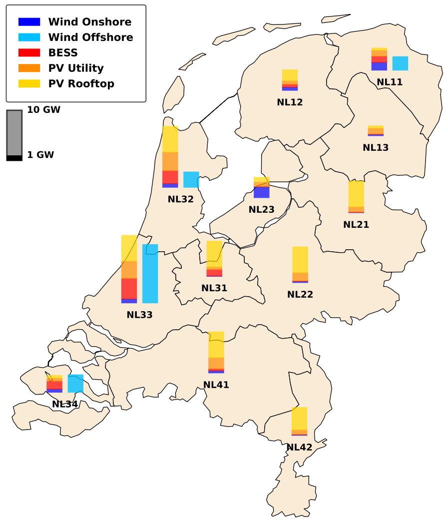


Figure 4.12: Installed renewable and BESS capacity for Flex ND scenario.

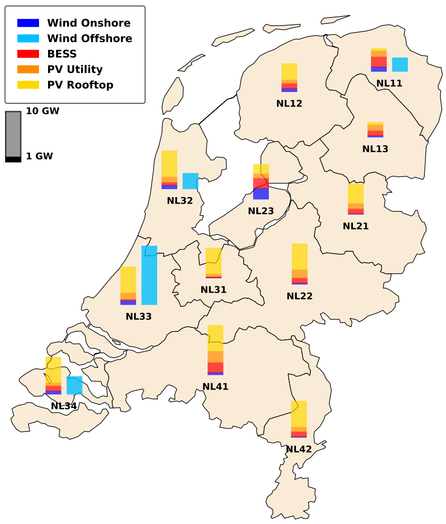


Figure 4.13: Installed renewable and BESS capacity for Central KA scenario.

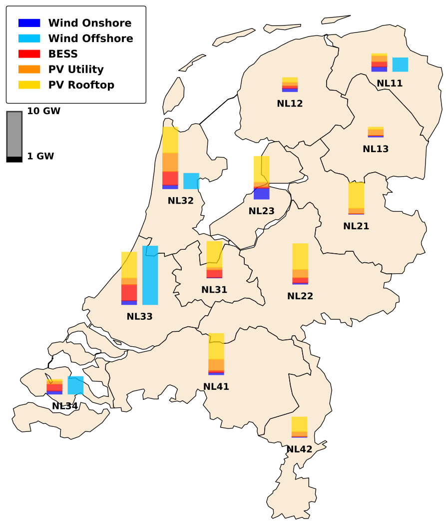


Figure 4.14: Installed renewable and BESS capacity for Flex KA scenario.

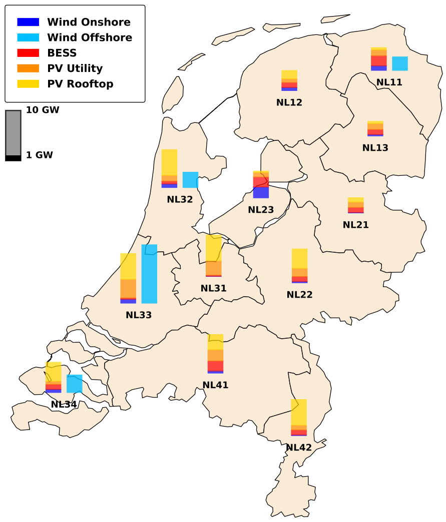


Figure 4.15: Installed renewable and BESS capacity for Central IA scenario.

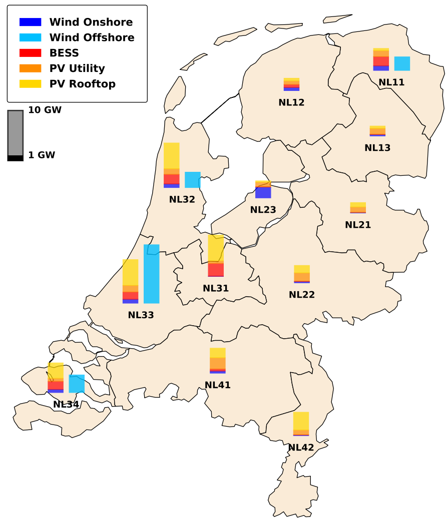


Figure 4.16: Installed renewable and BESS capacity for Flex IA scenario.

Across all scenarios, the Flexible configurations result in lower amounts of BESS capacity, from approximately 6.5% less in the KA scenario to 18. 6% in the IA and 7.5% in the ND scenario. However, where in the Central scenarios, Groningen, Zeeland and Noord-Brabant are assigned a relatively large amount of BESS, in the Flex scenarios, this is not necessarily the case. Indeed, BESS is installed in Groningen in the Flex scenarios (due to the connected offshore wind generation), but BESS is predominantly located in Noord-Holland, Zuid-Holland, Zeeland and Utrecht in the Flex scenarios. Although this indicates that BESS in the South and West would be particularly valuable in terms of minimizing costs, especially where the projected offshore wind is brought ashore, there is uncertainty about the extent to which hydrogen production could reduce the need for battery storage. Industrial parties in these regions may utilize offshore wind for electrolysis to produce green hydrogen, where the energy is stored chemically and later used in industrial processes or potentially reconverted to electricity. Hydrogen can serve as a form of long-duration storage in comparison to lithium-ion batteries, which excel at a shorter discharge time. Further research into the role of hydrogen production is therefore needed to better assess the business case and the required amount of BESS in these areas. However, while hydrogen may complement or partially displace battery storage, BESS still provides short-term flexibility, indicating that it will likely continue to play an important role in these areas. Besides Utrecht, these regions are all connected to large amounts of offshore wind generation, showing the need for storage in these areas to complement the potentially large renewable output.

Moreover, rooftop PV has a dominant role in all scenarios in terms of total installed capacity, especially in Central scenarios. The rooftop PV capacity in NL11 and NL13 is not substantially affected by the size of the demand and has small installed capacities in all scenarios. NL32, NL33, and NL31 also have a constant deployment of BESS, but in relatively large amounts. Especially in the Flex scenarios, NL32 and NL33, the regions with relatively large amounts of BESS and demand, while also being connected to offshore wind generation, have large amounts of complementary PV. The other regions have more uncertainty, and the deployment of rooftop PV changes with either Central or Flexible deployment of BESS and the demand scenario.

In terms of utility PV, except for IA, deployment is larger in the Flex scenarios. The additional capacity spikes in NL33, NL32, and NL31 in different scenarios. In other regions, the capacity of Utility PV is nearly constant.

There are almost no increases in onshore wind capacity in the results. Except for the ND scenarios, where onshore wind is deployed in Groningen. The deployment of offshore wind in this area might be biased because the capacity factor for onshore wind also accounts for the offshore potential connected to coastal regions.

Technology	Central ND	Flex ND	Central KA	Flex KA	Central IA	Flex IA
BESS	13.02	12.03	13.02	12.15	13.02	10.59
Gas CCGT	19.66	16.92	20.89	18.12	15.55	14.550
Rooftop PV	49.01	39.95	45.94	41.17	35.08	28.104
Utility PV	15.79	18.16	13.43	16.02	18.18	13.428
Onshore wind	7.60	7.620	6.99	6.99	6.99	6.99

Table 4.2: Installed capacities by technology (in GW) for each scenario.

The capacities described in Table 4.2 are presented in a diagram in Figure I.1 for easier comparison of the total generation capacity. The results indicate a significant increase compared to historical capacities (growth can be found in Table I.1). BESS increases from a few hundred MW to double digit GWs. At the same time, gas CCGT capacity increases, especially in the Central KA and ND scenarios. It is questionable whether such large investments in gas-fired power plants are feasible. Finding investors may be difficult due to regulatory and policy risk with respect to climate, making long-term investments in CCGT plants less attractive. Long-term assurances would be needed. At the same time, Carbon Capture Storage might address the environmental concerns of additional gas-fired power plants. However, as mentioned in Section 2.4.1, although ongoing projects show promise, the practical implementations and the potential of combining CCS with gas-fired power plants remains uncertain. The projected gas generation capacity is quite similar to the projections in the IP2024 scenarios, except for the Central ND and Central KA, where the installed capacity exceeds the maximum found in the IP2024 scenarios significantly (Netbeheer Nederland, 2023). Rooftop PV increases with 159% in the Flex IA scenario up to 352%. The range is roughly similar to the range of rooftop PV that is needed according to the quantification of the IP2024 scenarios for 2030. Utility PV stays within the range of the IP2024, but is more conservative than the IP2024 projections. Onshore wind projections are also conservative compared to the IP2024, with none to 600 MW of additional capacity.

Line loading

The next part of the analysis presents the line loading of interregional transmission lines in the scenarios. Figure 4.17 and Figure 4.17 show the line loading in the KA scenarios.

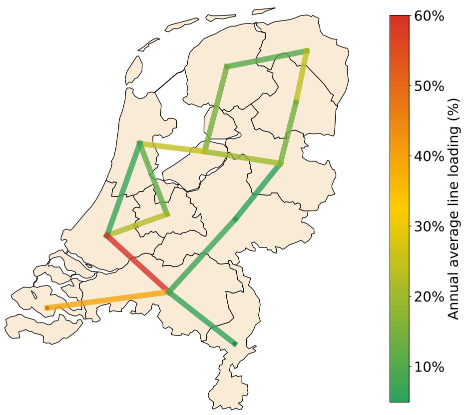


Figure 4.17: Average line loading for the Central KA scenario.

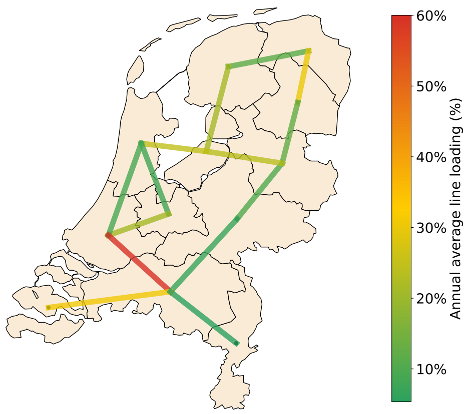


Figure 4.18: Average line loading for the Flex KA scenario.

In terms of line loading, Flexible allocation of BESS does not necessarily results in lower line utilization. In contrast, the lines connecting the North to the South via Flevoland and Groningen to Drenthe seem to have higher line loadings. The lines with the highest average line load are the lines between Zeeland and Noord-Brabant and the lines between Noord-Brabant and Zuid-Holland, and depending on the demand scenario the line between Utrecht and Zuid-Holland. Line loading in the IA and the ND scenarios is plotted in Figure I.4 and Figure I.3.

Table I.2 shows that the line connecting Groningen and Drenthe is in fact more overloaded in the Flex scenarios. Although the line connecting Flevoland and Friesland has a higher average line load in the Flex KA scenario, the congested line hours are higher in the Central scenarios. Further analysis of the table shows that the line connecting Zuid-Holland to Noord-Brabant is the most congested line by a large margin. The lines connecting Flevoland and Noord-Holland, Utrecht and Zuid-Holland, Zeeland and Noord-Brabant and Groningen and Drenthe are also subject to relatively large amounts of congested hours.

Trade-offs in cost-optimal system designs

Scenario	**Total costs** (BN. EUR)	**Emission reduction** (% w.r.t. 1990)	**Installed BESS** (GW)	**Avg. line load**	**Congested line hours**	**Capacity factor BESS**	**Imports** (TWh)
Central ND	42.577	55	13.02	20.1%	6,891	9.4%	12.33
Flex ND	41.307	55	12.03	19.3%	6,402	5.4%	20.34
Central KA	41.113	60.5	13.02	19.2%	6,823	9.6%	7.34
Flex KA	39.898	57.1	12.15	20.2%	6,820	6.2%	9.01
Central IA	39.518	66.7	13.02	19.5%	6,953	10.5%	7.87
Flex IA	38.174	59.8	10.59	20.6%	6,176	5.0%	10.44

Table 4.3: Comparison of key metrics across different scenarios.

Table 4.3 displays the key metrics. First, there is a trend in the costs, the larger the load in the scenario, the larger the costs. In addition, Flexible configurations result in lower costs (approximately 3%) compared to the Central alternative under the same load assumptions.

In terms of CO_2, the Flexible scenarios tend to result in higher emissions, except in the ND scenarios, where the emissions are equal to the allowed maximum in both cases. A potential explanation could be that in the Flexible KA and IA scenarios, there is a smaller amount of BESS in the North and East of the country. During hours with large renewable supply, the grid connecting the North and East to the South and West (or the grid in the south and west) might be overloaded. Insufficient BESS capacity in small demand areas results in excess renewable electricity during peak renewable hours in the North and East that cannot be stored. The results indicate larger exports in the Flex designs compared to the Central designs by approximately 10%, indicating that this excess power is exported in this case. In reality, it might not be possible to export this power, which might result in the waste of renewable power. The lack of storage in these regions could be an explanation for the increased dependence on gas power plants. This could also explain the smaller amounts of renewable technologies installed in the Flex scenarios compared to the Central scenarios in the North and East. The emissions increase with the demand and import in KA and IA are similar, while in ND the imports rise more severely because gas generation is constraint by the emission cap, indicating that either gas or imports can provide flexible power supply. In general, Flex scenarios include relatively high electricity imports from other countries.

The table confirms the larger deployment of BESS observed in the Central scenarios compared to Flex scenarios. However, the table also indicates that the capacity of the BESS systems is utilized more in the Central scenarios than the Flex scenarios.

Looking at the line loading statistics, in terms of averages, Flexible deployment does not necessarily lead to lower values. However, looking at the congested line hours, Flexible deployment results in significant improvements in the ND (-7%) and IA (-11%). The BESS capacity factor is lower in the Flex scenarios, pointing out that BESS focuses more on shaving local peaks in areas with large renewable output when the grid is congested. This illustrates the benefit of storing electricity locally at the source, i.e. before the meter (BTM). BESS in the Central scenarios is used more frequently. The output of BESS during the peak gas supply hours (90th quantile) in the ND scenario confirms the different application of BESS in the Flex and Central scenario, with the Flex scenario generating an above-average output during peak hours and a below-average output in the Central designs. This last observation is important, because to maximize profit BESS operators seek to discharge during hours where electricity prices are highest. This observation highlights a potential conflict of interest for BESS operators looking to maximize profit and TenneT looking to maintain a balanced grid. A BESS buys low and sells high to make a profit. This of course has implications for the business model of the BESS. As mentioned, TenneT imposes tariffs based on the utilization of a connection. The more batteries load and unload, the higher the costs of the grid connection, weakening the business case of BESS and reducing the investment incentives.

Table 4.4 describes the ouput per technology for each scenario. The table confirms the larger gas generation and imports and the lower BESS output in the Flex scenarios and the higher rooftop PV output in the Central scenarios.

Scenario	Import	Nuclear	Gas	BESS	Wind Offshore	Wind Onshore	Utility PV	Rooftop PV
Central ND	12.33	4.49	52.72	10.37	50.89	16.98	16.47	53.60
Flex ND	20.34	4.49	52.72	5.67	51.07	16.94	18.73	43.52
Central KA	7.34	4.49	46.41	10.29	50.13	15.15	14.02	50.26
Flex KA	9.01	4.49	50.25	7.12	50.22	14.95	16.09	44.83
Central IA	7.87	4.49	38.98	10.84	49.71	15.12	18.05	38.42
Flex IA	10.44	4.49	47.08	4.83	50.41	15.12	13.99	30.78

Table 4.4: Technology output by scenario (in TWh).

Figure 4.19 shows the total output of BESS in the six scenarios. In general, the Central scenarios tend to produce higher BESS outputs at nodes in the North and East compared to the Randstad area where BESS output is larger during the Flex scenarios. The model thus indicates, that a different allocation of BESS is more beneficial in terms of costs than the Central design, particularly when large solar deployments in the Flex scenario benefit from additional storage. Figures 4.15, 4.16, 4.13, 4.14, 4.11 and 4.12 illustrate this trend, with sizeable solar and BESS capacities in Noord-Holland, Utrecht, and Zuid-Holland.

However, one could argue whether the allocation of such large amounts of solar capacity at these nodes is feasible in terms of land use and habitability. The results show that the need for flexibility is affected by the amount of renewables that is allocated to a node. Groningen (NL11) stands out, as the region has significantly more BESS output in the Central scenarios. Meanwhile, Zeeland (NL34) shows comparatively less variation across scenarios, suggesting that demand scenarios impact the utilization of BESS here less. The smaller variation can be explained by the relatively small demand and the large amount of offshore wind capacity that is connected to the region (3.5 GW). In hours with large renewable generation, Zeeland's generation exceeds the demand, while the grid might also not be able to handle the transportation of electricity from Zeeland to Zuid-Holland. BESS provides an alternative for export and curtailment of the abundant renewable supply, so that excess power can either be used locally or transported to large demand areas at a later time. With some certainty, it can be concluded that the overall system would benefit from BESS in Zeeland.

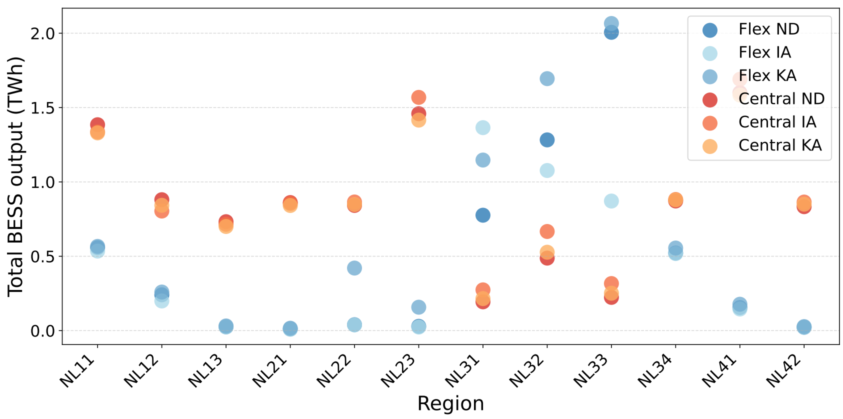


Figure 4.19: Output of BESS per NUTS2 region

Figure 4.20 shows the gas-fired output per node under the six scenarios. NL11, NL31, NL32 and NL33 have the largest variation in output. At most nodes, especially in the North and East (except for NL11), the spread in scenarios is relatively small. In NL11 the gas output is larger in the Flex scenarios. Looking at Figure 4.15, 4.16, 4.13, 4.14, 4.11 and 4.12 we can see that at this node the BESS capacity is lower in the Flex scenarios, which is an explanation for smaller BESS output in Figure 4.19. Gas output in NL31, NL32 and NL33 is larger in the Central scenarios, this can also be explained by the smaller BESS capacities at these nodes in the Central scenarios.

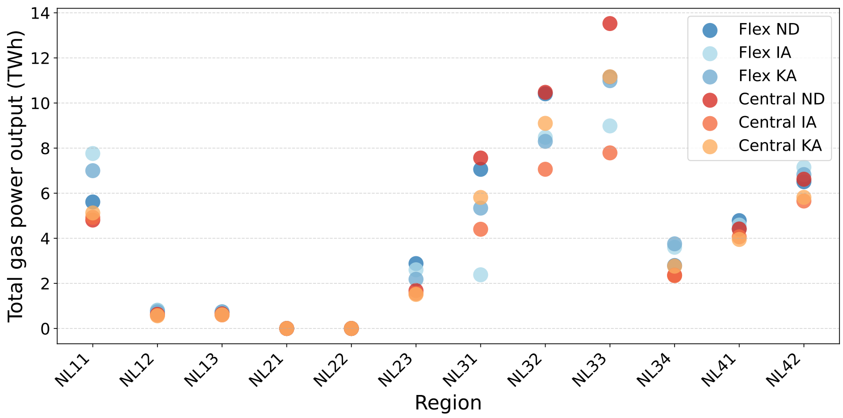


Figure 4.20: Output of CCGT power plants per NUTS2 region

A closer look at the data also reveals variations in the spread of total gas outputs for different locations. Some nodes, e.g. NL31, NL32 and NL33, show substantial spreads between scenario outcomes, indicating that changes in policy or market drivers have a significant effect on gas utilization in those regions. Meanwhile, other nodes, such as NL12, NL13, NL41 and NL42, show a smaller spread, implying that local system designs limit the impact of differing scenarios. Overall, these results highlight the importance of both geographic factors and scenario design when evaluating the role of gas-fired power in the Dutch electricity system.

Overall, assuming that there is no transmission capacity expansion, it can be concluded that the power system would benefit in terms of cost and congestion from larger deployment of BESS, especially in Zeeland, Zuid-Holland, Utrecht and Noord-Holland and less so in Noord-Brabant and the North and East of the country (which is, instead, what the TenneT design describes). However, looking at the increased dependence on gas generation and imports to balance the grid, one could argue whether this design is indeed desirable. To be less dependent on gas and ETS prices and balancing via import and export, BESS in the small demand areas can provide emission-free flexibility.

4.5. Minimal line load

By leveraging the total system costs of the cost-optimal solutions to create a near cost-optimal solution space in the line load minimization, it is possible to gain insights in potential options to reduce congestion on the high-voltage grid. Overall, Table I.3 shows that minimizing the line load results in larger gas generation, smaller rooftop PV, and higher utility PV capacities. BESS capacities depend on the demand size whereas onshore wind is equal or lower depending on the demand. First, lets focus on the results in Table 4.5. When optimizing for line load, the installed BESS capacity in the Flex scenarios is even larger than in the cost-optimal solution, again confirming the potential benefit of large amounts of storage. At the same time, the emissions are lower than in the cost-optimal solutions, even though smaller amounts of renewable capacity is installed. This implies that the absolute output of BESS compared to the output of gas plants is relatively large under line load optimization compared to cost optimization, which is confirmed by Table I.4. This results in additional emissions reductions compared to the cost-optimal objectives. However, this may also be explained by the large increase in imports, for which the model does not consider emissions. The table does emphasize that there is a potential of using imports to reducing congestion, which decreases by approximately 50% in all scenarios.

Scenario	**Total costs** (BN. EUR)	**Emissions** (% w.r.t. 1990)	**Installed BESS** (GW)	**Avg. line load**	**Congested line hours**	**Capacity factor BESS**	**Imports** (TWh)
Central ND	43.00	55.0	13.02	14.4%	3,397	11.2%	15.34
Flex ND	41.72	55.0	13.39	14.9%	3,530	7.8%	20.35
Central KA	41.52	62.0	13.02	14.4%	3,112	10.8%	13.12
Flex KA	40.30	56.2	11.54	14.1%	3,251	7.7%	13.13
Central IA	39.91	69.6	13.02	14.9%	3,134	11.5%	13.24
Flex IA	38.56	62.2	8.27	15.3%	2,810	6.9%	14.85

Table 4.5: Comparison of key metrics across different scenarios.

Figure 4.21 shows the allocation of the generation capacity for rooftop solar, onshore wind, BESS and gas. The orange triangles show the capacity for the cost-optimal solution whereas the red circles indicate line-load-optimal solutions. The first thing that stands out, is the spread arround the maximum allowed capacity per node of 5.15 GW. Especially at nodes NL31, NL32 and NL33, where the cost-optimal solutions tend to be close to the maximum. NL31, however, shows smaller capacities when minimizing for line load, indicating that a share of the rooftop PV capacity is installed to supply the high-demand areas. NL32 and NL33 are among regions with the largest annual load. The results thus indicate that in terms of costs the system benefits from allocating significant amounts of solar in these high load areas. On another note, the results show that NL11 does not have any variation across the runs and is equal to approximately 0.5 GW, potentially because of the large amount of offshore wind (2.7 GW) connected to the region and the relatively small annual load. In NL13, where the initial installed capacity of rooftop solar is low, there also is a relatively small spread. The other areas, which had a relatively low initial capacity such as NL12, NL21, NL34 and and NL23 show a larger spread. In NL12 and NL34 the line-load-optimal solutions tend to be more concentrated and smaller compared the the cost-optimal capacities which have a larger spread.

Onshore wind seems to be stable across all the scenarios. Except for NL11 and NL32, which both have one outlier.

The BESS capacities show similar patterns at most nodes in the cost-optimal solutions and the line-load optimal solutions. The figure shows that the minimal line load and cost-optimal designs result in similar distributions of capacities in the Flex scenarios. NL31, NL32 and NL33 each have solutions in the Flex scenarios that include a significantly larger BESS capacity to minimize the line load in the system. NL11 and NL34 also have storage in all scenarios. This highlights the benefit of additional BESS in these key areas in terms of line loading and costs compared to the Central scenarios, while the need for BESS in NL13, NL21, NL22, NL23 and NL42 is less beneficial in terms of line load and costs.

Gas generation capacity in NL31, NL32, NL33 and NL22 shows the most variation, indicating a certain degree of uncertainty in the decision whether or extra gas capacity would be beneficial. With the gas generation capacity at the other nodes remaining constant and the total gas capacity being higher in the Central scenarios, it is possible to conclude that the additional gas capacity in the Central scenarios is mainly built in Zuid-Holland, Utrecht and Noord-Holland as they lack the BESS capacity that is deployed in the Flex scenarios. It might not be feasible to gain new investments in gas generation capacity due to regulatory risks related to climate policies. While some of these risks can be mitigated by investing in the development of combined CCGT and CCS, the viability of large-scale deployment remains unclear. Consequently, prioritizing BESS in these key areas might be a more reliable approach for increasing system flexibility without jeopardizing climate objectives. Where in NL22 there is more spread and larger capacities in the line loading-optimal solution compared to the cost-optimal, in the other nodes the spread is similar for cost- and line load optimal results. With some certainty, it can be said that additional gas capacity at NL22 would help reduce the average line load.

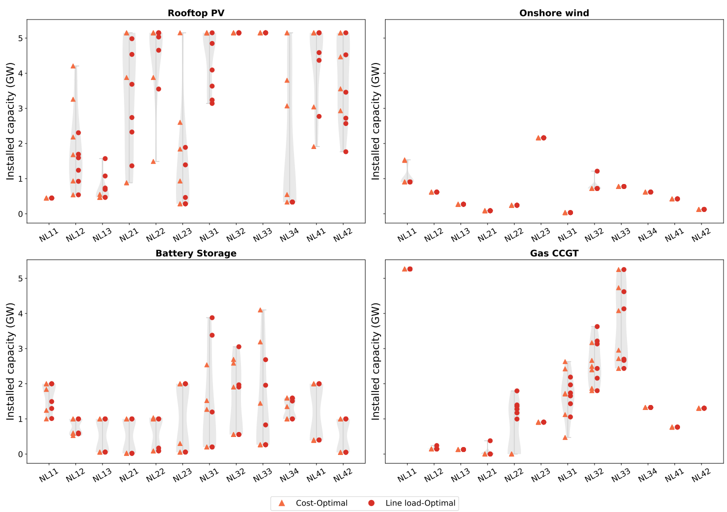


Figure 4.21: Comparison of installed capacity per technology when optimizing for line load

However, it is important to reflect on whether a low line utilization is indeed ”optimal”. Although limiting congestion would be beneficial, barely using lines might not be desirable. First, because of TenneT’s business model. TenneT’s revenue is based on fixed and variable tariffs. The fixed tariff is based on the contracted annual transport rights. The variable tariff is based on the peak use of the connection to the grid. Second, more extreme usage of the lines could also have implications for the wear an tear of the lines, potentially resulting in larger maintenance needs and earlier replacements. Lastly, because in principle it is not efficient to not use the transmission lines even though it would not cause congestion issues when there is sufficient transmission capacity and it is the most cost-efficient solution. The focus of the line load minimization should thus not be on limiting the overall line load but on limiting the congested hours.

It can be argued that the formulation of the line loading objective function in this study does not cut congested hours, but increases them. More specifically, this way of minimizing the line load causes a bias towards lines with relatively high NTCs, where it is more beneficial to transport an additional MWh on a line with a large NTC than on a line with a low NTC. This has to do with the way that the line load is defined, namely as the transported electricity on a line divided by the line’s NTC. As observed in Figure 4.22, in the line load optimization certain lines are not used at all while others operate near 100%, especially in the Central ND and KA scenarios. At the same time, transporting power from Drenthe to Zuid-Holland is relatively costly in terms of line load, because four different lines are used. Imports, only requiring transport on a single line, are thus used more often. Table I.4 shows that indeed the model prefers to import more electricity, underlining the potential role of imports in balancing the system and reducing congestion. Also, while the total capacities of utility PV are larger, the output does not grow at the same rate and even declines in some cases, indicating that to minimize line load, less productive generation sites are used. Line load minimization thus also comes at the expense of productivity and cost efficiency. Instead, the objective in minimizing line load should be focused on limiting the hours in which lines are used at their (almost) full capacity. In this way, the model utilizes the transmission lines in the most cost-efficient way, while decreasing the total congested line hours.

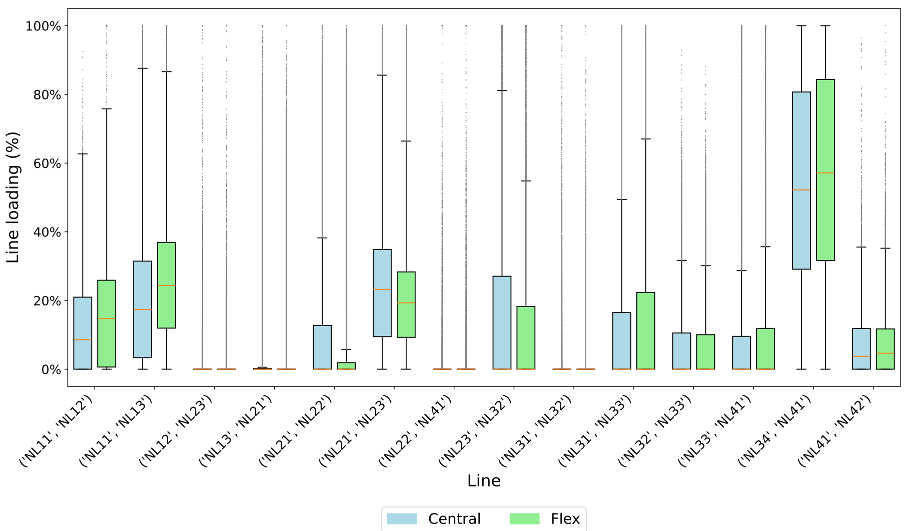


Figure 4.22: Line loading per line in the line load optimum.

4.6. Sensitivity analysis

The sensitivity analysis’s goal is to highlight the potential of different system designs by making changes to the model’s input. Two changes are proposed: A higher limit to solar PV per region, and allowing the model to expand the transmission capacity.

4.6.1. Loose solar solar

In this case, the maximum allowed capacity per region for solar generation technologies is increased. The max capacity of rooftop solar is equal to 7.725 GW per region, this is equal to 15% of the maximum installed capacity as per the IP2024 scenarios for 2030. As described in Section 2.4.1, in the original scenario runs, rooftop solar was allowed to increase up to a maximum of 5.15 GW per region. In this analysis, the model thus has more freedom to allocate rooftop PV in the most cost-efficient way. The goal is to see whether the constraint has a large impact on the model results. This is done by comparing the results from Central KA cost optimal with loose PV constraints to the results from the Central Central KA cost optimal case with strict PV constraints.

In the loose PV case, there is an increased rooftop PV capacity. You can find the total installed rooftop PV capacity per region in Table J.1. Table J.2 shows that relaxing the maximum PV constraint has a minimal effect on total costs (-0. 03%), emissions (-0. 061%) and BESS utilization (+0. 08%) while the capacity of local rooftop PV in some areas of high demand increases strongly (approximately 50%). The generation capacity in other regions, such as in Utrecht, decreases. Figure J.1 compares the pressure on land use, clearly showing a reduced pressure on land use in Utrecht. In the case of strict PV, rooftop solar is in some cases deployed to supply high-demand areas in close proximity. However, as costs and emissions increase only slightly, the benefit of additional local generation and storage in high-demand areas may not be linear. This is a relevant insight for infrastructure planning and the distribution of generation and storage technologies.

4.6.2. Transmission expansion

In the Central scenarios, the transmission capacity is expanded on the same two lines across demand scenarios. These are NL23:NL32 and NL33:NL41. The same lines undergo expansion in the Flex IA scenario. In the two other Flex scenarios many lines are targeted for capacity expansion, NL11:NL12, NL11:NL13, NL23:NL32, NL33:NL41, NL34:NL41 and NL41:NL42. Table J.3 displays key metrics to evaluate the impact of possible transmission expansion. While decreasing cost with 0.24% and 0.45%, the congested hours also decrease between 12,41% and 33,26%. In the Central scenarios the emissions decrease slightly, whereas the emissions grow in the Flex scenarios. In the Flex scenarios smaller amounts of BESS are deployed, illustrating the reduction in local flexible generation needs when increasing interconnectedness of the regions connected to the offshore wind generation. The geographical location of BESS however, does not change, again concentrating on deploying BESS in Zeeland, Zuid-Holland, Noord-Holland, Utrecht and Groningen.

5

Discussion

The goal of this research is to identify the tradeoffs in decentralized electricity system designs to make grounded recommendations for future infrastructure decision making. The final research question is:

'What are the trade-offs for future decentralized Dutch electricity system designs in the face of future load growth?'

The goal of this research is threefold. The first part is about finding the most accurate method for calculating NTCs to account for physical constraints such as resistances and voltages. This is highlighted in the first sub-question. The first sub-question also includes an assessment of the benefit of using grid data from PyPSA-EUR in the multi-node model. This step flows into the second sub-question, where the multi-node model is validated using the SGM and the PyPSA-EUR grid data. The validated model is then used in the phase of finding the trade-offs in designing a decentralized Dutch power system. The sub-questions are defined as follows:

- How can we calculate Net Transfer Capacities and how can we integrate correction factors for resistances and voltages and transferring it to a Net Transfer Capacity?
- How well does the model reflect the real electricity system's operation?
- What are potential decentralized design options for relieving congestion in the Dutch electricity system considering different scenarios for future load development?

5.1. Conclusions and recommendations

5.1.1. Methods for calculating NTCs

Nominal ratings provide a decent approximation of NTCs within the line length range included in this research. Nonetheless, this method provides overly optimistic NTCs as it does not account for resistances. In an effort to approximate line ratings, while accounting for physical constraints, the St. Clair approximation is applied. The St. Clair approximation, as in (Martin et al., 2017), resulted in an unpredictable bias in the case of relatively short lines. Even though the approximation is used to avoid overly optimistic NTC estimation for long transmission lines, the validation in Section 4.1 points out that the NTCs of the relatively long lines in the dataset are underestimated. This underlines the findings of the authors in terms of short transmission lines and provides a new perspective by showing the underestimation of NTCs of long transmission lines when using the St. Clair approximation. The efficiency per kilometer offers an alternative to find resistance-based losses using the nominal rating, line length and an efficiency rating per line type. This proves to be the most accurate method to approximate NTCs and is thus used further in this research. This abstract yet accurate method of capturing complex physics in NTCs is easily implemented in existing and new NTC based models to avoid overly optimistic NTC estimations. It enriches NTC based models by incorporating physical constraints, enabling more robust and realistic analyses of power systems, helping policymakers and system operators assess infrastructure needs more accurately without having to use computationally heavy and complex power-flow optimization models.

5.1.2. Using clustered grid data

The results indicated that the systemwide interregional capacity estimates throughout the system are relatively similar using CSGM and PyPSA-EUR grid data. Comparing the PyPSA-EUR clustered data to the data in the SGM it is evident that clustered and simplified grid data in this case is not properly aligned to actual local grid characteristics. The cluster fails to identify the voltages of the lines in some cases (i.e. 380kV instead of 220kV), which is an essential parameter in the proposed methods for calculating NTCs.

Moreover, the number of line crossings does not always align with the actual system. This also has a large impact on the approximation of interregional NTCs and thus on the infrastructure needs at each individual region. In short, using the grid data from this particular model will results in biased results in terms of infrastructure needs on a local level. Taking another perspective, as the systemwide NTC aligns quite well with the systemwide NTC as computed per the CSGM, the PyPSA-EUR data can, for example, be used in a model to evaluate system behavior, market dynamics, and the impact of policy alternatives.

5.1.3. Trade-offs for the design of decentralized systems

When designing the least-cost design, the Flex scenarios result in smaller total amounts of BESS in all demand scenarios. In Zeeland, Zuid-Holland and Noord-Holland however, there is a relatively large capacity of BESS in all scenarios. Showing that with a relatively high degree of certainty, the system would benefit from additional storage capacity in these regions. However, what is most beneficial in terms of costs might not be the most desirable. The tradeoffs are highlighted here.

During high renewable hours, the grid in the South-West is congested, this lies at the basis of the first trade-off: either store renewable generation in low-demand areas for later consumption at potentially higher costs, or store renewable power predominantly in locations with high weather dependent output and demand to reduce congestion. The latter involves more frequent export of excess renewable power from low demand areas to balance the grid, which in turn increases reliance on gas-generated power and imports during periods of low renewable output. While in the Flex scenarios renewable power form the North-East is more often exported or wasted at times that the grid in the high demand areas is congested, instead of stored, as in the TenneT design. This results in a larger share of gas generation in the generation mix and thus higher emissions (up to 7%). This indicates that, when optimizing for costs, the most optimal system designs do not always result in lower emissions. Because of the larger share of gas generation in the mix, the exposure to gas and ETS prices is larger. Besides a larger reliance on gas more imports and exports are needed to balance the grid in the Flex designs. When the BESS is allocated according to the TenneT estimations, the emissions are lower because they reduce the total need for gas output during low renewable hours. At the same time, all potential designs stay within the limits of the projected 55% reduction.

The geographical location of BESS has implications for the role of gas-fired power plants and the business case for BESS. BESS operators use price volatility to make profits, buying during times of excess renewable supply and selling during low renewable hours when prices are set by more expensive technologies such as gas. The TenneT estimates result in a higher overall utilization of the BESS capacity and larger total outputs during high gas output hours than BESS near offshore wind farms. However, the output during the peak gas generation hours is below the annual average for BESS in these designs, indicating a conflict between balancing requirements of TenneT and the profits of BESS operators. Consults should take place between TenneT, battery providers and DSOs to work out efficient and dynamic tariff design that considers the operators needs i.e. balancing responsibility and the business model while also strengthening the business case for BESS operators. At the same time, these parties should combine forces with local governments to smoothen permitting processes and identify precise locations that integrate BESS in public space, the distribution system as well as the transmission system to ensure smooth distribution of the storage systems.

Interconnectedness vs. decentralized balancing. The results indicate that increasing the capacity of transmission bottlenecks reduces congested line hours, significantly (up to 33.26%), while also slightly decreasing total system costs and storage needs. Thus, grid reinforcements and storage play a subsidiarity role to some extend. Although storage can reduce the need for transmission capacity and vice versa, they do not exclude one another. Indeed, the need for local storage in areas with large amounts of weather-dependent resources lessens with increased interconnectedness during hours with large renewable output, the need for emission-free flexible power output during low renewable hours remains.

The benefits of local generation in high-demand areas vs. land use. The results also showed that in order to decrease congestion, local PV generation capacity is important. Especially, in areas with large offshore capacities and demand (Noord-Holland and Zuid-Holland). However, once a certain threshold is reached, adding more PV in high-demand areas yields only marginal reductions in both congestion hours and total system costs. Where transmission capacity permits, reallocating some PV deployments to regions with lower demand for example Utrecht, despite slightly less productivity, can help reduce pressure on the land availability in high-demand areas while costs are only estimated to increase with 0.03-0.17%.

Double down on renewable generation and storage or continue to rely on fossil fuels. The results indicated that significant investments are needed in renewable generation and storage infrastructure. In particular, large amounts of rooftop photovoltaic are deployed in all scenarios, concentrating on high-demand areas, emphasizing the logical thought that it is efficient to allocate supply close to demand. With current incentives for rooftop PV being scaled down in the Netherlands, new incentive schemes are needed to support the uptake of rooftop PV systems while also considering grid local constraints and the time-value of electricity. Such schemes potentially involve time- and spatial-differentiated tariffs for power transport and promote local and smart electricity consumption. If the projected renewable and storage capacities are not realized, the system will rely on fossil generation for a longer period. This involves keeping the coal plants operational. At the same time, the results already indicate the need for additional investments in gas-fired generation capacity. The feasibility of such investments is questionable. Regulatory and policy risks with respect to climate objectives make long-term investments in CCGT plants less attractive without robust long-term guarantees. Continued investment in Carbon Capture and Storage could help address climate-related concerns related to gas-fired power.

5.2. Limitations and suggestions for future research

This final section is dedicated to highlighting the limitations of this research and potential directions for future research. First, the NTC calculations do not use the actual capacitance of the lines, as this data is not available in the SGM. Instead the typical values from PyPSA are used while results indicated that using clustered data to estimate NTCs in on a high spatial resolution can lead to inaccurate estimates because of discrepancies caused by simplifications and clustering. Future research could look into the accuracy of the applied standard value in the case of the Netherlands. At the same time, internal transmission and the distribution network ar assumed to have unlimited capacity, which is of course not realistic. Using an even higher resolution grid could capture the limits and possibilities of internal transmission within NUTS2 regions, to make a more realistic representation of the bottlenecks of the grid. This could give more accurate insights to the bottlenecks in the high-voltage grid, that can directly be translated into infrastructure additions.

The allocation of demand is based on current population density. The question remains to what extend population density is an accurate proxy for the load distribution. Other proxies could lead to different results. For example, future population and using different types of demand such as industrial and household demand. In future research it would be interesting to see if the demand disaggregation with Gregor can be complemented with an industrial proxy. By splitting the total demand in household and industrial demand and then performing two disaggregation, more accurate results might be achieved. It is evident that the research results are highly dependent on input data.

Also, the research did not include innovative technologies such as, long term storage options in hydrogen, other battery technologies, the cost developments of BESS and the development of CCS. Gas CCGT combined with CCS could provide an alternative to BESS as it offers flexible generation with less emissions to the atmosphere than regular CCGT. To evaluate the impact of promising technologies such as CCGT with CCS, hydrogen or other BESS technologies, future research could include such technologies. Although the study indicates that BESS in the South and West would be particularly valuable in terms of minimizing costs and congestion, especially where projected offshore wind is brought ashore, there is uncertainty about the extent to which hydrogen production could reduce the need for battery storage. Industrial parties in these regions may utilize offshore wind for electrolysis to produce green hydrogen, where the energy is stored chemically and later used in industrial processes or potentially reconverted to electricity. Further research into the role of hydrogen production is therefore needed to better assess the business case and the required amount of BESS in these areas. Nevertheless, while hydrogen may complement or partially displace battery storage in certain situations, BESS still provides short-term flexibility, indicating that it will likely continue to play an important role in these areas. Also, even though the research does not include combined CCGT and CCS, BESS is already being deployed on a utility scale whereas large-scale CCGT and CSS combinations are not proven. At the same time, current cost estimates are used for BESS system while, innovation could strengthen the case for decentralized system designs with large amounts of BESS.

The results showed different annual utilization rates of BESS in the different scenarios. The model does not include the balancing market and is unable to account for the balancing services that batteries can provide to the TSO, whereas that could be an important role and business opportunity for BESS in energy systems with large shares of renewables. In other words, this study focusses on finding the least-cost system design, without a reference to the different strategies that storage operators could have in different markets. In future research, this could be used to asses the contribution of BESS in each scenario to the balancing requirements of the whole system using different strategies. However, the results did indicate different charging and discharging moments for BESS, which lies at the basis of the recommendation regarding the dynamic tariff design that accounts for both the frequent charging and discharging rates of BESS and the business case, while also accounting for the balancing responsibility of TenneT.

Another potential limitation of the research is the definition of line loading optimization. In the current state the model tries to find the minimal line load by limiting the total system's line utilization, whereas minimizing the maximum load hours i.e. hours at which a line uses more than 99% of it's capacity might be more in line with the goal of limiting congestion. An option would be to create a binary condition where the line load cost in the model is equal to 1 if the line load is equal to or higher than 99% of the capacity and 0 if the line load is lower than 99%. By minimizing the line load cost the model will limit the congested line hours without refraining from high line utilization that is still beneath the congestion limit. However, this research took a step towards congestion minimization, highlighting the potential of storage and imports in reducing congestion and opening the door to more accurate congestion minimization in electricity system modeling.

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A

Appendix: Literature review

The database used in the literature review was Scopus. On Scopus the following search query resulted in a total of 130 documents that were initially reviewed:
(”electricity system” OR ”power system” OR ”electricity system”) W/10 model* AND optim* AND (sub-national OR region*) AND (cluster* OR resolution)
Out of these 130 documents, 22 were published before 2014. These documents were filtered before the initial scan. During the initial scan documents were selected on the title and abstract. In figure A.1 the selection procedure is visualized.
After the initial scan, 33 documents were reviewed based on a scan of the contents of the introduction and conclusion. This research has a focus on electricity transition problems on national scale with a high spatial resolution. The focus is thus to find documents describing similar research. The result, 17 documents to be reviewed. Snowballing from these documents led to an additional 4 documents for the final selection of 21 documents.
The research question provided key concepts for the search query to look for electricity system optimization models and approaches to use electricity system optimization models whilst accounting for regional differences. Synonyms for electricity system provided a more complete overview of the available literature and by adding the W/10 command results were narrowed down to literature about electricity system models. Using region* or sub-national, the search resulted in documents referring to the specific scale required in this research. The technique used for modelling the specific spatial configuration was found by adding ”cluster*” and ”resolution” to the search query. Clustering is used to combine multiple data points into a smaller number of points, so that the computational burden decreases. With this search query different approaches for clustering grid data to build accurate and computationally feasible models are found. Figure A.1 shows the process and selection criteria used to select relevant articles.

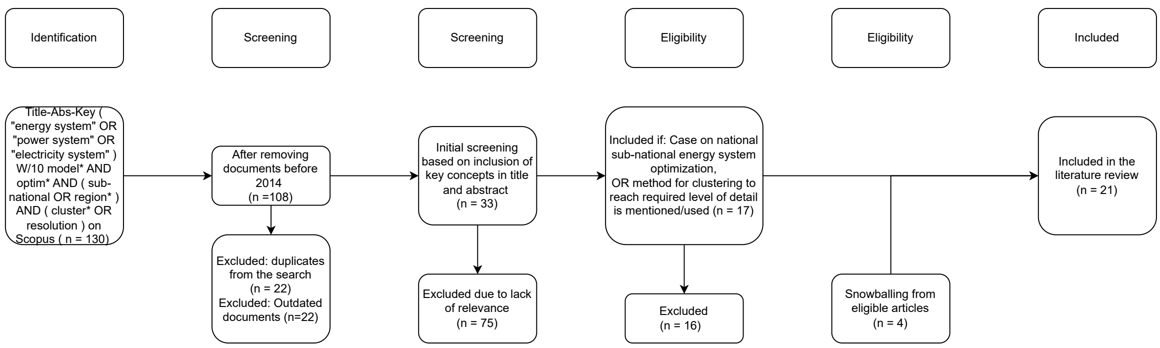


Figure A.1: Literature selection

A.1. Literature analysis

In the literature analysis you can find an overview of the relevant content of the selected documents.The relevant content is based on the sub questions asked in the literature review. Table A.1 shows the references used in the analysis:

Author
(Frysztacki et al., 2022)
(Lombardi et al., 2020)
(Pickering et al., 2022)
(Colbertaldo et al., 2023)
(Bogdanov et al., 2023)
(Klemm et al., 2023)
(Loustau et al., 2023)
(Patil et al., 2022)
(Schnidrig et al., 2022)
(Aryanpur et al., 2021)
(Frysztacki et al., 2021)
(Hu et al., 2021)
(Fleischer, 2020)
(Kueppers et al., 2020)
(Li et al., 2020)
(Pavičević et al., 2019)
(Rauner et al., 2016)
(Kost et al., 2015)
(Jaya Mabel Rani et al., 2014)
(Pfenninger & Pickering, 2018)
(Tröndle, 2020)

Table A.1: Literature table

Methods found in the literature

This section is dedicated to analyzing the literature based on methods to build high spatial resolution electricity systems. Aryanpur et al. (2021) shows that heterogeneous areas require more disaggregation than homogeneous areas, which might only need a single or a small number of model regions. Research in 2020 applied the so called SPORES approach to the Italian energy system. This system is divided by taking the country's 20 political zones and placing them into 6 bidding zones. SPORES is a method used to find different near-optimal solutions within a given solution space (Lombardi et al., 2020). Whereas, Colbertaldo et al. (2023) dives into a scenario for Italy for 2050 at a NUTS-2 resolution or regional level. Other work applied the SPORES approach in and energy system optimization model to 35 European countries and regionalized these countries according to the Seventh Framework Programme project e-HIGHWAY 2050 by the European Commission (Pickering et al., 2022). Here, the high-voltage transmission network is modelled according to the e-highway 2050, which conducted an analysis of the grid to generate simplified power capacities for connections between regions. This includes future additional transport capacities. Another example of regionalization is found in the work of Li et al. (2020), where the demand and supply of the Chinese energy system are modelled using the 30 provinces. By applying a spatial resolution from community perspective to a state perspective, Rauner et al. (2016) provided insights to spatial dissonance between renewable generation and demand in Germany. Kost et al. (2015) improve large-scale optimization models by integrating renewable generation and renewable potential in different areas, increasing the geographical resolution for renewable energy deployment. This allows for a more precise assessment of the impacts on conventional power plants, grid infrastructure, and regional transmission capacity planning as renewable energy in the system increases. Regarding the Calliope framework, Tröndle (2020) describes how the Euro-Calliope pre-built model work at three different spatial resolutions, continent, country and regional whilst accounting for renewable capacities and load at each node. Whereas the previously presented documents use political boundaries for regionalization, other researchers try to divide the area of interest into regions based on other characteristics. For example, Schnidrig et al. (2022) emphasizes the problem to form a global energy strategy due to the significant differences among regions in demand, generation capacity and renewable potential. The paper uses k-means clustering to cluster different regions within Canada into groups. Moreover, Frysztacki et al. (2021) and Hu et al. (2021) also apply k-means clustering for regionalization. Jaya Mabel Rani et al. (2014) applies a slightly different version, the Fuzzified Particle Swarm k-means clustering. Yet another

k-means method is found in the work of Loustau et al. (2023) in the form of Gaussian mixture k-means. The need for high spatial and temporal resolution in finding electricity system designs is often emphasized in the existing literature. To achieve that, hierarchical clustering is mentioned frequently. Bogdanov et al. (2023) uses hierarchical clustering for partial regionalization. The results showed no significant differences compared to other models, meaning that the model is more efficient than the base model whilst maintaining accuracy. On another note, to design a tool to help planning of renewable generation sites within a country, Kueppers et al. (2020) made a framework for regionalizing using hierarchical clustering based on demand, generation and renewable portfolio. They conclude that this method is indeed more efficient than using political regions. Frysztacki et al. (2022) goes further, and finds that, based on chosen parameters, hierarchical clustering based on a Brownfield capacity expansion also performs better than any of the included k-means clustering methods.
Other methods found for clustering generation is per unit, per typical unit and per technology (Pavičević et al., 2019). Fleischer (2020) applied max-p regions clustering algorithm based on population using wind, solar and pumped hydro generation and finds that it performed better than regionalizing based on political boundaries. Patil et al. (2022) takes another approach and advises to push aggregation on a spatial resolution based on renewable time series until no improvements are made. Afterwards, try to improve by using higher technological resolutions.
To compare different methods, Klemm et al. (2023) analyzed 12 models with different temporal resolution, 9 with different technospatial resolutions and 5 combined models. The recommendations are to run a pre-model to define technical boundaries, apply spatial submodelling on nodes in the network and to only model each nth day.

B

Method Validation

B.1. Comparison of NTC methods using the PyPSA-EUR data

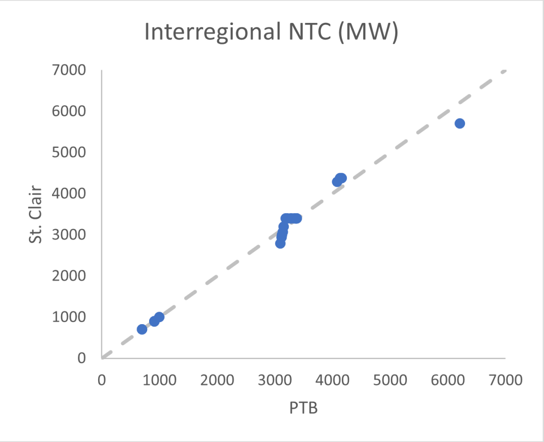


Figure B.1: The NTC between regions using the St. Clair approximation

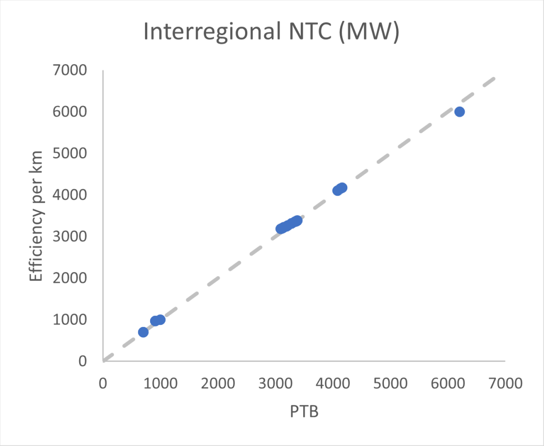


Figure B.2: The NTC between regions using an efficiency per kilometer

B.2. Overview of interregional NTCs using PyPSA-EUR data

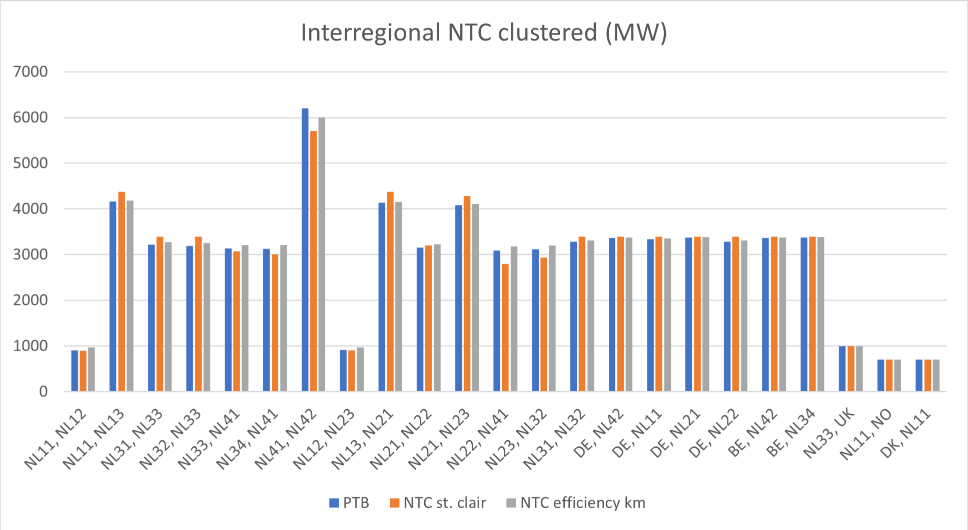


Figure B.3: The NTC of interregional lines using the clustered PyPSA-EUR grid data

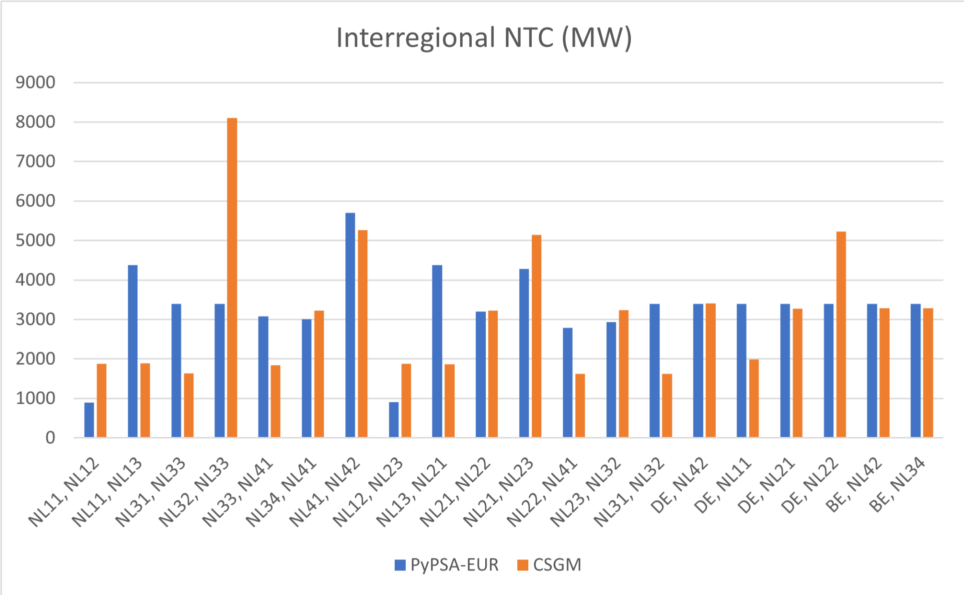


Figure B.4: Comparison of interregional NTC

Figure B.4 compares the interregional NTCs produced by the PyPSA cluster data (blue bars) and TenneT’s official data (orange bars) for a all cross border lines.

C
Appendix: Timeseries data

Demand for electricity is based on historic demand and the IP2024 scenarios for 2030. In the future demand scenarios, demand from other carriers and conversion technologies is neglected. Thus, the demand does not account for reformers or hydrogen related demand for electricity.

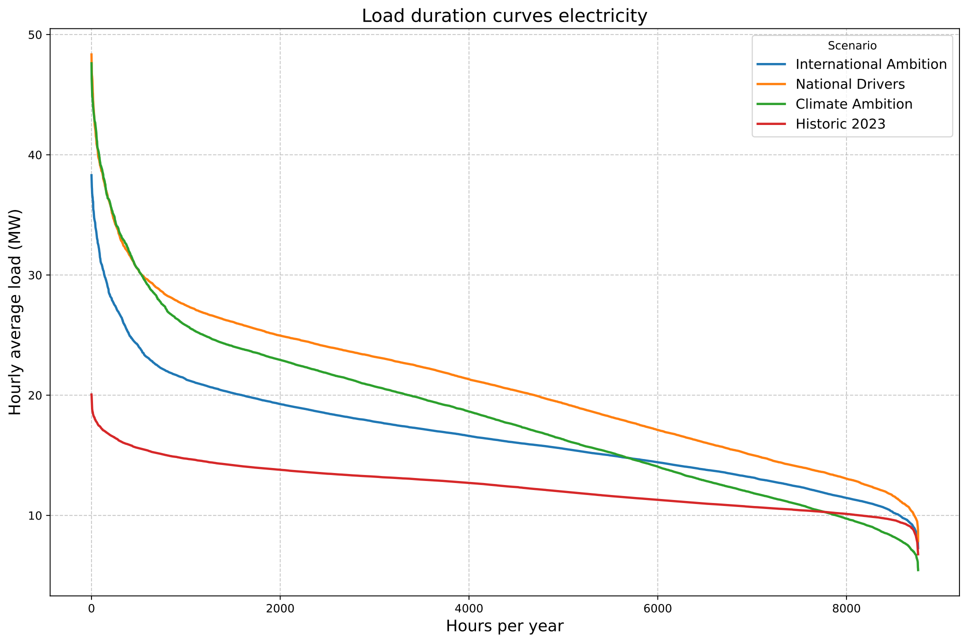


Figure C.1: Load duration curves electricity

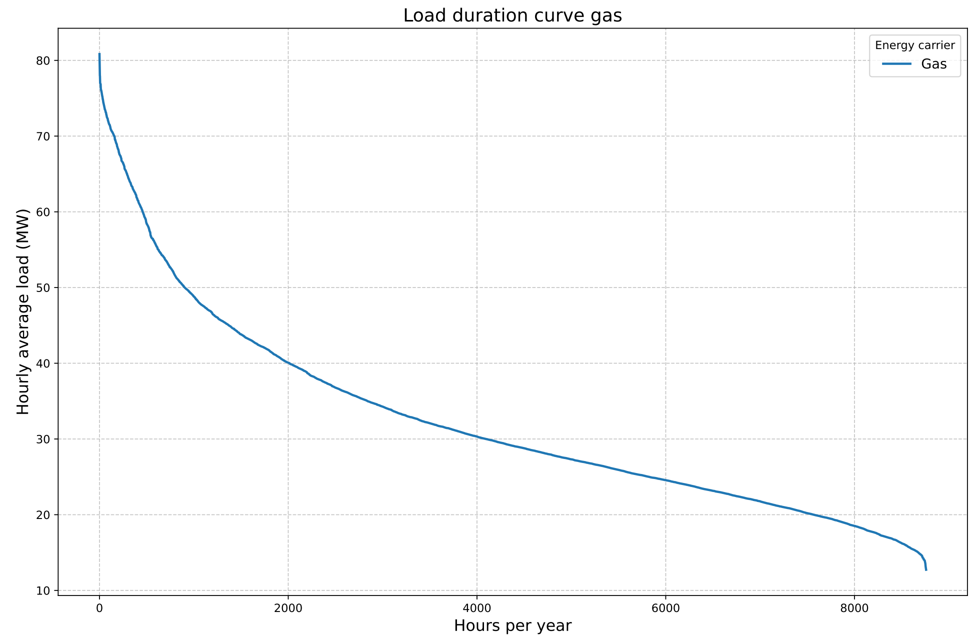


Figure C.2: Load duration curve gas

Cross border electricity prices are based on historic day-ahead prices from 2023.

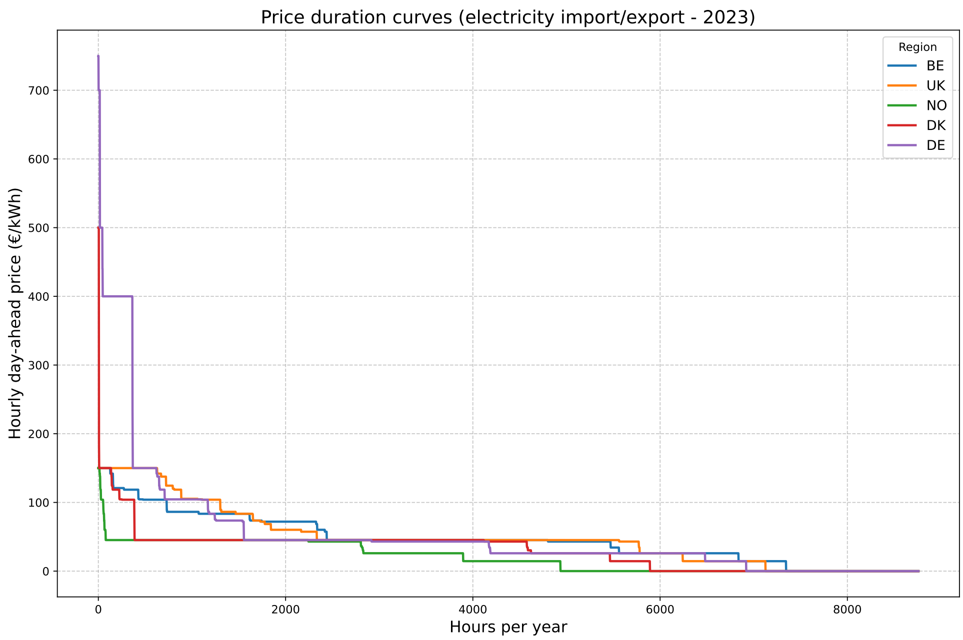


Figure C.3: Price duration curves 2023

Renewable capacity factors are retrieved from Renewables.ninja . This platform offers renewable capacity factors on a NUTS2 level for many years. For the purpose of this research, the year 2019 is selected. Within the wind timeseries, renewables.ninja accounts for both onshore and offshore wind while calculating a capacity factor per NUTS2 region. For rooftop and utility solar capacity factors the same timeseries is applied.

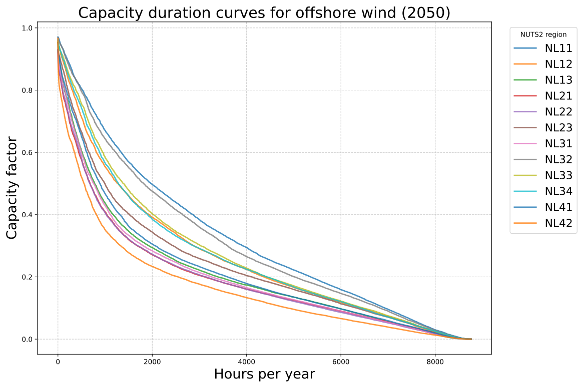


Figure C.4: Capacity duration curves wind

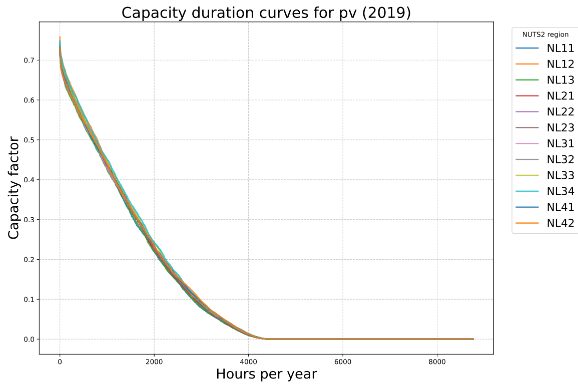


Figure C.5: Capacity duration curves solar

D

Appendix: Cost assumptions

This appendix describes the technologies as provided by the TNO single-node model.

D.1. Included technologies

Technology	Short name
Wind Offshore	wind_offshore
Wind Onshore	wind_onshore
Solar PV Rooftop	pv_rooftop
Solar PV Utility	pv_utility
Curtailment of electricity	curtailment_elc
Biomass Power Plant	pp_biomass_standalone
Hard Coal Power Plant	pp_hard_coal
Nuclear Generation (Gen 3)	pp_nuclear_gen3
Nuclear Small Modular Reactor	pp_nuclear_smr
CCGT Gas	pp_ccgt_gas
CCGT Gas CCS	pp_ccgt_gas_ccs
Gas production fields	production_gas_fields
Saltcavern gas storage	saltcavern_gas
Import terminal for LNG	import_lng_terminal
Battery Storage (Li-ion)	bss_liion
HVAC transmission	transmission_hvac
HVDC transmission	transmission_hvdc
Gas pipelines	free_gas_transmission
Import interconnector for NL	import_elc_interconnector
Export interconnector for NL	export_elc_interconnector

Table D.1: Technologies and their short names

D.2. Overview of cost assumptions

Different technologies have other levels of dispatch flexibility. Some can be freely adjusted across their entire operational range, whereas others must respect a minimum output threshold. Moreover, privately owned photovoltaic (PV) installations typically remain uncontrolled. To capture these differing control requirements, the following categories are introduced:

- **Must-run**: Follows its predefined generation profile.
- **Curtailed**: Follows its profile, but output can be curtailed if needed.
- **Minimum-run**: Operates above a defined threshold or does not run at all.
- **Free-run**: Operates without dispatch constraints.

- **Cyclic-run**: Applies to storage: the year-end energy level must match the year's starting level.
- **Disabled**: Excluded from the model entirely.

Table D.2: Cost data and lifetime of technologies

Tech	In	Out	Eff (%)	CAPEX (M€/GW)	OPEX (M€/GW/yr)	IR (%)	Lifetime (yr)	Dispatch	Ref
Offshore wind turbines	–	Electricity	100	3,487	110	10	25	Curtailed	A [1]
Onshore wind turbines	–	Electricity	100	1,572	33	10	25	Curtailed	A [1]
Solar PV - rooftop	–	Electricity	100	1,049	12	0	25	Must	B [1]
Solar PV - utility	–	Electricity	100	478	8	10	25	Curtailed	B [1]
Gas fired plants (CCGT + CCS)	Natural gas	Electricity	60	2,853	41	10	25	Free	C [1]
Open Cycle Gas Turbine	Natural gas	Electricity	34	659	12.8	10	25	Free	[1]
Hard coal power plant	Coal	Electricity	39.5	2,145.6	51.36	10	40	Free	[1]
Biomass standalone	Biomass	Electricity	42	2,000	48	10	25	Free	D [1]
Waste incineration	Waste	Electricity	42	2,000	48	10	25	Disabled	D [1]
Nuclear (GEN 3)	Uranium	Electricity	32	9,571	165	10	60	Must	E [1]
Small Modular Reactor	Uranium	Electricity	66	8,822	129	10	40	Free	E [1]
Battery storage (Li-ion)	Electricity	Electricity	92	352	9.0	10	10	Cyclic	F [1]
Gas storage (salt caverns)	Natural gas	Natural gas	95	88.4	4.74	10	30	Cyclic	[2]

Table D.3: Cost data for additional technologies and emissions management

Tech	Out	CAPEX	OPEX	Var OPEX	Comment Ref
LNG import	Natural gas	946 M€/GW	28.4 M€/GW/yr	50 €/MWh	TNO assumptions
Emissions ETS allowances	-	-	-	300 EUR/ton CO2	TNO assumptions
ETS penalty	-	-	-	500 EUR/ton CO2	TNO assumptions
Load shedding	Electricity/gas	-	-	8000 EUR/MWh	TNO assumptions
Imbalance market downregulation (curtailment)	Electricity	-	-	5000 EUR/MWh	TNO assumptions

[1] The global and national energy systems techno-economic (GNESTE) database (Hatton et al., 2024)
[2] TNO internal data
A: CAPEX and OPEX values are obtained from a database study, representing average costs for onshore and offshore wind technologies during the period 2020–2024.
B: Data for CAPEX and OPEX are sourced from the TYNDP 2022 report, specifically the DE scenario for 2025. Rooftop solar PV assumes private financing (0% interest rate).
C: The carbon capture efficiency is set at 85%
D: Specific data for biomass and waste incineration plants is unavailable, estimated values are adapted from coal plants for the period 2020–2024.
E: Cost estimates for this category are applied to the 2020–2024 timeframe.
F: CAPEX estimates are calculated as the median of available projections for lithium-ion batteries in 2050. OPEX is derived as 2.55% of CAPEX annually, based on NREL data. Efficiency is from the DEA dataset.
Fuel costs:
[1] Fuel costs coal: 14.8e-3 MEUR/GWh
[2] Fuel costs gasfields: 17e-3 MEUR/GWh
[3] Fuel costs LNG: 38e-3 MEUR/GWh, which is equal to the recent avg TTF price 2023 - 2024
[4] Uranium fuel price 69 EUR/kg assuming 3.456e6 MJ/kg

D.3. Zero-interest assumption

Immediately, the zero-interest assumption for rooftop PV stands out. Table D.4 illustrates a timeline that shows the CAPEX, OPEX, expected generation for a capacity of 1 GW of rooftop PV. Using Excel, these timelines are built for rooftop PV (including and excluding 10% interest), Utility PV and onshore wind to calculate the Net Present Value (NPV) and the Levelized Cost Of Electricity (LCOE). In the LCOE estimates, average capacity factors for 2030 from the Joint Research Center (JRC) are used (JRC, 2014). The goal is to find what the impact of the zero-interest assumption is. LCOE is equal to the NPV of the total costs of the generation technology being deployed divided by the NPV of the total generation. The NPV is calculated using the timeline, where the NPV is equal to:

$$\text{NPV} = \sum_{t=0}^{T} \frac{C_t}{(1+r)^t} + C_0$$

Year	0	1	2	…	23	24	25
Generation	0	2000	2000	…	2000	2000	2000
Capex	1049	0	0	…	0	0	0
Opex	0	12	12	…	12	12	12

Table D.4: Example of timeline used to calculate NPV and LCOE and rooftop PV

where: C_t is the costs in year t, r is the interest rate and T is the total period.
The NPV of OPEX and CAPEX is calculated using the formula above. The NPV of generation in year t is calculated using the same formula, but instead of C_t the dividend is equal to the generation in year t and C_0 is changed for the generation in year 0. The LCOE is equal to the sum of the NPV of OPEX and CAPEX divided by the NPV of the generation. The resulting LCOE rooftop PV (including and excluding 10% interest), Utility PV and onshore wind are shown in Table D.5.

Technology	LCOE (M€/GWh)
Rooftop PV (excluding interest)	0.039
Rooftop PV (including interest)	0.091
Onshore Wind	0.067
Utility PV	0.043

Table D.5: LCOE of renewable technologies.

D.3.1. Cross check with Euro-Calliope cost assumptions

Interest is 7,3% and lifetime 25 years. In terms of the Capex and Opex, Euro-Calliope, by default uses the values from the JRC for 2050 (JRC, 2014). The LCOE calculations in Table D.6 are based on the same average capacity factor used in Table D.5.

Technology	CAPEX [M€/GW]	OPEX[M€/GW/yr]	LCOE (M€/GWh)
Rooftop PV	880.0	17.60	0.068
Onshore Wind	1,100.0	18.70	0.038
Utility PV	520.0	8.84	0.039

Table D.6: Capital and operational costs of renewable energy technologies Euro-Calliope default.

E

Appendix: Historic NUTS2 capacities

Table E.1: Technologies and capacity sources

Technology	Source
Wind Offshore	Opgesteld vermogen as per the (Rijksoverheid, 2022)
Wind Onshore	Opgesteld vermogen as per the Regionale klimaatmonitor (RVO, 2023)
Solar PV Rooftop	Opgesteld vermogen per NUTS2 region (CBS, 2024)
Solar PV Utility	Opgesteld vermogen per NUTS2 region (CBS, 2024)
Biomass Power Plant	Estimate based on national installed capacity (ENTSO-E, 2024) and the generation per region (Centraal Bureau voor de Statistiek, 2023)
Hard Coal Power Plant	Data collected from the global power plant database (World Resource Institute, 2024), filtered for the Netherlands and for primary fuel Coal.
Nuclear Generation (Gen 3)	Single-node model
Nuclear Small Modular Reactor	-
CCGT Gas	Retrieved from the capacity per production unit from the ENTSO-E Transparency Platform (ENTSO-E, 2023)
CCGT Gas CCS	-
Gas production fields	Single-node model
Saltcavern gas storage	Single-node model
Import terminal for LNG	Single-node model
Battery Storage (Li-ion)	Energy Storage NL
Import interconnector for NL	Single-node model
Export interconnector for NL	Single-node model

F

Appendix: Model formulation

In Figure F.1 you can see the formulation of the objective in the base case, where the focus is on minimizing the monetary costs. Hence, monetary has the value 1 whilst the other cost classes are assigned a value of 0.

```
objective_options: {
    'cost_class': {'monetary': 1, 'line_load': 0, 'spores_score': 0, 'excl_score': 0},
    'sense': 'minimize'
}
```

Figure F.1: Optimization formulation - base.

The code snippet in Figure F.2 shows the formulation of the objective function in the model runs that minimize line loading. This set up is complemented with a total system cost constraint so that the model looks for designs that limit line loading whilst staying within the near cost optimal solution space.

```
objective_options: {
    'cost_class': {'monetary': 0, 'line_load': 1, 'spores_score': 0, 'excl_score': 0},
    'sense': 'minimize'
}
```

Figure F.2: Optimization formulation - line loading.

The line load cost is defined per link as cost per produced GW times one over the line's NTC. Figure F.3 shows an example.

```
NL11,NL12:
    techs:
        transmission_hvac:
            distance: 78.08059088268635
            constraints:
                #energy_cap_min: 0.6882
                #energy_cap_max: 3.4401
            costs:
                line_load:
                    om_prod: 0.000758 # 1/NTC
```

Figure F.3: Example of the definition of the line load cost.

Figure F.4 gives an example of the formulation of the total system cost constraints per the Central scenarios, limiting the additional costs when minimizing the line loading to 10% of the costs in the cost optimal solution.

```yaml
overrides:

# within 10% max
    central_nd_101:
        group_constraints:
            central_nd_10:
                cost_max:
                    monetary: 4.276e+4 #+10%
```

Figure F.4: System cost constraints for line loading optimization runs.

G
Formulas inductance and capacitance

The characteristic impedance of a line is calculated with the following formula:

$$Z_{0,i} = \sqrt{\frac{L_i}{C_i}} \tag{G.1}$$

With the data in the Static Grid model and the PyPSA, it is possible to calculate the inductance, using this formula:

$$L_i = \frac{2 \cdot U_i}{I_i^2} \tag{G.2}$$

In high-voltage transmission systems, the capacitance per unit length is influenced by the spacing between conductors and their physical properties. For long parallel transmission lines, the capacitance per unit length (C) can be determined using an expression derived from *Gauss's Law* and electrostatic principles:

$$C = \frac{2\pi\varepsilon_0}{\ln(d/r)} \tag{G.3}$$

where:

- C represents the capacitance per unit length, measured in farads per meter (F/m),
- $\varepsilon_0 = 8.85 \times 10^{-12}$ F/m is the permittivity of free space,
- d denotes the distance between conductors in meters, and
- r is the radius of each conductor in meters.

H
Appendix: Model validation

Figure H.1 and Figure H.2 show the monghtly generation per technology for the PyPSA-network and the TenneT network respectively. The network topologies results in an almost identical generation mix. It can be concluded that on an aggregated level (summed over all the time steps and all the locations) the network topology hardly impacts the generation mix of the mult-node model.

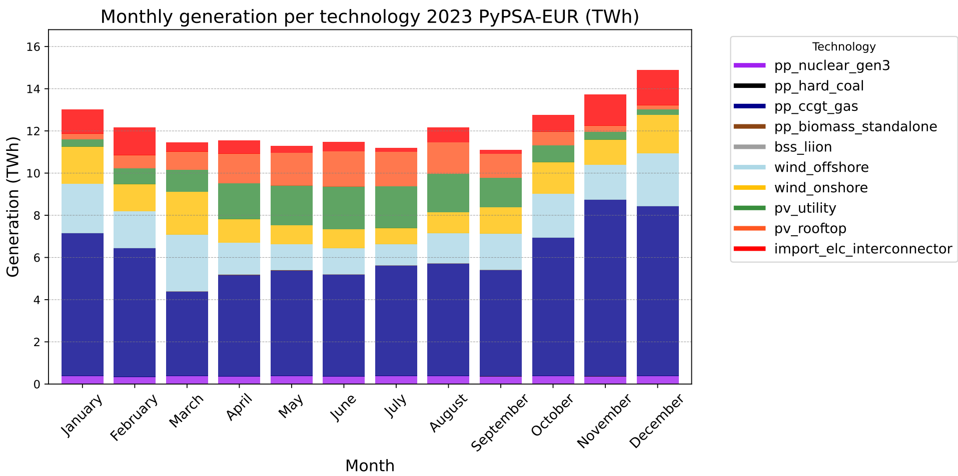


Figure H.1: Monthly generation per technology PyPSA network

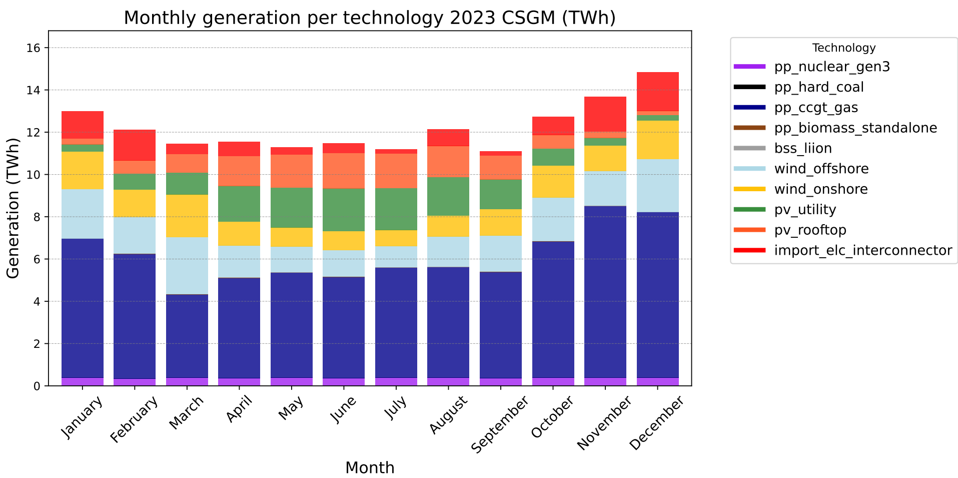


Figure H.2: Monthly generation per technology TenneT network

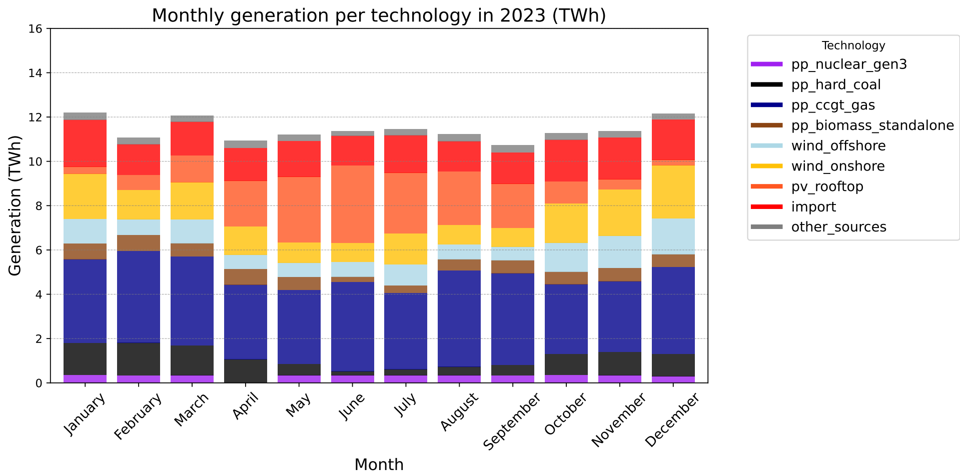


Figure H.3: Historic monthly generation per technology 2023

In terms of gas production, the TenneT and PyPSA models have no production during the largest renewable hour. Thus, from this perspective they are similar during the max renewable hour. However, in the highest load hour, the output is different as shown in Figure H.4.

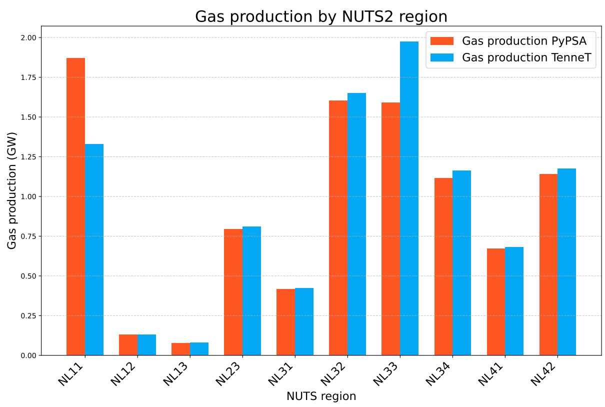


Figure H.4: Gas generation during largest load hour

Appendix: Results scenarios analysis

I.1. Installed capacity in the cost optimum

Technology	Central ND	Flex ND	Central KA	Flex KA	Central IA	Flex IA
BESS	13.0 (+4671%)	12.0 (+4309%)	13.0 (+4671%)	12.2 (+4352%)	13.0 (+4671%)	10.6 (+3782%)
Gas CCGT	19.7 (+35.1%)	16.9 (+16.3%)	20.9 (+43.5%)	18.1 (+24.5%)	15.6 (+6.9%)	14.6 (+0.0%)
Rooftop PV	49.0 (+352%)	40.0 (+268%)	45.9 (+324%)	41.2 (+280%)	35.1 (+224%)	28.1 (+159%)
Utility PV	15.8 (+17.6%)	18.2 (+35.2%)	13.4 (+0.0%)	16.0 (+19.3%)	18.2 (+35.4%)	13.4 (+0.0%)
Onshore wind	7.6 (+8.7%)	7.6 (+9.0%)	7.0 (+0.0%)	7.0 (+0.0%)	7.0 (+0.0%)	7.0 (+0.0%)

Table I.1: Installed capacities by technology (in GW) for each scenario with percentage increase compared to historic capacity.

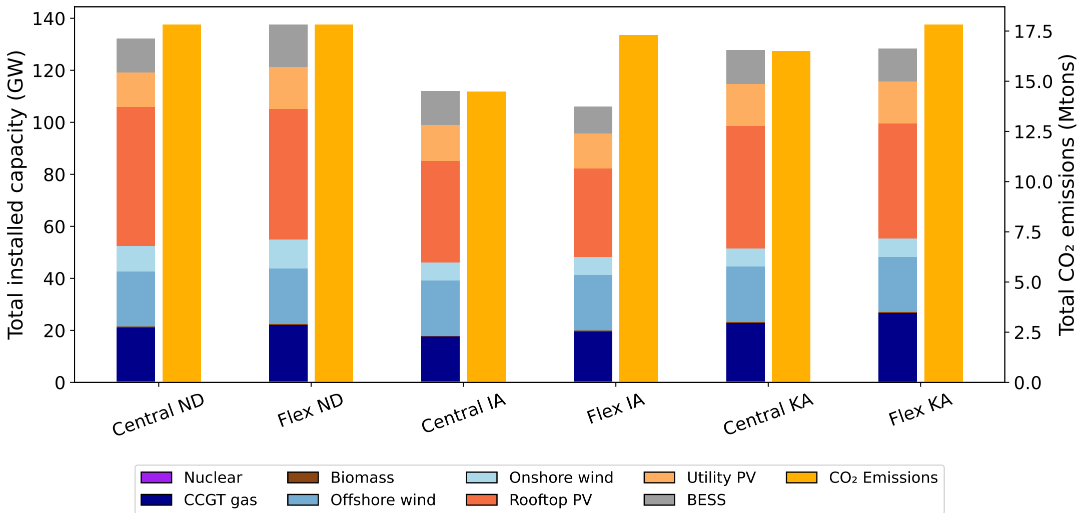


Figure I.1: Installed capacity per technology and emission per demand scenario in the cost-optimization.

Figure I.2 shows that there is almost no variation in terms of land use between the Central and Flex scenarios. Across demand scenarios, the differences are also relatively small. In Overijssel and Gelderland the required land use does decrease in scenarios with smaller demands.

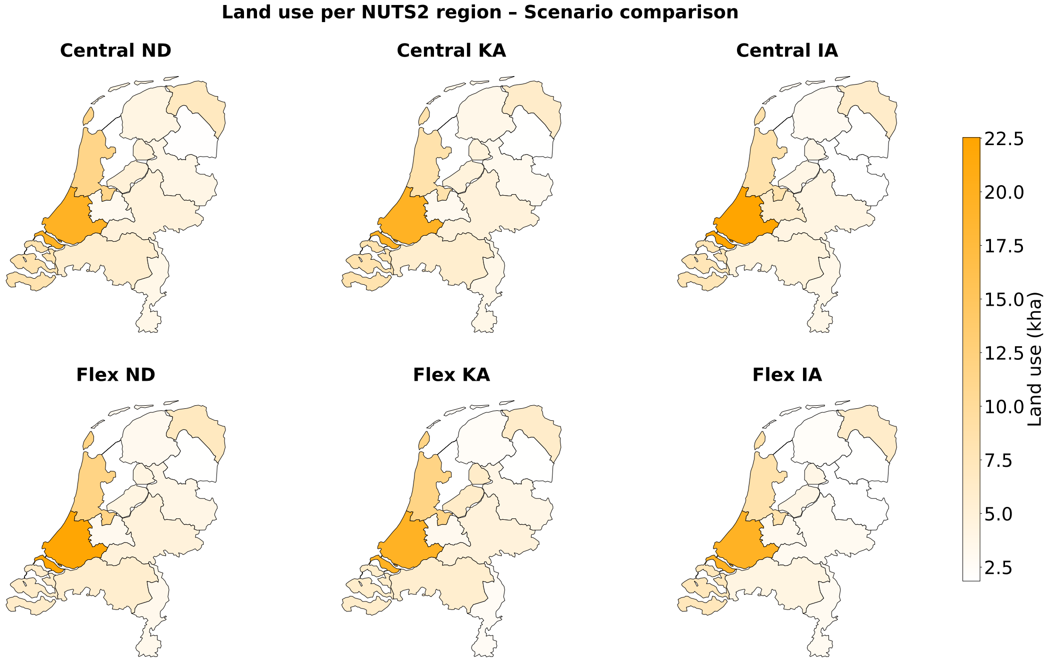
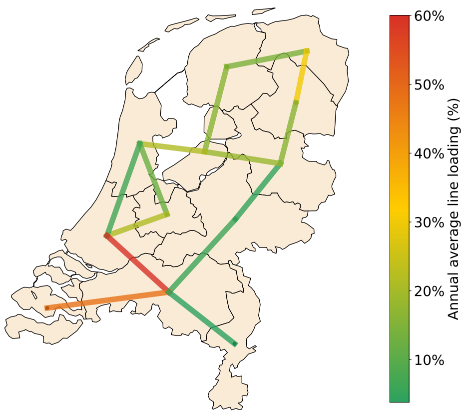
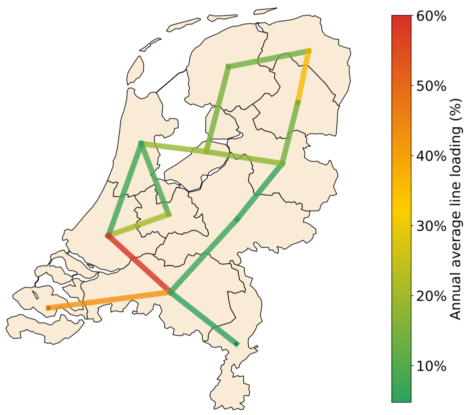


Figure I.2: Land use of renewable technologies across scenarios

I.2. Line load in the cost optimum

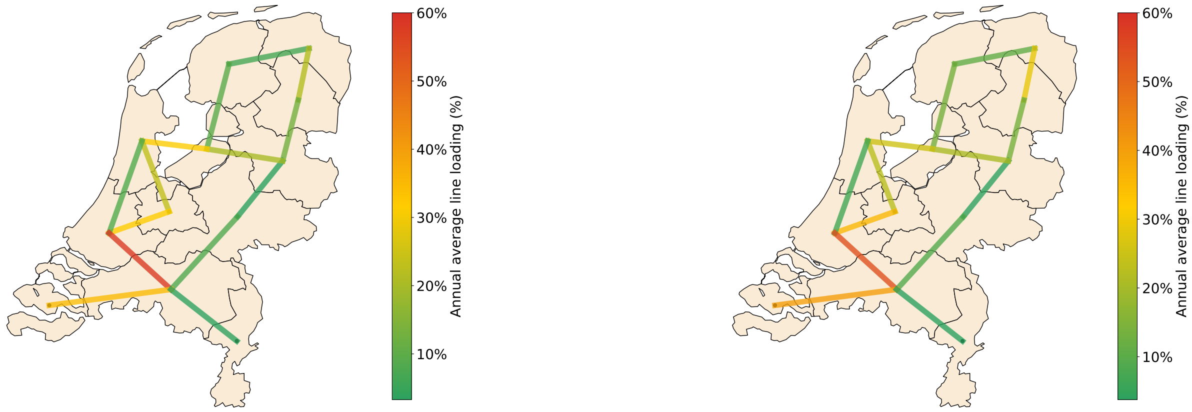


(a) Central ND



(b) Flex ND

Figure I.3: Average line loading for ND scenarios.



(a) Central IA (b) Flex IA

Figure I.4: Average line loading for IA scenarios.

Line (from, to)	Central ND	Central KA	Central IA	Flex ND	Flex KA	Flex IA
(NL11, NL12)	212	39	33	70	114	262
(NL11, NL13)	537	280	336	**863**	**493**	**698**
(NL12, NL23)	45	25	2	9	77	–
(NL13, NL21)	225	264	208	27	167	–
(NL21, NL22)	23	20	4	44	89	–
(NL21, NL23)	313	352	298	270	380	319
(NL22, NL41)	122	99	117	114	81	195
(NL23, NL32)	**720**	**934**	**1406**	550	**844**	**973**
(NL31, NL32)	7	74	504	1	1	45
(NL31, NL33)	**634**	442	**629**	542	395	–
(NL33, NL41)	**3426**	**3850**	**3256**	**3150**	**3942**	**2620**
(NL34, NL41)	627	**444**	160	**759**	234	395
(NL41, NL42)	–	–	–	3	3	–

Table I.2: Overloaded line hours per line pair across six scenarios.

I.3. Installed capacity in the line load optimum

Technology	Central ND	Flex ND	Central IA	Flex IA	Central KA	Flex KA
BESS	0.0	11.3	0.0	-22.0	0.0	-5.0
Gas CCGT	7.0	6.4	9.9	13.3	5.7	16.0
Rooftop PV	-15.6	-8.8	-10.7	-10.8	-16.8	-22.9
Utility PV	27.4	11.3	-0.3	0.0	8.9	1.5
Onshore wind	-8.1	-1.8	0.0	0.0	0.0	0.0

Table I.3: Percentage change in installed capacity per technology compared to the cost-optimal solutions.

Scenario	Import	Gas	BESS	Onshore Wind	Utility PV	Rooftop PV
Central ND	24.4%	0.0%	17.6%	-11.6%	18.2%	-16.0%
Flex ND	0.0%	0.0%	59.9%	-7.1%	-4.2%	-8.8%
Central KA	78.7%	-4.2%	14.4%	-1.9%	2.3%	-17.1%
Flex KA	45.7%	2.1%	13.8%	-3.3%	-9.2%	-22.8%
Central IA	68.2%	-8.6%	9.3%	-1.4%	-6.6%	-11.1%
Flex IA	42.2%	-5.9%	11.9%	-3.5%	-10.2%	-11.2%

Table I.4: Percentage change in technology output compared to base scenario (in TWh).

J Appendix: Sensitivity analysis

Table J.1: Installed PV Rooftop Capacity and Percentage Change from Previous Values

Region	Capacity (GW)	% Change from Previous
NL11::pv_rooftop	0.45	0.00%
NL12::pv_rooftop	3.09	-5.23%
NL13::pv_rooftop	0.47	0.00%
NL21::pv_rooftop	0.88	-77.22%
NL22::pv_rooftop	7.39	43.49%
NL23::pv_rooftop	1.30	-29.26%
NL31::pv_rooftop	1.07	-79.24%
NL32::pv_rooftop	7.73	50.02%
NL33::pv_rooftop	7.14	38.58%
NL34::pv_rooftop	4.80	-6.75%
NL41::pv_rooftop	5.36	4.00%
NL42::pv_rooftop	6.89	33.75%

Scenario	**Total costs** (BN. EUR)	**Emissions** (Mton CO_2)	**Installed BESS** (GW)	**Avg. line load**	**Congested line hours**	**Capacity factor BESS**	**Imports** (TWh)
Central KA	41.102 -0.03%	15.59 -0.61%	13.02 0.00%	19.9% 0.67%	7.195 5.45%	9.7% 0.08%	7.30 -0.49%

Table J.2: System performance indicators for the Central KA scenario, including percentage change from stricter PV design.

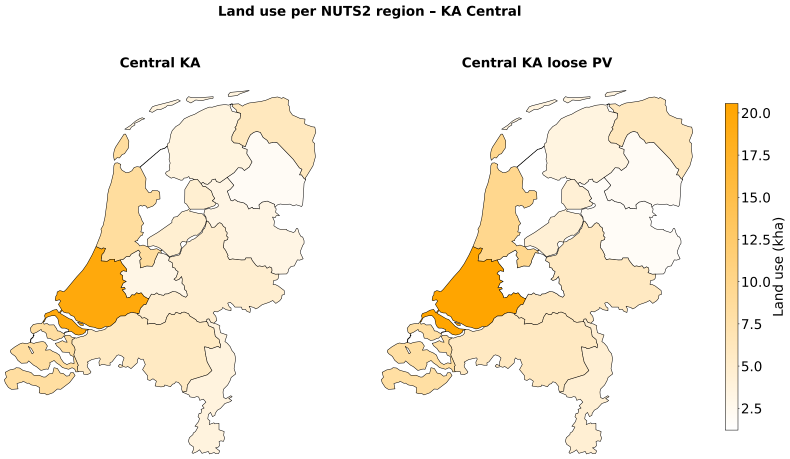


Figure J.1: The land use in the Central KA scenario under strict and less strict rooftop PV scenarios.

Scenario	**Total costs** (BN. EUR)	**Emissions** (Mton CO_2)	**Installed BESS** (GW)	**Congested line hours**	**Capacity factor BESS**	**Imports** (TWh)
Central ND	42.43 (-0.34%)	17.82 (0.00%)	13.02	5.220 (24.25%)	9.3%	12.70
Central KA	40.96 (-0.38%)	15.73 (-0.26%)	13.02	5.246 (23.11%)	9.4%	7.09
Central IA	39.36 (-0.41%)	13.00 (1.32%)	13.02	6.090 (12.41%)	10.2%	8.58
Flex ND	41.17 (-0.34%)	17.82 (0.00%)	11.25	4.611 (27.98%)	5.2%	21.02
Flex KA	39.72 (-0.45%)	17.41 (-2.49%)	10.45	4.552 (33.26%)	6.1%	9.26
Flex IA	38.08 (-0.24%)	16.21 (-1.84%)	7.45	5.244 (15.09%)	5.7%	10.61

Table J.3: Scenario overview with transmission expansion including total costs, emissions, storage, grid congestion, and imports. Reductions in costs, emissions, and congestion are shown in brackets.