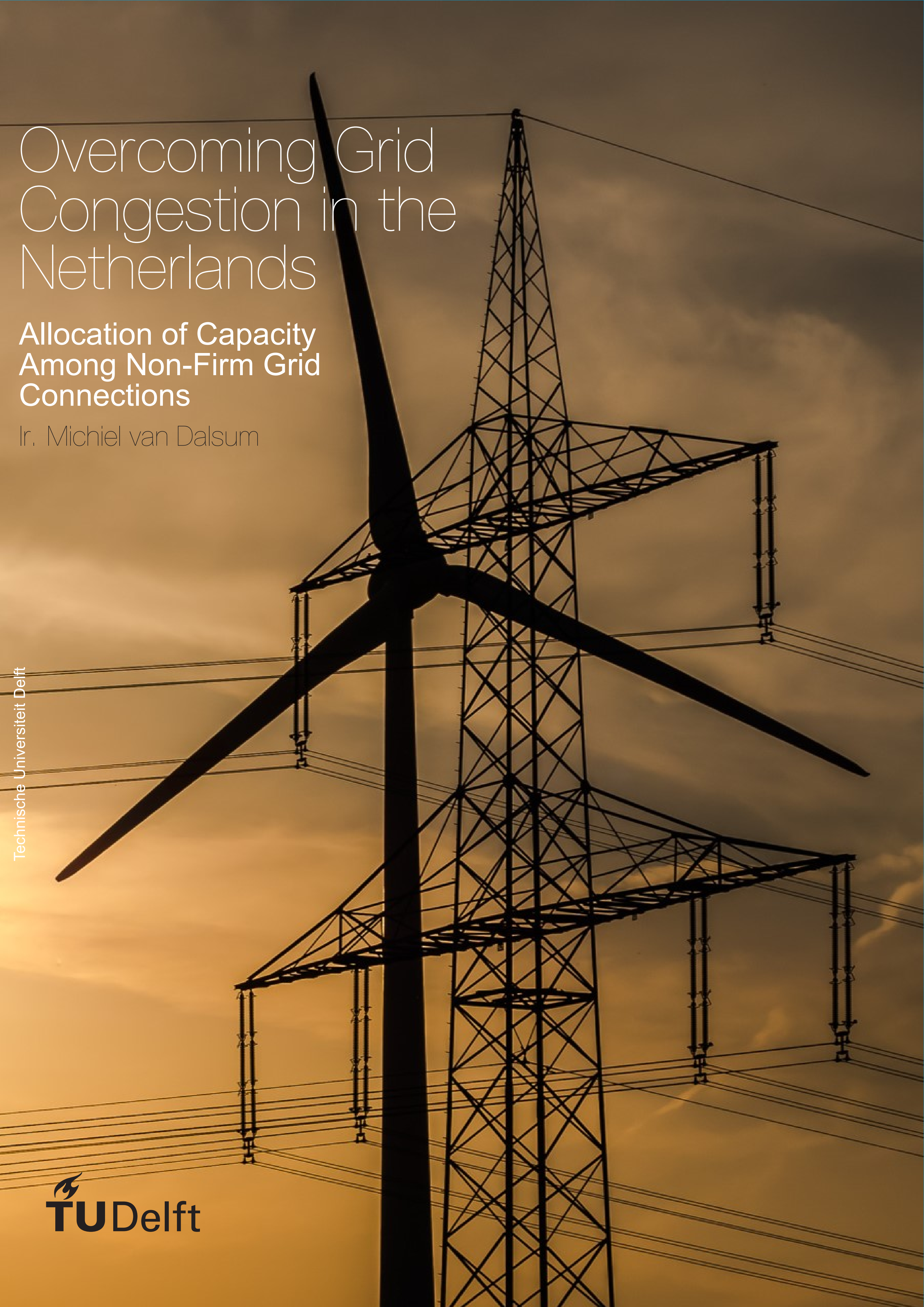
Overcoming Grid Congestion in the Netherlands

Allocation of Capacity Among Non-Firm Grid Connections

Ir. Michiel van Dalsum



Technische Universiteit Delft

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Allocation of Capacity Among Non-Firm Grid Connections

by

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Abstract

With the energy transition already underway in the Netherlands, one of the largest obstacles currently facing this process is the widespread grid congestion. To deal with this grid congestion, many different flexibility solutions have been proposed. One of these solutions is the use of non-firm grid connections, which dynamically allocate grid capacity to connected parties based on the free space available on their specific part of the grid. A key design parameter of this flexibility options is the manner in which the available capacity is allocated across the non-firm connections. In this work, a comparison is made between five methodologies for allocating capacity among non-firm grid connections: a contract age based methodology (and a variation upon it which also takes into account the location of a connection in the grid), a rotating priority list, a pure mathematical optimisation of total allocated capacity as well as a proportional allocation methodology which tries to allocate equally between loads. To compare these different methodologies, a set of metrics is devised, which attempt to capture the three key dimensions of relevance in this space, each representing a stakeholder: the customer/connection side, the grid operator side and the societal/wider grid user side. It is found from this comparison across these metrics that each of the methodologies excels at different metrics, making each of them viable in their own respect.

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[1] Cover image courtesy of Beck et al. (2022). Rapid Response: The future of European energy security. EnergySource. https://www.atlanticcouncil.org/blogs/energysource/rapid-response-the-future-of-european-energy-security/

Preface

This work was written as a thesis for the MSc Sustainable Energy Technology at the Faculty of Electrical Engineering, Mathematics and Computer Science of Delft University of Technology. It was completed during an internship with the Dutch distribution network operator Alliander.

From the former, I would like to express my full appreciation to the members of my committee, as their input was incredibly helpful in developing my work and challenging myself to do better. Specifically I would also like to thank Wouter Zomerdijk, who added a touch of perspective to many of the discussions for me.

From Alliander, I would like to thank Alex van de Schootbrugge and Ioulia Papaioannou. Their guidance was invaluable and they gave me a great insight into the world of grid operators. I hope to encounter you again in my future work!

In my personal life, I would like to acknowledge my family who, even though my studies might not always have made a lot of sense to them, always supported me and gave me the tools I needed to get here. I would also like to thank my partner, Bo, who had to deal with two of my theses whilst working on their own. I appreciate you always.

Ir. Michiel van Dalsum
Salento, August 2024

Contents

1 Introduction

In an effort to reduce greenhouse emissions, the Dutch government has established the goal of 70% of total electricity production being renewable by 2030 (Rijksoverheid, 2019). As part of this energy transition, major changes are occurring in the production and consumption of electricity. On one side, a lot of renewable generation is appearing spread throughout the grid, including the distribution grid, and on the other side we see technologies like electric vehicles and heat pumps increasing demand on the electricity grid. These developments create a serious need for investment in the electricity grid, as well as a significant shift in the utilisation of this grid, especially on the distribution level. These challenges are critical to grid operators, which are responsible for creating the infrastructure necessary to achieve the energy transition in the electricity grid. One of the key issues that grid operators are dealing with is distribution network congestion. This phenomenon, its characteristics, and solutions will be the focus of our research. Let us discuss the origins of this issue, what the consequences are, and how stakeholders are attempting to overcome it.

1.1. Grid Congestion

Grid congestion, especially on the distribution networks, primarily occurs due to increased load as a result of electrification and the proliferation of technologies like heat pumps and electric vehicles. However, as the energy transition leads us away from fossil fuel electricity generation and towards renewable sources, we can also observe a shift in the patterns of electricity flow in the grid which the existing infrastructure is not equipped for. The cause of this shift can be found in large part due to four changes in the electricity grid.

Firstly, the location of generation in the grid has changed. In the past, electricity grids were designed with large, centralised power generation facilities in mind, like coal power plants (Netbeheer Nederland, n.d.-b). This meant that the structure of the electricity grid was specifically tailored for this. Namely, it was designed to transport energy in one direction, from a large, centralised producer to many smaller consumers at the ends of the distribution grid. Thus, the further upstream one went, the higher the capacity of the various power lines and transportation equipment were in order to cope with the increased amount of power that was transported there. With renewable generation sources however, this pattern of generation is starting to shift. Renewable generation sources like wind and solar, also known as Distributed Energy Resources (DERs), do not need to be (and most commonly are not) centralised in nature. Wind turbines are spread across the grid in the most convenient and high yield locations, and solar panels are placed in a plethora of places, ranging from rooftops to fields where animals can graze under them (Doyob & Fischer, 2021). This spread of DERs means that the historical assumptions that were made when sizing the grid do not always apply anymore. The location where generation occurs is shifting away from the places where big power plants can be built towards the places where the relevant energy resource can be harvested (be it wind, sun, hydro, etc.). Furthermore, the generation is now also spread widely throughout the grid, as opposed to occurring in a limited number of centralised locations. All of this leads to larger energy flows in parts of the grid that were not historically sized for it.

Next, we have the change in the direction that electricity flows. This second difference mostly applies to smaller DERs like rooftop solar, but is also relevant to other types of generation to a limited extent. Where in the past, lower voltage distribution grids solely saw electricity flows in a single direction —from the substation to the consumers—these days, with the rise of prosumers (consumers who also produce electricity (Office of Energy Efficiency & Renewable Energy, n.d.)), electricity flows are no longer only variable in magnitude but also in direction. In the past equipment like circuit breakers and busbars only had to be sized to deal with issues like undervoltage and excessive flows in one direction. These days, they have to also consider loading in the opposite direction in their design and layout as well as additional functionality requirements like providing smart grid functionality. Furthermore, energy might now also be transported between different parts of the distribution grid, leading to issues which were quite uncommon in the past (e.g. overvoltage on long lines as a results of many rooftop solar installations feeding in). It is important to note that congestion can be separated in direction: supply congestion (ODN, *Ontvangst Door Netbeheerder*) is due to an excess supply leading to issues, whilst demand congestion (LDN, *Levering Door Netbeheerder*) is due to excessive loads on the system.

Next, the temporal aspect also plays a role. Because the generation of DERs like wind and solar are heavily dependent on external conditions like the weather, time of day, and time of year, there is a significant difference between their peak and average output. Therefore, grid sizing for these generators is significantly different than for controllable generation sources like gas, coal, and nuclear. Although this is primarily an issue for balancing the grid (matching demand and supply), these issues also lead to a lot of unused capacity on the grid during times where there is a limited amount of sun or wind. This capacity is currently left unused, as any new connections (or increases in transport capacity for existing connections) would have to be matched by an increase in the capacity of the lines and other components in the system to accommodate the peak loads. This means that there is a lot of ”capacity” currently left unused during the times between peaks for which, until recently, there was no clear solution. However, it is important to distinguish this ”unused capacity” from the capacity that might not be used due to grid performance requirements, like the N-1 criterion. The N-1 criterion is a constraint that requires transmission grid operators to design the grid in such a way that: ”according to which the elements remaining in operation within a TSO’s control area after occurrence of a contingency are capable of accommodating the new operational situation without violating operational security limits” (Commission, 2017). Although not mandatory for distribution network operators, many do follow this rule (Commission, 2017). An illustration of this unused capacity is presented in Figure 1.1.

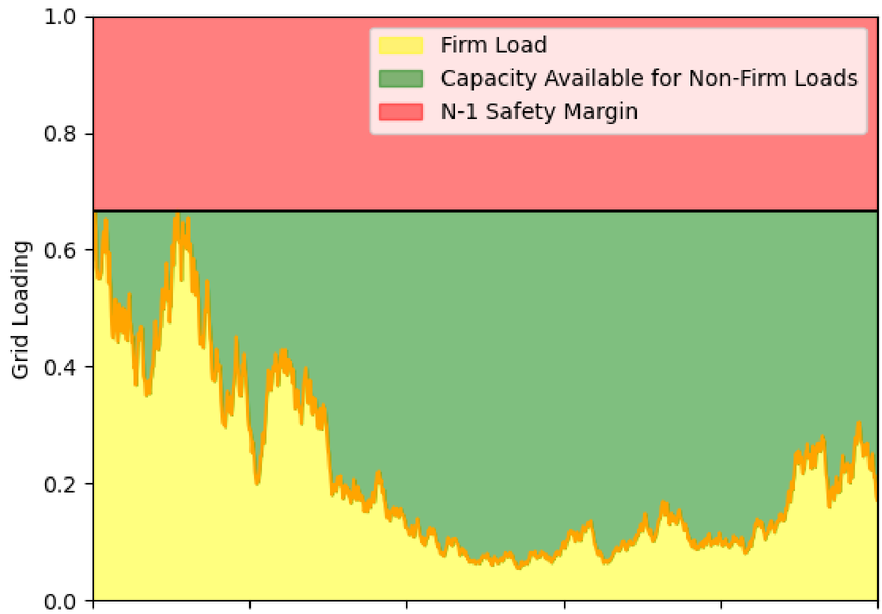

Figure 1.1: An illustration of the "unused capacity" available in the grid. The green area is the unused grid capacity that can be used by loads, whilst the red area is capacity reserved for grid performance requirements like N-1 reserves.

Finally, another major factor at play in the appearance of congestion is the way in which the regulatory framework for grid operators has been set up in the Netherlands (van Hest & Kleinnijenhuis, 2022). Due to their unique position as semi-monopolistic parties and the fact that electricity is a social commodity, grid operators in the Netherlands are closely monitored by the government and the national regulatory authority Autoriteit Consument & Markt (ACM). This entails that certain aspects like the prices they are allowed to charge their customers, the amount of profit that they can make, and their investment plans are all subject to the scrutiny of the regulator. At the close of the previous century, there was a societal desire to make the grid operators as efficient as possible, which drove them to limit investment into the grid to those areas where it was essential. Even though grid operators saw the writing on the wall with respect to the issues that would arise as a consequence of the energy transition, they were limited in their ability to prepare adequately due to the way the incentive structure was designed for these companies. This is not to say that the rationale behind the incentive structure was not sound when it was originally devised, but rather that the operating conditions have changed over the years, with the associated consequence being a grid which is not completely prepared for a fast transition to sustainable energy sources (van Hest & Kleinnijenhuis, 2022).

All of the above factors contribute to the phenomenon that is called "network congestion". Network congestion means that there is insufficient capacity in the grid to accommodate all of the transport of electricity that various consumers and producers request. However, it is important to distinguish between the issue of short-term/real-time congestion, which takes place due to short-term variations like a sunny day, and longer-term congestion as a result of insufficient grid capacity to accommodate new connections. Whereas the former entails primarily a safety concern about the loading and performance of the grid, which must stay within thermal and voltage limits, the latter is more relevant when considering the grid from a societal perspective. We can now discuss these two types in more detail to determine why they are so relevant for our research.

1.2. Consequences of congestion

The consequences of longer-term congestion on the electricity network for society are readily apparent. Firms trying to electrify their operations (Netbeheer Nederland, n.d.-a), new neighbourhoods being constructed to deal with the housing shortage which require a connection to the grid (NOS Nieuws, 2023), and new renewable energy projects (Netbeheer Nederland, 2024) are all examples of important societal projects that are being delayed or even postponed due to a lack of grid capacity leading to congestion.

Aside from these straightforward implications, the energy transition and the associated appearance of grid congestion have also forced a significant shift in the responsibilities of the distribution network operator. In the past, the operation of distribution networks was a relatively narrow responsibility which, combined with the fact that until 1998 grid operators still functioned as energy suppliers in the Netherlands, meant that operators were mostly concerned with running a top-down, efficient grid (Joosten, 2019). These days however, the role of the distribution grid operator (DSO) has significantly shifted, making them a key player not only in the larger national energy strategy, but also in areas like flexibility services and congestion management (van Werven & Scheepers, 2005). In the past, distribution grid operators were mostly concerned with asset management, whilst these days their focus has shifted to also include aspects like capacity management. All of these new responsibilities entail significant expansions of their operations, as well as a lot of experimentation on how to most efficiently respond to the potential opportunities and challenges brought forth by problems like grid congestion. Although congestion is, at face value, certainly a net negative, it has also forced a societal reevaluation of how we perceive and use our energy system. This means that when it comes to grid congestion, distribution grid operators have a lot of challenges on their plate while trying to navigate these issues in a satisfactory fashion.

Furthermore, the scope of these congestion issues is quite extensive. Netbeheer Nederland, which is an association of Dutch grid operators, publishes maps of the capacity available for new or larger grid connections which can be seen in Figure 1.2 below.

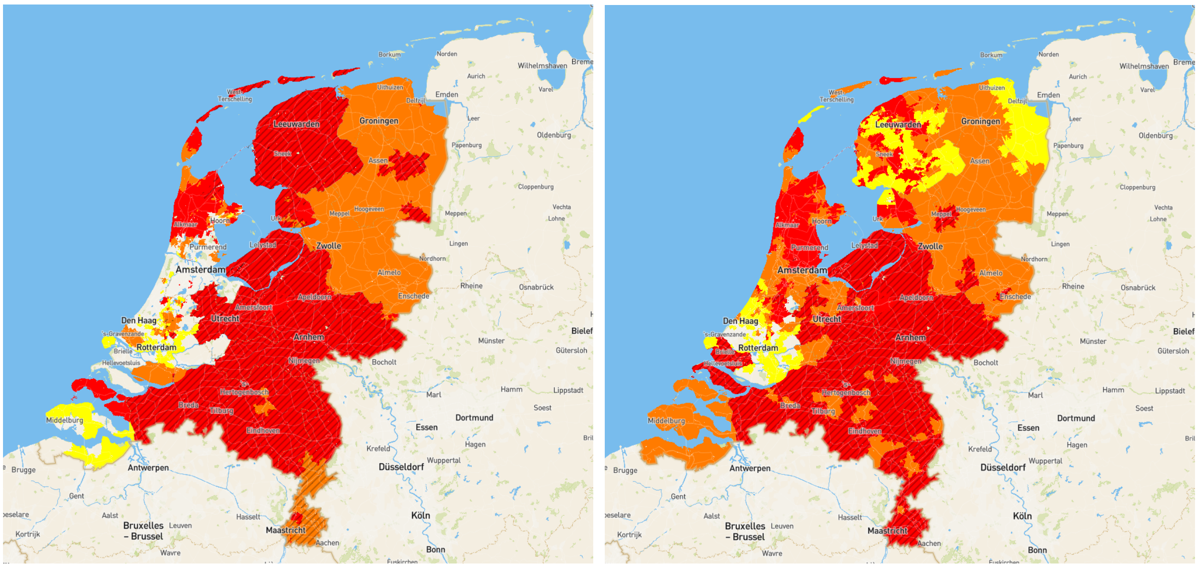

Figure 1.2: Capacity map production (left) and consumption (right) for connections >3x80A (Netbeheer Nederland, 2024)

In the red areas, no transport capacity is available at all, requiring significant expansions into the grid before new connections larger than $3x80Amperes$ can be connected. In the yellow zones, there is only limited capacity available, with long waiting times. Finally, in the orange zones, congestion management is being applied, in order to cope with the limited capacity of the grid. This is currently considered to be the most fruitful approach to dealing with congestion in the foreseeable future. Let us discuss this topic in more detail.

1.3. Solutions to Long-Term Congestion

To overcome longer-term congestion in the electricity grid, a host of solutions have been proposed. Of course, the most straightforward solution is grid expansion and reinforcement. By increasing the capacity of the lines and equipment in the grid, congestion issues can be alleviated, allowing new and larger connections to the grid. However, as Spiliotis et al. (2016) underlines, there are a multitude of issues with this solution. Primarily, the process of constructing grid infrastructure takes a long time and costs a lot of money. Netbeheer Nederland produced the illustrations presented in Figure 1.3 presented below which provide a an insight to how long some grid expansions can take.

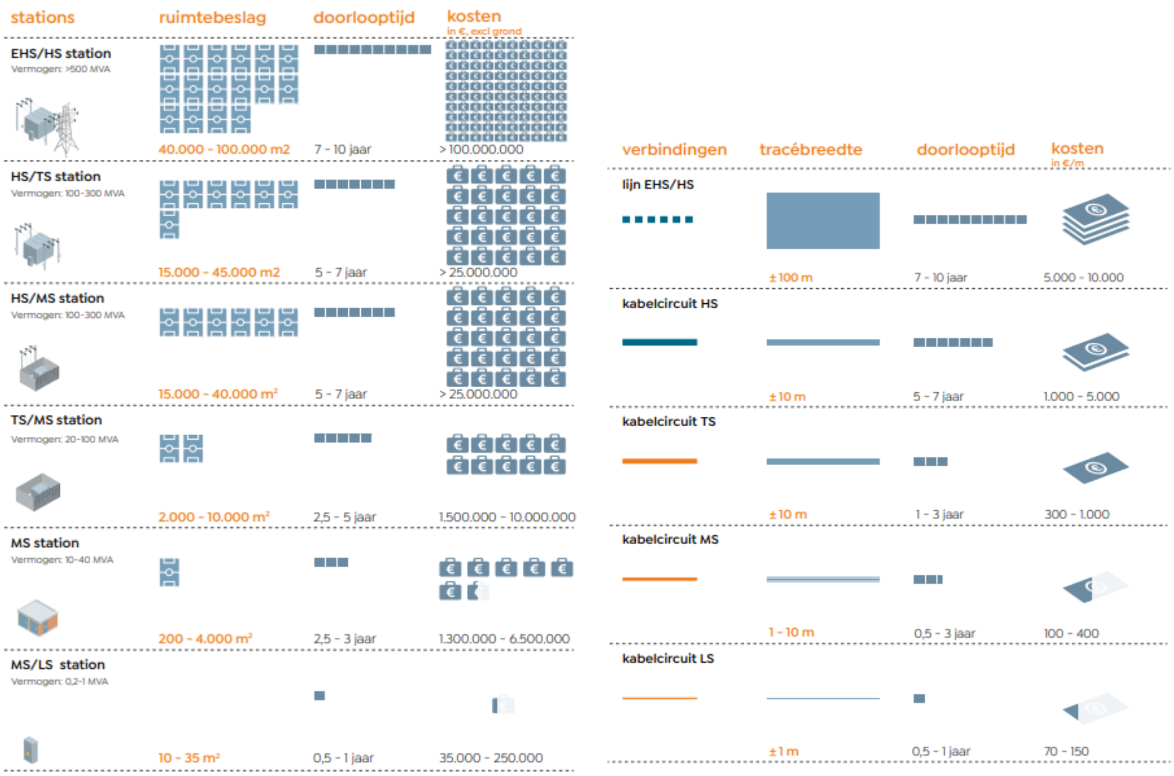

Figure 1.3: Area, time and costs of different parts of the grid infrastructure (left) as well as lines (right) (Netbeheer Nederland, n.d.-b)(Netbeheer Nederland, 2024)

It is apparent from looking at this figure in combination with Figure 1.2 that the extent of the required investment, as well as the space and time associated, is significant. Another factor that needs to be considered, beyond the capital requirements as well as the multi-year lead time, is the shortage of trained personnel to work on these grid expansions (de Boer, 2023). The Netherlands as a whole is dealing with a technical-skilled labour shortage, which is especially felt by grid operators, who are critically dependent on this group of people for their operations. Therefore, although grid operators in the Netherlands are working on expanding and reinforcing the grid in order to deal with congestion and increasing demand on the system, this work will only start to bear fruit on a longer time scale, leaving the issue of grid congestion on the agenda for the near future.

In addition, even though it is already underway, it might also be beneficial to consider if such a ”brute force” approach is really worth it as it would, to a certain extent, return us to the situation in which we found ourselves two decades ago. As Skok et al. (2022) mention in their work, transitioning to a more flexible, responsive, and efficient energy system by incorporating solutions like the ones we will discuss below, is a development which in spirit aligns itself with the fundamental goal of the energy transition: the adoption of a sustainable system of production of consumption of energy. They argue that ”flexibility is of particular importance to the DSOs because most of the distributed generation and new loads are connected directly at the distribution level (20kV and lower). In essence, if the DSO [sic] use of flexibility would make the current grid last longer by requiring less infrastructure upgrades or reinforcements, while at the same time achieving better voltage quality and continuity of supply, there is the potential to better utilize and efficiently develop the distribution system.”

With the above in mind, there is a need to consider solutions which are focused more on the short-term resolution of congestion issues, in a less capital intensive manner as well as those that lead to a more efficient utilisation of the current grid capacity. Utilising the ’unused capacity’ as presented in Figure 1.1 would allow for more efficient use of the grid without requiring expansion. This leads us to four main avenues of dealing with network congestion (aside from grid reinforcement) by more efficiently utilising the grid, outlined in Figure 1.4 below:

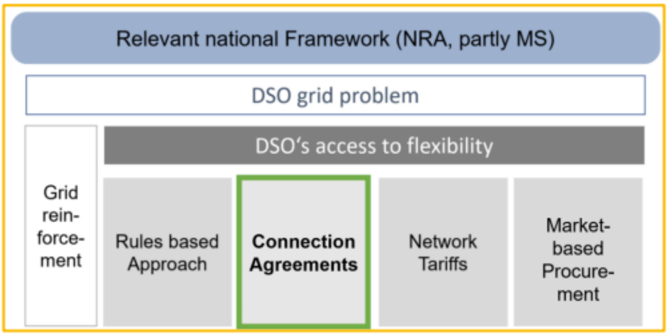

Figure 1.4: An overview of the solutions to grid congestion as presented by CEER (Distribution Systems Working Group, 2023)

Firstly, there is the rules-based approach. In this solution, flexibility for the grid operator is derived through relevant instruments like the grid code and other similar rules. An example of this would be the installation of a facility at the customer connection point to the grid which would allow the operator to reduce the available capacity to the customer on a need basis. Of course, this is a solution that requires a comprehensive framework regarding the manner of the execution, communication, and so forth. In their research on this topic, the Distribution Systems Working Group (2020) already outlined that "imposed rules under this approach should not be unduly restrictive and should only be considered if other possible solutions cannot be implemented at lower system cost." Thus, there is significant scrutiny of the implementation of such extensive measures.

On the other end of the spectrum are network tariffs, which take a significantly more voluntary approach to procuring flexibility from customers. Under such a scheme, a financial incentive (or penalty) is created for parties to offer flexibility services in return for lower (or higher if they fail to do so) grid connection costs. For large customers, these discounts can already be quite significant, in the order of tens of thousands of euros for large consumers or producers (Liander, n.d.). This approach does preclude a larger uncertainty for the grid operator, especially as some customers might "show different behaviours than expected or may not be able to shift or reduce their demand for network capacity" (Distribution Systems Working Group, 2023).

Taking a step back, the next solution concerns market-based procurement of flexibility services. This system combines the previous two solutions and tries to internalise the certainty from the former with the financial incentive of the latter. In the Netherlands, this market solution is mostly run through the GOPACS platform where congestion management services are traded on multiple time scales. As stated in Distribution Systems Working Group (2020), this method of procuring flexibility is the preferred option of the EU ETC. However, for this solution to succeed, there is a need for a sufficient amount of liquidity and information transparency available to all parties involved (Distribution Systems Working Group, 2023)]. Furthermore, such a platform requires potential flexibility providers [i.e. grid customers] to either have a dedicated team for organizing this or relying on a dedicated broker which interacts with the market in their name. Reducing the need for this additional complexity is where the final solution comes in.

This final presented solution is flexibility through the use of connection agreements. These agreements are established between the grid operator and the customer directly, reducing the need for intermediaries. They can take different forms with regards to their implementation, but normally entail an agreement wherein the grid operator can specify how much capacity the customer can use at a certain moment in time subject to the contract conditions. One of the most straightforward implementations of these contracts in the Netherlands is the Non-Firm ATO (Connection and Transport Agreement). Under this agreement, a customer agrees to a reduction in grid tariffs in return for not being guaranteed a firm connection (i.e. Non-Firm)(Hennig et al., 2023). This arrangement can take many forms, but the four main ones are described below (Netbeheer Nederland, n.d.-a):

- Time based: The customer has certain time windows (be it based on time of day, week, month, etc) in which they are not guaranteed capacity.

- Capacity based: The customer is guaranteed a certain volume of transport capacity.
- Limited availability based: The grid operator has a limited amount of time per time window (week, month, year, etc) in which they are allowed to limit the transport capacity of the customer.
- No guaranteed capacity: The grid operator allocates capacity to the customer based on availability limitations in their network.

All of these methods are relatively straightforward and can be agreed upon in the form of standard contracts (Netbeheer Nederland, n.d.-a). They are also optional for existing customers and are offered as an option to new customers as well as those parties who wish to expand their grid connection in a congested area of the grid. However, there are some limitations to these methods.

Firstly, most customers prefer firm connection agreements (Hennig et al., 2023). The rationale behind this is very clear: the potential added uncertainty in firms' business processes add an additional degree of risk to projects, unless significant reductions in tariffs are offered. Furthermore, not all customers have the ability to adjust their consumption or production to the capacity available on the grid, nor is it always desirable. This limitation was clearly a relevant factor when developing this option of providing flexibility, as the way it is being formulated currently in Distribution Systems Working Group (2023) and Autoriteit Consument & Markt (2024), these kinds of contracts are only possible for commercial and industrial customers, and outside of the scope of residential customers or societally essential connections like hospitals.

Secondly, there is the issue of effectiveness. The fundamental goal behind using flexibility services and contracts like these is to do more with the grid that is already there, using the 'unused capacity' illustrated in Figure 1.1. If these contracts are not sufficiently attractive to potential customers, both in their implementation and in their incentive framework, they will not lead to significant gains in reducing congestion and achieving higher grid utilisation. On the other hand, increasing the incentive structure excessively without incorporating sufficient safeguards might also risk gaming by connected parties, as well as becoming a potential burden to firm customers, who then might risk paying a disproportionate contribution to the operation of the grid. The implementation of this flexibility option with an excessive incentive structure could also lead to a reduced supply of flexibility available for real-time congestion management, leading to a significant market distortion there.

Finally, and more fundamentally, the non-firm contract is inherently limited in scope. In a specific part of the network with a given capacity, the more customers are connected through a non-firm connection, the less capacity there is for each individual customer. The division of the available capacity is therefore also a key aspect of the implementation of these agreements, which can make or break them in terms of their appeal to potential customers as well as to grid operators themselves.

This last uncertainty was underlined by Boehme et al. (2010), who wrote that: "Many non-firm connections may operate under a 'last-in first-out' arrangement wherein earlier connected plant has some degree of priority over newer applications (...). This arrangement has some similarities with firm connections operating on a 'first come first served' basis and work to investigate the impact of priority schemes on the ability of the network to accommodate generating capacity appears to be warranted. " We have thus arrived at the focus of our research, and can therefore formulate our research gap:

There is a lack of exploration into the implication of different priority schemes for the allocation of capacity among non-firm connection agreements in the context of distribution grid congestion.

Our focus thus lies on the long term grid congestion that we identified previously, which will structurally lead to insufficient grid capacity to accomodate more firm loads. From this follows our research question:

"What strategies and mechanisms can be employed by grid operators to efficiently allocate and distribute the available capacity among non-firm grid connection agreements (ATO) in the distribution grid, ensuring fair treatment of customers whilst improving grid utilisation?"

This thesis is structured to provide a comprehensive investigation into this research question. It is structured as follows.

In chapter 2 we discuss the state of the art concerning the topic of distribution network congestion and the applications of non-firm connection agreements through a review of relevant literature. In this chapter, we will attempt to reframe the research question and research gap described above in their proper context in scientific research. Finally, we will also investigate the prioritisation methods under consideration, as well as the indices that we use to determine the effectiveness of these methods.

Subsequently in chapter 3, we describe the methodology that we followed in our research. We will cover the modelling approach that we adopted to answer our research question, as well as the data that we drew upon. In addition, in this chapter we also go over the implementation of the different methodologies, scenarios, and indices. The limitations and assumptions of our research are also introduced here.

This will be followed by chapter 4, where the results of our research are presented. We will interpret these findings and attempt to contextualise them in order to determine their relevance to our research question. We will also discuss the sensitivity analysis and its outcomes to determine the impact of our assumptions.

Finally, chapter 5 will round off this work, where we will attempt to synthesise our findings and draw overarching conclusions that address the research question and objectives outlined in the introduction. Furthermore, this chapter will offer recommendations for future research endeavors, highlighting avenues for further exploration within the field.

2

State of the Art Literature

With the establishment of the research gap and our research question in the previous chapter, in this chapter we can now focus on establishing the current state of knowledge surrounding mechanisms to resolve grid congestion, and specifically those mechanisms based on non-firm connection agreements. Thus, the relevant areas that we are looking into are as follows: the application of congestion management, research on the use of non-firm connection agreements, methodologies of allocating capacity as well as determining relevant indicators for measuring the effectiveness of these methodologies.

2.1. Congestion Management

Before we discuss current research on our specific gap, we must first clearly establish the scope of the problem that we will be looking at. The topic of congestion management has seen abundant research, both in terms of studying the issue and potential solutions. In their work Hennig et al. (2023) include an extensive typology of congestion issues. They identify that congestion in the electricity grid has four main parameters which describe the nature of the problem:

- Location: Congestion can occur on low, medium, or high voltage parts of the grid, with a resultant variation in affected grid area, ranging from a highly localised issue to an extensive bottleneck with an impact across the system.
- Timing (Predictability): With regards to timing, according to Hennig et al. (2023) there is ”structural” congestion which is regular and predictable long in advance, and “sporadic” congestion which is irregular and predictable only in the near term or near real-time.
- Type of Network Limitation: The nature of congestion can be due to thermal, voltage, or reactive power constraints. The cause (i.e. the direction: supply or demand originated) is also relevant, namely whether the issues are a result of excessive consumption or production on the relevant part of the grid.
- External Factors: Hennig et al. (2023) also identified that external circumstances can play a significant role in the nature of congestion issues. They state that factors like ”the existence of and need for new flexibility resources, the organizational structure of network operation (e.g., number of customers per DSO and interactions between DSOs with each other and the TSO), the regulatory landscape and pre-existing approaches for CM [congestion management]” all influence the nature and severity of congestion issues.

It is therefore important to clearly identify the type of congestion that this thesis is focusing on. We will discuss this in our research in chapter 3. For now, let us review which approaches there are to congestion management, such that we may properly position the topic of our research question: non-firm contracting agreements.

In chapter 1 we introduced the main techniques for grid operators to access flexibility through demand response for the purpose of dealing with grid limitations. However, congestion management methods go beyond this type of flexibility. Gumpu et al. (2019) created an extensive overview of the different methods that grid operators might choose to adopt in their congestion management processes, presented in Figure 2.1. However, many of these methods do not apply to Low Voltage or Medium Voltage grids.

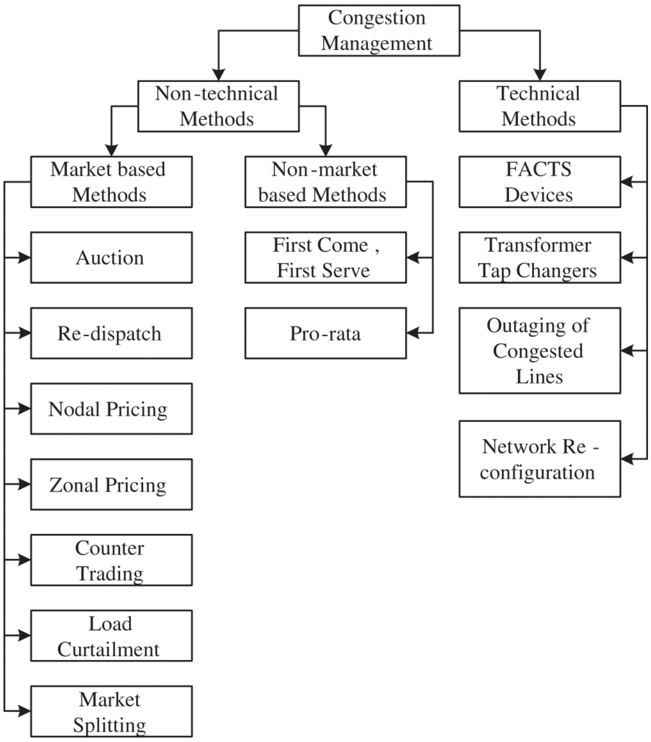

Figure 2.1: Overview of "Conventional Congestion Management Methods" (Gumpu et al., 2019)

From Figure 2.1 it is apparent that the first main divide can be found between technical and non-technical methods. With regard to the former, Gautam et al. (2023) also described these methods as "cost-free methods" as these can be performed by the grid operators without increasing operational cost (which would be required for congestion management by auction, for example). They identify that all of these technical or cost-free methods in some form or another include a "modification of the system topology, installing transformer taps, and implementing phase shifting transformers and flexible AC transmission system (FACTS) device".

However, FACTS devices and the outaging of congested lines are both methods that are of only limited applicability to DSO's, as their networks consist of mostly lower voltage lines with limited redundancy (Hadush & Meeus, 2018). Transformer tap changes and network re-configuration are both methods that are within the purview of the DSO, and can be used in situations with limited congestion (Pal et al., 2015).

On the other hand, non-technical solutions are further divided between market-based methods and non-market-based methods. When comparing these methods with the four types of demand response delineated in Distribution Systems Working Group (2020), which are identical to the ones we identified in chapter 1, it can be seen that a different aggregation method is chosen. The rules-based approach from this publication aligns itself best with the non-technical, non-market-based methods. Knops et al. (2001) gives the following explanation for these two methods: "first-come-first-serve (capacity is allocated in the order of requests), (...) and pro rata (all capacity requesting market parties receive an amount of inter-connector capacity proportional to their share of the total requests)". These methods have extra relevance for us, as we will discuss later. The market-based methods, which are described in more detail in Pantoš (2020), are an amalgamation of the network tariffs and market-based procurement approaches. Things like nodal and zonal pricing fall more under the category of tariffs, while re-dispatch and auction are more market-based. Explicit counter trading and redispatching are "corrective actions more or less separate from the market" (Knops et al., 2001), but still fall within the category of market-based procurement.

Just like with the technical methods, not all of the non-technical methods are actually available to DSO's. For example, the nodal and zonal pricing congestion methods are the purview of the TSO, which is responsible for these decisions. Similarly, market splitting (which in essence is a reframing of zonal and nodal pricing) is also not a method that a DSO can adopt. Finally, counter trading is also outside of the scope of the DSO's responsibilities.

It should be noted that none of the above publications except for Distribution Systems Working Group (2020) make reference to the concept of non-firm connection agreements as a method. What is more, Knops et al. (2001) explicitly states that ”congestion management should (...) provide firm capacity and not curtail contracts”. The concept is discussed in more detail however in Distribution Systems Working Group (2023) and Hennig et al. (2023), where in the former it is mentioned that non-firm contracts are ”agreements that deviate in one or more attributes from the traditional firm connection agreements”, whilst the latter defines them as agreements where ”the network access capacity is dynamically dependent on the network state and may be reduced during network congestion. In this latter case, specifications may also include the maximal allowable number and duration of load reductions”.

Although most of these methods go beyond the scope of our research, it is important to underline their existence to illustrate that although demand response will be the main focus in this review of literature moving forward, there exist several other methods which are relevant for grid operators.

If we thus update Figure 2.1 to better reflect the framing of Distribution Systems Working Group (2023) and remove those methods that are not applicable to DSO's, we arrive at Figure 2.2.

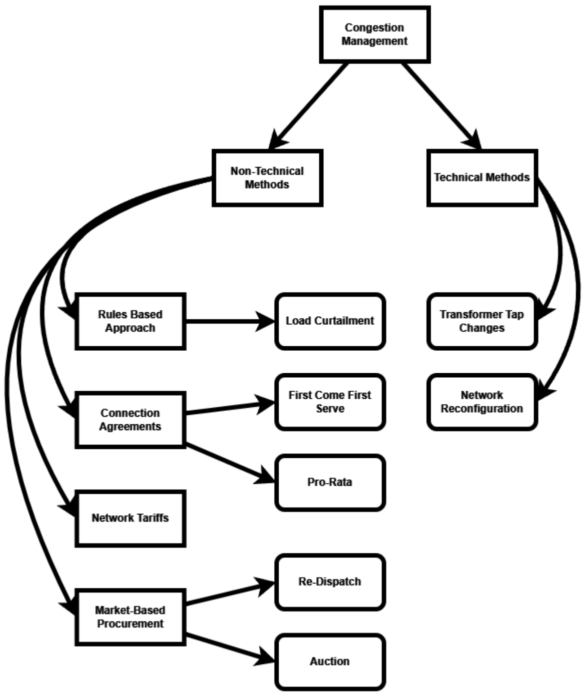

Figure 2.2: Overview of congestion methods applicable to the DSO, framed according to the structure in (Distribution Systems Working Group, 2023).

In Figure 2.2 we can see that the different methods discussed in Figure 2.1 have been reorganised, and now are more specific to those that are available to distribution grid operators. This gives a good overview of the methods to which we should compare non-firm grid connection agreements, as these are the actual valid alternatives.

2.2. Non-Firm Grid Connection Agreements

This brings us to the specific focus of our research: non-firm grid connection agreements. As Gómez et al. (2020) mentions, ”conventionally, grid operators have granted network access on a firm basis to both consumers and generators. Thus, network users were entitled to inject or withdraw as much power to and from the grid as they wanted, provided that they did not surpass the maximum capacity allocated". This has advantages and disadvantages: "the main benefit of firm access is its simplicity, as it eliminates the need for real-time management of injections and withdrawals."(Gómez et al., 2020) However, they also state that "firm access may result in an inefficient capacity allocation and/or inefficient grid expansion, as grid operators tend to follow excessively conservative criteria. As a result, some network components are only used at their rated values for a few hours of the year, if ever. Additionally, the need to provide new users with firm network access often results in denial of the right to connect to the network due to lack of firm hosting capacity." (Gómez et al., 2020) Non-firm grid connection agreements are therefore an alternative which only recently have come under consideration in the Netherlands (Autoriteit Consument & Markt, 2024). Similarly, in Distribution Systems Working Group (2023), it is mentioned how until the passing of EU Directive 2019/944, grid operators were only allowed to offer firm grid connections to customers ("Directive (Eu) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU", 2019). This new directive, however, aimed at creating "incentives for the use of flexibility in distribution networks", one of which was the procurement of flexibility through non-firm grid connections ("Directive (Eu) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU", 2019). An important note to add to this, however, is that this system has only been approved for commercial and industrial grid connections (Autoriteit Consument en Markt, 2024). Residential and similar grid connections are required to remain firm at all times. As Skok et al. (2022) argues, however, this is a sensible decision as a non-firm connection requires "a certain degree of flexibility from system users, and might not be an interesting or viable option for all system users as their supply and/or demand is inflexible; e.g. Ofgem (UK) did not consider flexible connections suitable for small, domestic households." An important consideration to add to this however is that the proliferation of electric vehicles, heat pumps and solar generators connected to battery might actually allow for more flexibility in residential consumption patterns than expected.

In the United Kingdom and Scotland specifically, however, these connection agreements have already received significant research as a result of large levels of distributed generation in areas like the Orkney Islands, where significant wind generation was installed, leading to significant feed-in congestion (Boehme et al., 2010). Under the system of firm connection agreements, however, there was no incentive against installing more generation in this area (Newberry, 2021; Simshauser & Newbery, 2023). Simshauser and Newbery (2023) argues that "with a single zonal wholesale price, no Marginal Loss Factors (MLFs) and curtailment risks borne by consumers – unsurprisingly – there has been an excess entry result in the north of Great Britain (Scotland) where wind resources exceed network transfer capacity to the south where major load centres are located." The introduction of these non-firm grid connections therefore allow for the internalisation of these costs, and to create a signal towards DER investors to take the capacity of the grid into their calculations. Similarly, Newberry (2021) argues, "in congested areas offering non-firm connection offers to new entrants until cost-effective reinforcement relaxes the export constraint (...), and would provide a good locational signal."

Through the use of non-firm grid contracts, the grid operator can "maximize the net active power export from the distribution network, at the interconnection point with the higher voltage network"(Džamarija & Keane, 2013). An important consideration in achieving this objective is to allocate the capacity in a way that gives sufficient margin for uncertainty in aspects like grid voltage and security (Ault et al., 2006). Furthermore, as discussed in Muller and Cadoux (2023) "non-firm connections make economic sense in situations where connecting the new generator to the grid would create a mild constraint, that is to say a constraint that would not be too deep nor too frequent. In such a case, grid reinforcement can be avoided by curtailing only a limited amount of energy, hence by incurring a limited and acceptable loss-of-gain for the producer."

The appeal of non-firm grid connections to customers lies in the fact that the grid operator can charge lower network tariffs (Hennig et al., 2023). For example, Anaya and Pollitt (2014) presented a case study in Ireland where "non-firm access, which is subject to interruptions, generators are usually offered cheaper connection costs, and in many cases without any compensation when curtailment is required." An important consideration therefore is the amount of requested capacity that cannot be allocated. For example, in France, the following rule is used: "... at the request of the (...) connection applicant, the grid operator proposes, if the network capacities allow it, an alternative connection offer (...) [for which] the minimum non-guaranteed power for injection is less than or equal to 30% of the requested connection power; [and] the annual curtailed energy does not exceed 5% of the annual production of the generator.” (Muller & Cadoux, 2023)

Next, as discussed in chapter 1, the methodology that is used to divide the available capacity between the non-firm grid connections is also key (Danzerl et al., 2016). We shall now discuss this in more detail.

2.3. Methodologies for Dividing Capacity Among Connections

As mentioned above, one of the key questions that is relevant when implementing non-firm grid connections is the division of available capacity among multiple parties with such a contract. The selection of the methodology for dividing the available capacity has a significant impact on the attractiveness of such contracts, with different strategies benefiting different parties (Jupe et al., 2010). Sun and Harrison (2013) states that ”inappropriately chosen priority of curtailment resulted in reduced hosting capacity, lower overall energy capture and lower benefits from [non-firm grid connections]”.

An important point to note is that most of the research concerning prioritisation methodologies for non-firm grid connections takes a curtailment, rather than an allocation approach. The difference between the two is straightforward: whereas with curtailment the baseline assumption is the availability of the full connection capacity, subject to changes by the grid operator, with allocation the baseline is zero transport capacity available at the connection, subject to changes by the grid operator (Anaya & Pollitt, 2014). Thus, although the methodologies found in the literature have similar applicability in both the curtailment and allocation cases, it should be considered that these were designed with a curtailment frame of reference. To take an example, Last In First Out (LIFO) gives priority to generators based on the length of time that they have been connected. In the curtailment framing, this generator gets curtailed last, if and only if all of the other generators have already been fully curtailed. With the capacity allocation framing, the generator that was connected to the grid the earliest, gets allocated their requested capacity first, independent of the requests of other generators.

Currie et al. (2011) presented an extensive list of methodologies for Active Network Management (ANM) through non-firm connections. The methodologies, named ”Principles of Access (POA)”, are as follows:

- **Last In First Out** This POA curtails the last generator added to the ANM scheme first. Adding a new generator connection to the Last In First Out priority-list (in the position of least priority) does not alter the priority position of existing generator units with interruptible contracts.
- **Generator Size** This POA curtails the largest generator that is contributing to a constraint first. The total amount of curtailment required to alleviate a constraint is allocated in order of size. Generator Size may refer to the installed rated capacity of the generator unit or the power output at any given time when constraints arise.
- **Greatest Carbon Benefit** This POA aims to minimise the carbon emissions associated with actively managed generation by curtailing the largest carbon emitting generators first. Based on a carbon metric such as $CO2$/MWh per generator the network operator could prioritise generation.
- **Shared Percentage** The Shared Percentage POA divides the required curtailment equally between all generators contributing to the constraint. The total amount of curtailment would be shared by each of the generators based on the ratio of rated or actual generator output to total required curtailment.
- **Market Based** Under a Market Based POA, generators with interruptible contracts could pay for access to the network for a period and capacity allocated to those offering the highest payment. Alternatively, generators may offer a price to be curtailed with a market mechanism to proportion curtailment accordingly.
- **Technical Best** A Technical Best POA aims to curtail the generators in order of contribution to the prevailing constraint or based on which generator(s) response characteristics are deemed best for meeting the prevailing constraint. This may vary for different types of constraints and network configurations.

- **Most Convenient** The POA based on Most Convenient allows system operators to curtail the generator they know to be the most convenient for responding to network constraints. This assessment may be influenced by system operator (or control room engineer) preference.

However, in their identification of these methodologies they also indicate that some of these methodologies are difficult to implement, like for example the Greatest Carbon Benefit methodology for which ”Determining the real carbon footprint of each generation technology in a clear, open and fair manner is not a simple task”(Currie et al., 2011).

Sun and Harrison (2013) used three of these methodologies in their work, where they investigated their impact on network hosting capacity. These were Last In First Out (LIFO), proportional curtailment (Shared Percentage) and optimal curtailment (Technical Best). In addition, they expanded LIFO into two versions, one which which prioritised connections closest to the Grid Supply Point (GSP, the connection to the higher voltage grid levels), and one which prioritised connections farthest from the GSP. They found that the selection of priority methodology could lead to a difference in revenue for generators of up to 20%.

In Anaya and Pollitt (2014) the LIFO, Pro Rata (Shared Percentage) and Market Based are reviewed across different projects, where the advantages and disadvantages presented in Figure 2.3 were identified.

Principle of Access	Advantage	Disadvantage
LIFO	1. No need for regulatory or technological changes in order to be applied 2. Best for social optimality (only last-in generator faces the marginal costs)	1. Does not incentive the connection of new and more efficient technologies 2. Higher variance of returns on later projects
Pro Rata	1. Increase the attractiveness of later individual projects 2. Less discriminatory (fairness)	1. Marginal generation is cross-subsidised (curtailment costs imposed to all generators)
Market-Based	1. Provide a better signal of true costs of curtailment 2. Most optimal allocation rule (akin to optimal dispatch, unit commitment)	1. Significant transaction costs 2. Expose generators to the risk induced by the bids of other generators behind the same constraint 3. Subject to optimal market conditions

Figure 2.3: Comparison between three different methodologies of curtailment (Anaya & Pollitt, 2014)

As mentioned in Section 2.1, this research concerned curtailment of capacity, however, rather than the allocation of it.

Because LIFO is already extensively in use, this methodology has also received significant amounts of research (Andoni et al., 2017; Georgiopoulos & Graham, 2014). Danzerl et al. (2016) investigated the effect that the LIFO method had on the connection of distributed wind generation. They found that ”when applied under voltage constrained situations it can lead to a reduction in renewable energy levels.” This was in addition to their finding that ”applying LIFO POA rule that gives high priority to generators located at weak sections of the network can impose significantly, greater curtailment on other generators regardless of their own local network strength and as a result may lead to reduced energy yields”.

Pro Rata has also been investigated by multiple publications as a result of being incorporated into UK Power Networks’ ”Flexible Plug and Play” programme (Andoni et al., 2017; Hubert & Coley, 2021; Kane & Ault, 2015). Anaya and Pollitt (2014) mentions how ”the Pro Rata arrangement ensures an equal allocation of curtailment across all generators contributing to the constraint, which is considered by some to be a ’fairer’ way to assign curtailment.” On the other hand, Andoni et al. (2017) mention a few key drawbacks: ”all participating generators are curtailed at all times when curtailment is required, leading to increased disruption. Pro Rata might not always be desirable (technically speaking, it may require modified pitch-controlled wind turbines, such that their output can be adjusted as needed, which may be more expensive), as in several occasions, it is technically preferable to curtail a larger amount of power from one generator than smaller amounts from all generators at a single event.”

Finally, one additional method was mentioned by the publications on the ”Flexible Plug and Play” project. This method was called the ”Rota” method, where generators are curtailed on a rotational basis or at a predetermined rota specified by the system operator. The advantages of using this methodology lies in that the ”Rota arrangement brings an element of ’fairness’ to the PoA choice by changing the position on the priority stack of each non-firm wind generator every 24 h. This sees an 8% increase in output of the most curtailed generator in the case study when compared to LIFO" (Kane & Ault, 2015). Furthermore, Kane and Ault (2014) mention how "as the level of generation connected under a rota arrangement increases, the level of curtailment may increase however the length of time spent at the bottom of the priority stack would decrease". This is a definite advantage when compared to Pro Rata and LIFO, where an increase in connections is usually perceived as a pure negative. However, a big drawback is that "the Rota scheme is a simple approach which does not take into account the size of the generator or its actual contribution to the network constraint. This results in disproportionate losses of revenue, especially to smaller sized generators" (Andoni et al., 2017).

From all of these works mentioned above, we can see that significant research effort has been focused on the identification and comparison of this expansive list of methods. However, most of this work has been qualitative in nature, and where the work has been quantitative, like in Danzerl et al. (2016) and Dolan et al. (2014), the comparison has usually been focused on a single parameter, such as cost or energy yield.

We can now use Figure 2.3 as a basis, and expand it with the additional methods we have discussed. The results of this can be seen in Table 2.1. In the left column, we have the methodology, in the middle column and the right column the advantages and disadvantages as discussed above.

Table 2.1: Advantages and disadvantages of different methodologies of allocating capacity.

Methodology	Advantages	Disadvantages
Last In First Out	1. Simple 2. Marginal cost to last connected party	1. Disincentives later connections 2. Reduction in total connected capacity
Generator Size	1. Simple	1. Disincentivises larger connections
Greatest Carbon Benefit	1. Conceptually straightforward 2. Aligns with goal of energy transition	1. Difficult to implement (hard to quantify)
Shared Percentage/Pro Rata	1. Incentives later connections 2. "Fair"	1. Marginal cost to all connected parties 2. Increased technical requirements
Market Based	1. Optimal economic allocation	1. Transaction costs 2. Increased risk 3. Subject to market conditions
Technical Best	1. Efficient	1. Complex to implement
Most Convenient	1. Simple	1. Disincentives non-firm grid connections
Rota	1. "Fair" 2. Time spent at bottom of allocation divided equally	1. Lower amount of allocation 2. Does not take into account size of generator or contribution to network constraint

With these methodologies now established, we can now build further by investigating how we can further compare them.

2.4. Measuring the Effectiveness of Each Methodology

As we mentioned above, research into the effectiveness of different methodologies has used several different performance indicators as indices. These indices allow for the side-by-side comparison of methodologies to determine which methodology for dividing non-firm grid capacity is most appropriate. We have divided these parameters into three large categories. Firstly, we have indices that are relevant for grid customers. Thus, these place emphasis on the factors that are important to customers who are eligible to participate in these connection agreements, like industrial or commercial customers with large grid connections. Secondly, there are the indices that focus on societal value. These indices try to measure which methodology is societally the most desirable, by using the infrastructure to the fullest extent for example. Finally, there are the relevant indices for grid operators. These try to capture specific factors that are crucial in maintaining and building a reliable and resilient electricity grid.

2.4.1. Relevant Indices for Customers

The first and most obvious measure relevant to customers is how much of their requested capacity is allocated. The importance of this measure is underlined even further by how, according to Muller and Cadoux (2023), in French legislation: "... at the request of the (...) connection applicant, the grid operator proposes, if the network capacities allow it, an alternative connection offer (...) [for which] the minimum non-guaranteed power for injection is less than or equal to 30% of the requested connection power; [and] the annual curtailed energy does not exceed 5% of the annual production of the generator." Sedzro et al. (2021) discusses how a methodology which prioritises maximum allocation is found to be more attractive to new connections to the grid than a prioritisation scheme such as LIFO, where connection age gives priority. In their work, Anaya and Pollitt (2015) performed a cost-benefit analysis for a new DER connection in a congested grid area to decide between a non-firm and firm connection, and found that higher allocation directly corresponded to an increase in value for a non-firm connection. Finally, Muller and Cadoux (2023) underlines the importance for DER developers of maximising the output of their installations and thus having minimum curtailment.

Aside from the absolute level of allocation, another important index is the relative levels of allocation. As Muller and Cadoux (2023) discusses, the perceived fairness of a specific methodology is very important, both for the perception of the customer themselves, as well as to meet the requirements set out by regulators for non-discriminatory approaches. This fairness also presents itself in the work of Sun and Harrison (2013), where it is mentioned that fairness can be quantified by comparing how much each customer gets allocated proportionally to their requested capacity. Improving the ”fairness” of a methodology was also the driver behind the work of Sedzro et al. (2021), who developed an adapted version of the LIFO methodology which takes into account the location of a connection in the grid as a factor in their prioritisation. Finally, Ault et al. (2006) also discussed how fairness was an important factor in the operation of active network management, which needed to be taken into account as an additional consideration outside of maximising allocated capacity. An important note to consider with this index is the potential for gaming. As Anaya and Pollitt (2014) discusses, innovative arrangements for distributing network capacity can be vulnerable to gaming, and thus should be closely scrutinised. This problem is underlined in Hennig et al. (2023), which identified that local flexibility markets (like non-firm connection agreements) are vulnerable to gaming by the manipulation of their consumption levels.

One other factor which is key to investors and existing customers is the predictability of allocation. Newbery (2023) discusses how for DER investors ”the more predictable and certain are the costs and revenue streams after the final investment decision, the higher the share of debt:equity and the lower the [weighted average cost of capital]”. This makes the investment more attractive for them, leading to increased DER penetration. Currie et al. (2011) follows this, stating how a methodology is more attractive to customers when “it is transparent to all network stakeholders and achieves consistency for both existing generation units and new generation units by not impacting on their connection agreements. This de-risks the interruptible contract for the investor as the long-term impact of curtailment can be modelled based on a fixed position in a priority stack for access to capacity.” The higher the predictability (and thus the lower the risk), the more attractive these non-firm grid connections become (Simshauser & Newbery, 2023). This is affirmed by Eicke et al. (2020), who underline the importance of predictable grid access, and thus investment returns. They also mention how ”the effect of many of the locational instruments on investment decisions is reduced due to lack of predictability, low levels of transparency, and insufficient spatial and temporal accuracy”(Eicke et al., 2020). This locational signalling was determined to be significant in our discussion of non-firm grid connections Section 2.2, therefore by association making the predictability of allocation significant. Of course, this predictability also aids the grid operator. As Savelli et al. (2022) discusses, more predictable investment allows grid operators to run their operations (like reinforcing the grid and procuring market based flexibility) more efficiently. The main takeaway of this factor is therefore that although congestion is not always predictable for grid operators but, the more predictable the methodology of allocation, the more attractive a non-firm grid connection may be (Currie et al., 2011; Eicke et al., 2020; Hennig et al., 2023)

2.4.2. Relevant Indices for Society

The second dimensions for indices that we identified in literature were those parameters that measured the value that different methodologies have from a social perspective.

Anaya and Pollitt (2014) directly addressed this dimension in their work, discussing how the goal of any smart grid arrangement like non-firm grid connections should aim to be ”(1) cost-effective for DNOs and generators, (2) economically efficient (making the best use of the network—reduce costs of given DG for consumers), and (3) socially efficient (maximising social welfare and the social value of more connected renewables)”. To achieve this token of economic efficiency, they argue that the system should be allocating the maximum amount of capacity, as upgrade costs are borne by the larger group of grid users (thus leading to the highest ”bang for the buck”). The importance of using the network as efficiently as possible is also affirmed by Currie et al. (2011), who state that any prioritisation mechanism should support efficient network operation. For example, they criticise LIFO, arguing that ”this [methodology] could also limit the technical utilisation of the distribution network". In the same manner, Simshauser and Newbery (2023) states that in the case of non-firm curtailment, "if a wind generator is curtailed for any reason, they are compensated for the lost profit of the curtailed energy, paid by consumers. British consumers therefore (currently) bear the risk and financial consequence of renewable plant curtailment—including poor locational decisions." To rephrase thus, an important societal consideration when evaluating different methodologies is how efficiently the network is used, and thus maximising the allocated capacity. An additional consideration to this societal value is presented by Simshauser and Newbery (2023), who mention the importance of also differentiating the marginal and average curtailment. The latter is straightforward, being a function of the allocation among all of the generators. The former, however, quantifies exactly how much an additional MW of capacity or new connection would be curtailed. Both the average and marginal allocation are therefore important. A final note is the discussion by Anaya and Pollitt (2014). They mention the following: "a key question is what is the socially optimal approach to curtailment? LIFO is an approach where each generator is exposed to their marginal curtailment cost to the system. Pro Rata exposes each generator to the average cost of curtailment. If the marginal benefit to the system of each additional unit of capacity is constant (i.e. if all wind generators behind a constraint had the same subsidy regime and the same technology) the marginal system benefits would include the value of the energy produced and the value of the subsidy net of production costs. For social optimality this marginal benefit should reflect all of the social benefits of additional wind capacity (i.e. the subsidy should reflect the environmental benefits)." This note adds additional consideration to the comparison between different methodologies, as quantifying how much exact social benefit is created by the additional capacity allocated by a methodology is difficult. Following this line of thinking, purely looking at the total allocated capacity is insufficient to determine which methodology would be most desirable, as the way of achieving that capacity is paramount. This underlines the need for all indices to be taken into consideration, not just those that are straightforward and easily understandable.

2.4.3. Relevant Indices for Grid Operators

The final dimension that should be taken into account when comparing different methodologies of allocating capacity among non-firm grid connections is the one focused on the parameters relevant for grid operators.

As we mentioned previously, one of the key considerations that grid operators need to take into account when allocating this capacity is the uncertainty inherent in the forecasting of the grid. Therefore, the methodology should be able to cope with these uncertainties. To that effect, Muller and Cadoux (2023) explained that allocation should take into account parameters like the voltage of the grid supply point when allocating capacity. This is corroborated by Danzerl et al. (2016), who identify that methodologies like LIFO struggle when dealing with an area of the grid that is voltage constrained, as the methodology does not take the location of the grid limitation into account when allocating capacity. Following the same line of reasoning, Sedzro et al. (2021) developed an alternative to pure LIFO which took into account the electrical distance to a network limitation. Thus, a critical parameter when comparing methodologies is how these methodologies deal with uncertainty leading to issues with regard to "voltage control, power flow management, fault level management and network security" (Ault et al., 2006).

Looking at this from another perspective, it is important for the grid operator that a methodology allows them to service all customers in as efficient a manner as possible. To this end, Skok et al. (2022) argues "if the DSO use of flexibility would make the current grid last longer by requiring less infrastructure upgrades or reinforcements, while at the same time achieving better voltage quality and continuity of supply, there is the potential to better utilize and efficiently develop the distribution system." In the same vein, Džamarija and Keane (2013) indicates that the optimal methodology allows the grid operator to "maximize the net active power export from the distribution network, at the interconnection point with the higher voltage network. The net active power export is maximized by formulating a trade-off between the active power output of the allocated generation and the power losses." This is affirmed by Sun and Harrison (2013), who state that a risk with LIFO, for example, is that "the [oldest] connection may be located at a network position where managing the output of DG has limited impact on relieving network constraints whereas the same voltage or thermal control effect could provided by other DG connections for less curtailment."

3 Methodology

Based on the research question that we have now formulated, as well as the relevant state of the art on research surrounding the topic of non-firm connection agreements in distribution grids, we can now discuss the methodology that we will be adopting in our research.

This chapter will cover our research approach in Section 3.1, including the more extensively formulated research question. Here we will also touch upon what kind of recommendations and outputs we looked to develop. In Section 3.2 we will go into depth on how we translated the different aspects of the research approach into a specific modelling approach, and how we implemented those in code. Finally, in Section 3.3 we will go over the different assumptions that we made throughout our research, and what impact we expect these to have on our final results. In addition, we will also touch upon the limitations imposed on our outcomes by our research and modelling approach.

3.1. Research Approach

To answer our research question, we adopted an experimental research approach, where we simulated a specific substation in the Dutch electricity grid. We performed our research in an internship for the Dutch distribution grid operator Liander.

3.1.1. General Overview of Approach

With the background of our research now clearly established in the previous chapters, let us discuss what the high level approach was that we adopted to answer our research question. Before we do this however, let us revisit the research question that we posed in the previous chapter, and divide this into sub-questions that capture the different aspects of the main question.

RQ: "What strategies and mechanisms can be employed by grid operators to efficiently allocate and distribute the available capacity among non-firm grid connection agreements (ATO) in the distribution grid, ensuring fair treatment of customers whilst improving grid utilisation?"

- SQ1: What mechanisms have been devised for allocating capacity in the context of non-firm grid connection agreements?
- SQ2: How can we measure the performance of these different mechanisms to ensure fair treatment of customers and improved grid utilisation?
- SQ3: How do the different mechanisms score on these measures when compared to each other?
- SQ4: What is the effect of the forecast uncertainty in these results?
- SQ5: What are the implications of this comparison for grid operators when selecting their approach to dividing non-firm capacity among connected parties?

Our research approach for answering these questions will follow the process presented in Figure 3.1.

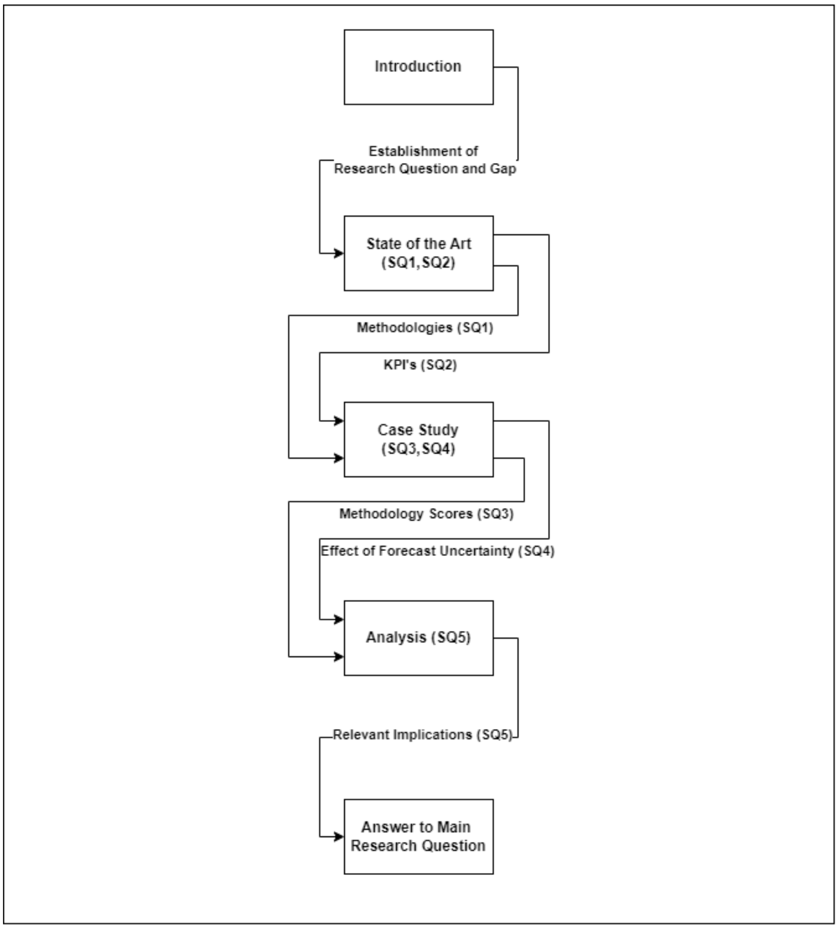

Figure 3.1: An overview of the research approach adopted in this work.

Based on the literature review in chapter 2, we can answer the first two sub-questions in the next two sections. These are then used as inputs to perform our case study, which is described in the subsequent section after. Out of our case study came the different scores for the methodologies as well as the effect of the forecast uncertainty on these scores, which combined informed our analysis for the final sub-question. After synthesising all of this information, we could then come up with the relevant implications for the grid operator and allow us to answer our main research question.

An important note to discuss before we move further, is the meaning of the terms capacity and utilisation in the context of our work. In our research, when we use the term capacity, we are referring to the ability of components of the distribution grid to accommodate power running through them. For example, the capacity of a line is defined as its operational voltage level multiplied by its current limit. Utilisation on the other hand, is a measure of how close the actual power running through a component is to the maximum power (i.e. the capacity of the component) that it can accommodate. An utilisation of fifty percent thus means that the actual power is half of the maximum power that the component can accommodate. When a methodology allocates capacity to a customer, what it is actually doing is giving that customer the opportunity to use a certain amount capacity of the grid. An allocation of capacity of 5 MW for example, means that there is capacity in the system for at least 5 MW, which can be used by that specific customer. A full utilisation of the allocated capacity by a customer does therefore not automatically mean a full utilisation of the system components, as other customers might also have been allocated capacity but are not using it at that moment. The term capacity and utilisation therefore apply to both system components and customers/connected parties, and have different implications for each of them.

3.1.2. Methodologies Under Consideration

From our investigation into the literature on the topic of capacity allocation, the following five methodologies were found to be the most prevalent and worthy of inclusion. The main reasoning behind their inclusion is also stated. The selection of methodologies was based upon the scope of our research, choosing those methodologies which were both feasible in reality as well as realistic in the time frame of our research.

- **Technical Best/ Maximal Allocation (Mathematical Optimum):** This methodology is meant to give us an indicator of how much capacity could be allocated and among which sources.
- **Last In, First Out (LIFO):** This methodology is the most straightforward, has been implemented in other countries and does not lead to existing non-firm connections losing their value with the addition of new ones.
- **Adapted LIFO:** Takes into account topology of grid as additional factor combined with duration of contract allowing for more nuanced allocation.
- **Rota/Carousel:** A ”fair” option that also ensures that all non-firm grid connections still get value out of their contract, no matter the duration that they have been connected.
- **Pro Rata/Proportional:** The ”fairest” option, that allows all connections to participate proportionally.

For Mathematical Optimum (MO), the approach is rather straightforward conceptually, but harder to implement practically. This methodology pays no heed to allocating the capacity in a fair or consistent manner, but rather considers the relevant system as a whole and determines what the maximal allocation of capacity is given the different constraints of the system. As we mentioned in the justification for the methodology above, this method of allocating capacity should give us a baseline of how much capacity could be allocated at the most. We can then compare the other methodologies to it to see how close they get to this ’maximum’ solution. It is important to underline here that ’optimal’ allocation in the context of our research is allocating as much capacity to customers as possible taking into account grid limitations, both physical and regulatory.

The second methodology is the LIFO approach, where capacity is allocated on the basis of a fixed priority-list, where the age of the connection agreement determines the position in the list (from oldest to newest). The rationale for this methodology is to ensure that the connection agreement does not diminish in value over time, as more non-firm connection agreements are added. As mentioned in the justification, this methodology has already been widely implemented for allocation of curtailment rather than capacity, and it is therefore interesting to see how it performs in this flipped context.

The third methodology builds on the previous concept by following the same rationale but giving priority to grid connections that are located closer to the upstream network, i.e. located at a higher voltage level. This is especially relevant for non-firm grid connection agreements that are connected to long lines with multiple customers on them, however this is not applicable in our research as we will discuss in Section 3.1.4. We included this methodology here primarily to compare it to the pure LIFO approach, and to determine if even in our selected case study it could increase LIFO’s attractiveness.

Next, there is the Carousel methodology, which involves a similar priority-list as in LIFO but shifts that priority-list after a fixed amount of time. This leads to a ’fairer’ approach than pure LIFO, and ensures that all connections are guaranteed the first spot in line at least sometimes. Including this methodology was mostly done as it provides an interesting trade-off for grid operators, whilst still being pretty transparent for customers.

Finally we have Pro Rata. This methodology attempt to maximise the ’fairness’ of the allocation, adding an additional constraint to the mathematical optimum by requiring the ratio between the allocated and requested capacity to be identical across all non-firm loads. This means that although the capacity might vary in absolute numbers, each customer will get a proportional amount of their requested capacity. As is probably apparent already, this methodology is sensitive to ’gaming’ by customers, requiring the cost-structure to be set up in such a way to discourage excessive capacity requests. We reflect on this at the end of this thesis.

3.1.3. Evaluation Parameters Used

Similarly to the methodologies above, our selection of relevant evaluation parameters, hereafter called Key Performance Indices (KPI's), was based on the finding in the State of the Art section. These KPI's are as follows:

- **Fairness**
  - How much do the connected parties get to use their requested capacity (as a % of requested capacity)
  - How much do the connected parties get with respect to each other (difference in % of highest allocated vs lowest allocated requested capacity)
  - How predictable is the allocation of capacity (the variance of the allocation of capacity)
- **Grid Utilisation**
  - How much is the total capacity of the grid used more when compared to the base scenario per allocated unit of capacity (average load allocated (MWh) per % loading increase of lines)
  - How much total load/demand is unable to be allocated (sum of capacity unable to allocated in MW/MWh)
- **Grid Performance**
  - How regularly does the allocated capacity still have to be curtailed in the real time operation of the grid (# of exceedances)
  - And to what extent does the allocated capacity need to be curtailed (average size of exceedance (MW))

Once again, these KPI's have been split into three main categories. Firstly, there are those primarily of relevant to customers currently considering or already having a non-firm connection agreement. As was mentioned in chapter 1, the perception that customers have of a certain tool like non-firm connection agreements is paramount in its attractiveness and thus in its adoption. It is therefore desirable that allocation of capacity occurs in a predictable, transparent and consistent manner. To quantify this desirability we use three KPI's, the first of which straightforwardly evaluates how much of their requested capacity connected parties get allocated. Secondly, there is the relative difference in allocated capacity as a percentage of requested capacity. A large disparity in this measure of 'fairness' might strongly dissuade connected parties and potentially lead to less efficient grid utilisation. Finally, the predictability of the allocation is important. Connected parties need to evaluate their risk when considering a non-firm connection agreements, and a higher predictability increases the attractiveness of such a product as the uncertainty lowers.

The second category takes the societal perspective, and tries to utilise grid resources (which are payed for by all users on the grid) as efficiently as possible. We split this into two metrics: first, how much extra capacity can be allocated per increase in the loading on the system, and secondly, how much of the requested capacity is unable to be allocated. This latter metric captures to a certain extent how much potential output or value is lost by the customers with the non-firm connection agreements, which entails an inefficient grid.

Finally, in the third and last category we find the metrics that the grid operator cares about: what is the effect on the grid. Namely, how does each methodology contribute to potential grid exceedances, where the operator would have to step in and either curtail allocated capacity or perform corrective actions somewhere else in the grid through congestion management. We split this interest into two KPI's measuring the number of exceedances as well as their severity. This aids us in determining which of these methodologies reduces the amount of active congestion management that has to be performed by grid operators.

3.1.4. Case Study Description

To investigate the effectiveness of these different methodologies, we selected a case study which we could use to experimentally simulate these different methodologies and their way of allocating capacity. In addition, the case study allowed us to develop experience with implementing these methodologies, giving us a good insight into some of the considerations that might be relevant for a grid operator when implementing such methodologies themselves.

The case study itself is a representation of the Heerhugowaard-Noord substation, located in the grid of the dutch grid operator Liander. This specific scoping was chosen as it allowed us to have two potential voltage levels for our loads, which is relevant for the Adapted LIFO methodology. The substation consists of a few core components, which are as follows.

- A 20kV bus, to which one customer is connected.
- 3 lines from the 20kV bus to the upstream network grid supply point, which is considered the 'source' in our case study.
- Two 10kV busses (A and B), with 6 and 4 customers connected respectively.
- 2 Transformers, which each connect one of the 10kV busses to the 20kV bus.

A source/grid supply point is a virtual representation of an upstream network which provides the voltage reference and can absorb or dispense power as needed. We have visualized these different components in the network graph Figure 3.2 below.

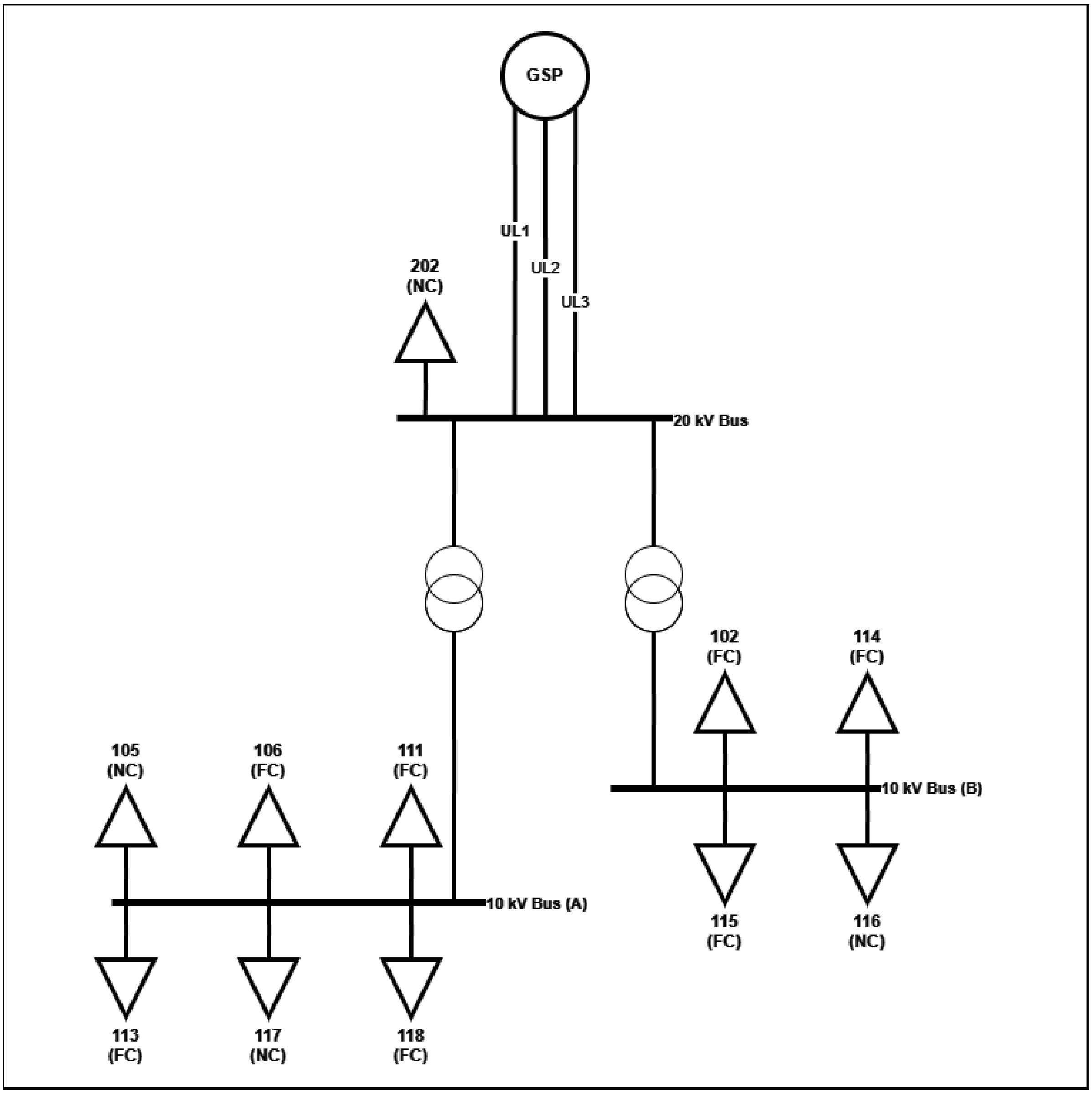

Figure 3.2: Network Graph of the case study.

In Figure 3.2, the different components of the system may be observed. Firstly, at the top we have the grid supply point (GSP), which is a representation of the upstream network. It is connected to the 20 kV bus by three upstream lines (UL1 through UL3). Below this, we find the 20 kV bus to which one load is connected (identifier 202, non-firm connection. Additionally, two transformers are connected to this bus. The first transformer connects to the first 10 kV bus, bus A, with two non-firm and four firm connections (FC), whilst the second transformer connects to 10 kV bus B. This bus has one non-firm and three firm connections.

This grid in reality only has firm connections currently. To represent the non-firm load, loads 105, 116, 117 and 202 were assigned as non-firm connections. This choice was made as these loads were the only direct connections to customers, with all of the other loads representing a line which connected multiple other customers to the substation. Although representing these in our model might have enhanced our outputs, the decision was made to represent these lines as single loads to keep the research within scope of the thesis.

Furthermore, it should be mentioned that this grid is currently appropriately sized to accommodate all of the connections on it, and thus experience relative little to no congestion. To create this congestion, the line limits were artificially lowered of the three lines to the upstream network. It should be underlined that the limiting factor to the capacity of the system is based on the constrained capacity of the lines. Therefore issues like voltage exceedances or transformer overloading were not taken into account in the allocation of capacity. We did however measure the outputs of these parameters, to verify the validity of these decisions.

With respect to the 'capacity' therefore, we are referring to the unused capacity already shown in Figure 1.1. In Figure 3.3 we have combined this with what the non-firm loading could look like, using this available capacity. The total available grid capacity (thus without firm loads) is therefore the product of the line capacity (in Amperes) and the voltage of the system. The exact formula is presented in Equation 3.1 below.

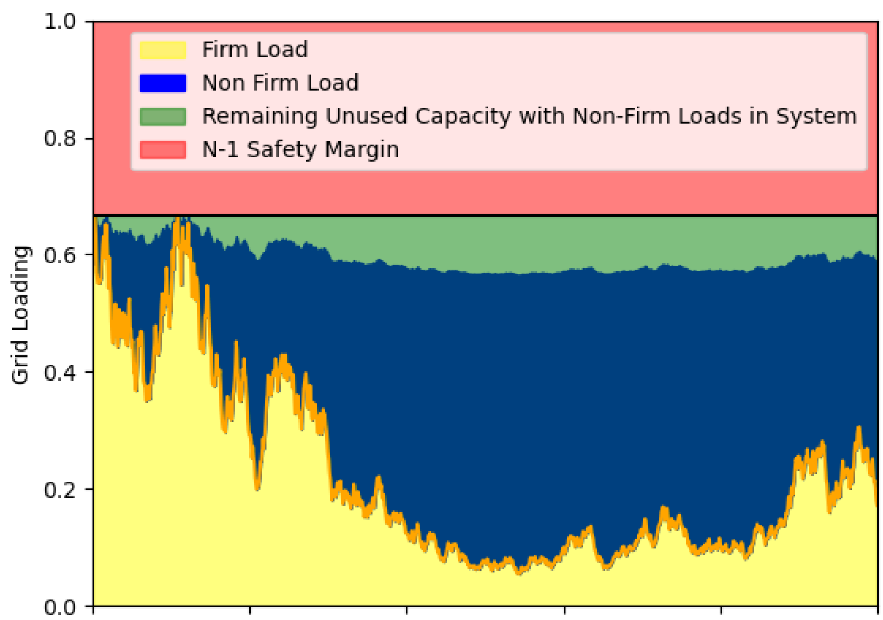

Figure 3.3: An illustration of the same system shown in Figure 1.1 but with added non-firm loads. The unused capacity is not fully utilised by the non-firm loads.

A note to take from Figure 3.3 is that the allocation of non-firm capacity does not automatically mean that there will be no more unused capacity, as this is highly dependent on the requested capacity of all of the non-firm loads. Simply, the unused capacity should be smaller with the addition of the non-firm load.

3.1.5. Expected Outcomes and Recommendations

With the overall research approach now outlined, we can now discuss what our expected outcomes are, and which kind of recommendations could be drawn from them. The validity of these expectations are touched upon again in chapter 5.

The primary outcome of our research is intended to be a comparison of different methodologies for allocating capacity to non-firm grid connections in a medium voltage distribution station. The methodologies would give, if not a comprehensive, at least a thorough overview of the possible ways that a grid operator might perform this allocation process. The comparison would be based on a set of KPI's which captured three relevant dimensions, each primarily of interest for a respective stakeholder. These stakeholders were:

- The customer that uses a non-firm connection agreement.
- The grid operator who provides such a non-firm connection agreement.
- The larger set of customers who pay for the operation and maintenance of the grid through the connection and transport tariffs.

The KPI's would therefore try to capture what measures are important to each of these stakeholders. Based on them, a comparison between the methodologies could be made, allowing us to identify which of the methodologies scores best, both in absolute terms as well as per relevant group of stakeholders. It is important to underline here that these KPI's would allow us to make a relative evaluation of the methodologies, i.e. with respect to each other. The scores do not (and arguably cannot) provide an absolute evaluation on the effectiveness or merit of the methodologies by themselves. What is more, the comparison itself would also only be valid for the given boundary conditions that we have stated above, as well as the assumptions and decisions that we will state below. To extrapolate larger conclusions from this comparison would necessitate a substantial consideration of the limiting factors of the analysis.

The secondary outcome of our research would be an analysis of the sensitivity of the comparison to important parameters like the forecast uncertainty that the grid operator, as well as the level of congestion present on the considered grid. With regards to the former, it would allow us to determine how each methodology compares both to itself under more ideal circumstances, as well as with the other methodologies in their manner of dealing with higher levels of uncertainty. On the later sensitivity to the congestion on the grid, it would allow us to determine how much the 'unused capacity' left on the grid plays a role in how effective each methodology is.

Based on the outcomes mentioned, the main recommendation of our work would centre around the considerations that should be relevant to grid operators, both when choosing which methodology to adopt in their own grids, but also when implementing these methodologies. Thus our research should give a first indication on what the different methodologies require, and do well on. In addition to this, we would be able to indicate what the potential effects of forecast uncertainty would be on these considerations, as well as what the level of congestion means for the performance of the different methodologies.

Aside from these operator focused recommendations, we would also be looking to use our research as a basis to reflect on the current implementation of the concept of non-firm grid connections in the Netherlands, and to identify where there might be room for improvement.

3.2. Modelling Approach

Based on the description of the research approach, we can now go into the actual modelling implementation of our research, specifically on the workflow that we adopted to achieve our findings. In Figure 3.4 below, a top-level overview of the modelling approach is given, with the process subdivided into three main parts. These are the external inputs to our modelling, the calculations and actions that we performed, and then the outputs that we were looking to deliver. On the bottom we find the assumptions and decisions that were made or taken, which influenced the process in their respective ways.

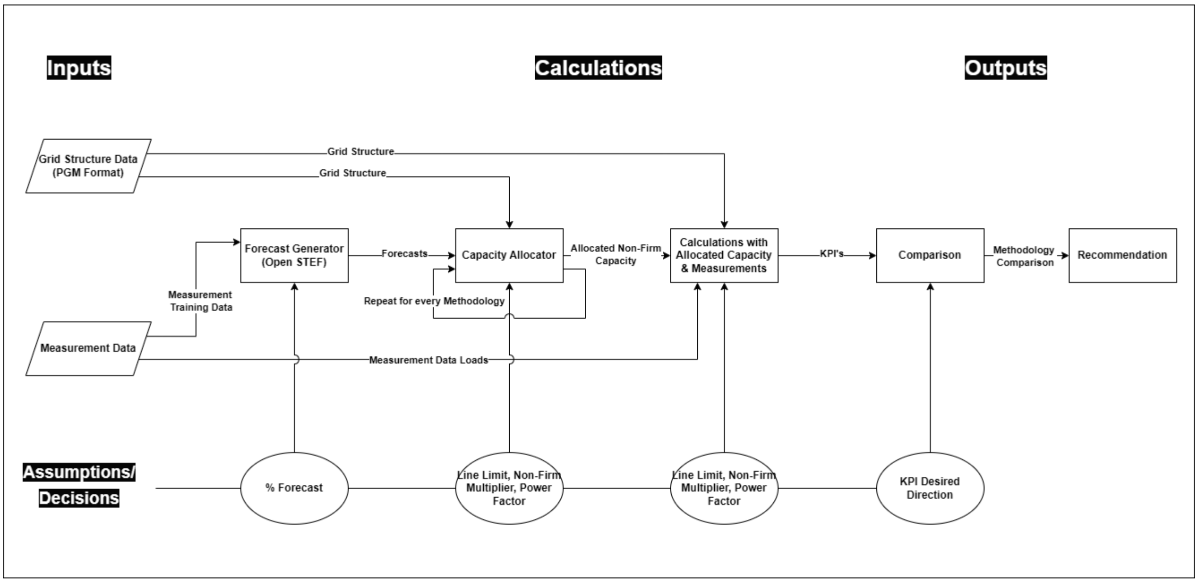

Figure 3.4: A Top Level View of The Modelling Approach

As can be seen from the left hand side of Figure 3.4, we are dependent on two primary inputs for our research. The first of these, the grid structure data, contains most of the information we need to run our simulations, like the line and transformer characteristics, as well as the different connections between the loads and the busses. The second set of input data are the measurement data that we use both for generating our forecasts as well as running the simulations (these are trapezoidal in nature, i.e. ramping up and down). This measurement data runs from May 2023 to January 2024, described in more detail in the next section.

In the middle of the figure we find the process of our research, namely three distinct steps. These are the generation of forecast based on the measurements, the allocation of capacity based on these forecasts, and then finally the translation of this allocated capacity to the real time measurement calculations in the third step of the process. For both the allocation and the calculation steps we make use of the Python Package Power Grid Model, which is a library for steady state distribution power system analysis. It is developed and used by Alliander, which was the main reason for our decision to use the library. Similarly, the generation of the forecasts based on the measurements was done through the Open STEF tool (Short Term Energy Forecasting) which is an open source library, partly developed by Alliander.

Finally, at the end of the figure we find the outputs, where we can use the KPI's output from the calculations step to compare the different methodologies to each other, as well as determine the effect of the forecast uncertainty and the congestion levels in the grid. Based on all of these, we can then base our recommendation to grid operators on which methodology would be most appropriate depending on the relevant considerations.

3.2.1. General Setup

Before we zoom into each of the three phases described above, we must first establish the general setup of our modelling approach. This is as follows: based on the measurement data we generate a backcasted forecast with a resolution of 15 minutes (the standard time unit for most energy markets). This forecast can use all of the measurements up to the day-ahead market close at 6AM the preceding day (thus for the forecast of Monday from 12AM to 12PM the forecast is generated with the measurements up to Sunday morning 6AM).

This forecast is then used to allocate the capacity to the non-firm loads, based on the unused capacity on the grid after the the forecast consumption profiles of the firm loads. The forecasted values of the non-firm loads are taken to be the their 'requested' capacities, as in reality non-firm loads would have to indicate their expected consumption. Based on this, the selected methodology is used to allocate the capacity to the different non-firm loads. The allocated capacity gives a bound for transport capacity, thus both supply and demand, This data is then passed to the calculation phase.

In the calculation phase, for the firm loads the measurement data is used. For the non-firm loads, the allocated capacity is used as an upper boundary for the measurement data of these loads. This means that the measurement data is used when it is within the bounds of the allocated capacity, otherwise the allocated capacity (positive or negative bound depending on value of measurement) is used. We have illustrated this in Figure 3.5, where we compare the measurement data and the allocated capacity for one of our non-firm loads.

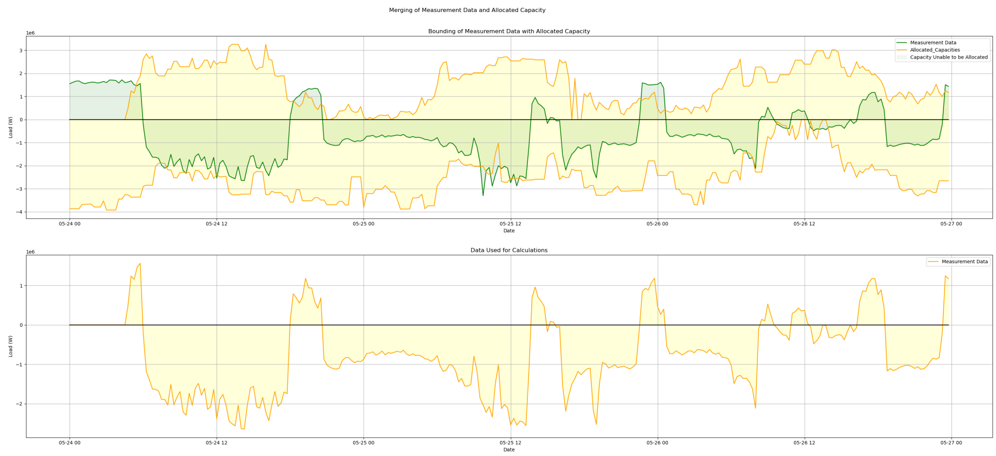

Figure 3.5: The merging of measurement data and the allocated capacity for a non-firm load.

We can clearly see in the upper figure that where the measurement data exceeds the allocated capacity, the calculation data is cut off at the allocated capacity bound. This calculation input data represented in the bottom figure is then used for the next phase, where the calculation data is used in the Power Grid Model power flow calculations, the outputs of which are used to determine the KPI's. Let us now go into more detail on each of the phases of the process.

3.2.2. Forecasting

The first step in our modelling approach concerns the generation of forecasts. As mentioned previously, these forecasts are generated by back-casting using the measurement data as an input for the Open Short Term Energy Forecast library. Back-casting means that we train the forecast model on the measurement data, and then use this model to predict ahead. In our specific case, the model was allowed to use all data until the allocation moment (day-ahead, at 6AM) and then generated a forecast 18 hours ahead for a full 24 hours. This is then done for each day of the dataset. Like in all of the other parts of our research, a resolution of 15 minutes was used. The reason for using this tool, and not simply taking a random variation of the measurements is because this tool is actually used by a distribution grid operator (Alliander) and gives us a good indication of the uncertainty that we could expect in real life forecasts.

Each forecast has a certain probability associated with them. For our baseline results, we took the 99th percentile for demand by a load and the 1st percentile for supply by a load. The reason that these two have to be split is illustrated in Figure 3.6. In short, in the sign convention that is used by grid operators, when a customer draws power from the grid, it is considered a positive value (+) load, whilst if a customer supplies power to the grid, it is considered a negative value (-) load.

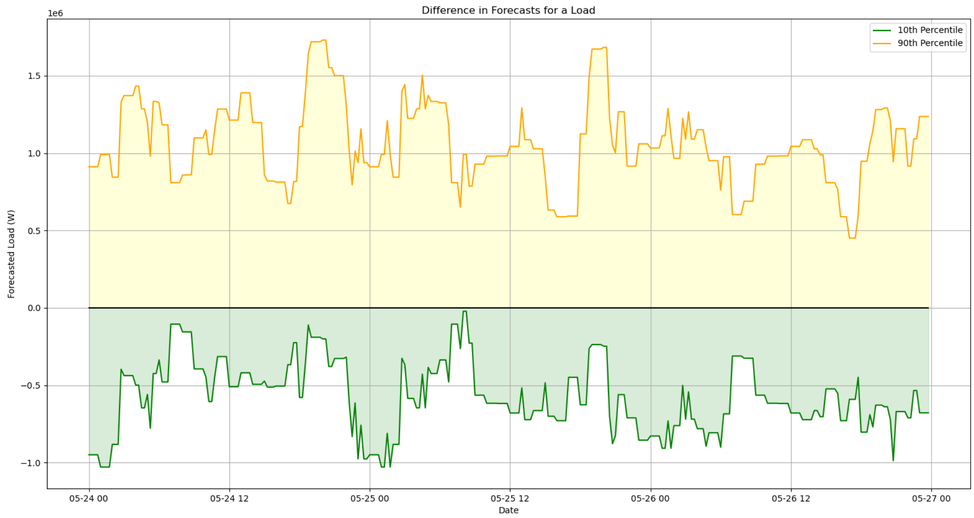

Figure 3.6: A comparison of the 10th and 90th percentile forecast

As can be seen in the figure, the 90th percentile in orange gives us a high predicted load (which is positive in the sign convention) whilst the 10th percentile in green gives us a 'low' predicted load (which is negative in the sign convention). Because the loads in our case study are both suppliers and consumers, we use the 90th percentile forecast when the mean forecast is positive, whilst we use the 10th percentile when the mean forecast is negative. This way we can ensure we have sufficient margin in our forecast for both directions that power might flow from a customer.

Aside from the baseline results, for sub-question 4 we also investigated the effects of different levels of forecast uncertainty, i.e. different percentiles instead of the 99th/01st mix that we adopt in the baseline scenario. To determine these effects, we generated a sampling of forecast percentiles for all of our loads, ranging from the 99/1st percentile all the way to the 45/55th percentile, which means that in the last of these forecasts, the loads are even assumed to be of a smaller magnitude than the mean (which would be the equivalent of the 50/50th percentile). In total, we tested our methodologies under a range of 50 forecasts, with the exact values presented in Appendix A.

Although a larger sampling would have enhanced our analysis, as we already mentioned in Section 3.2.1, each individual run was already reaching close to two hours. Due to the limited time available to us therefore, we drew upon this smaller sample size of forecast percentiles. An important note to add to this however, is that additional forecast percentiles would not necessarily result in a finer analysis, as these would simply mean that our outputs would get closer and closer to their true averages. Furthermore, the large amounts of assumptions inherent in our work, as we will explain in Section 3.3, means that any additional effort put towards our sensitivity analysis would only be of limited effect, as those assumptions were much more significant in our outputs. We therefore chose to stick with 50 forecast percentiles for our research, in a balance between time invested and payoff.

The final point worth mentioning is our comparison between the measurement and forecast data. We found that although the forecast was quite capable of achieving similar averages for each load, it was unable to predict the timing of peaks in the system with a high certainty. As we will discuss in chapter 4 this led to many exceedances being the result of peaks in the firm loads rather than the non-firm allocated capacity as the forecasts could not appropriately predict these peaks.

With all of the above in mind, let us now move on to the next section and discuss how these forecasts were used to allocate the available capacity to the non-firm loads.

3.2.3. Capacity Allocation & Methodologies

Referring back to Figure 3.4, we now move on to the capacity allocation phase of our modelling approach. In this stage, the forecasts and the grid structure data is used to determine the available capacity in the grid as illustrated in Figure 3.7. Then the selected methodology is applied to divide this capacity among the loads. Subsequently, the resultant allocated capacities are passed to the solution checker which runs a Power Grid Model power flow calculation to determine if the allocated capacities indeed do not exceed the limits of the system. If this is indeed true, the allocated capacities are then passed to the next phase in the process.

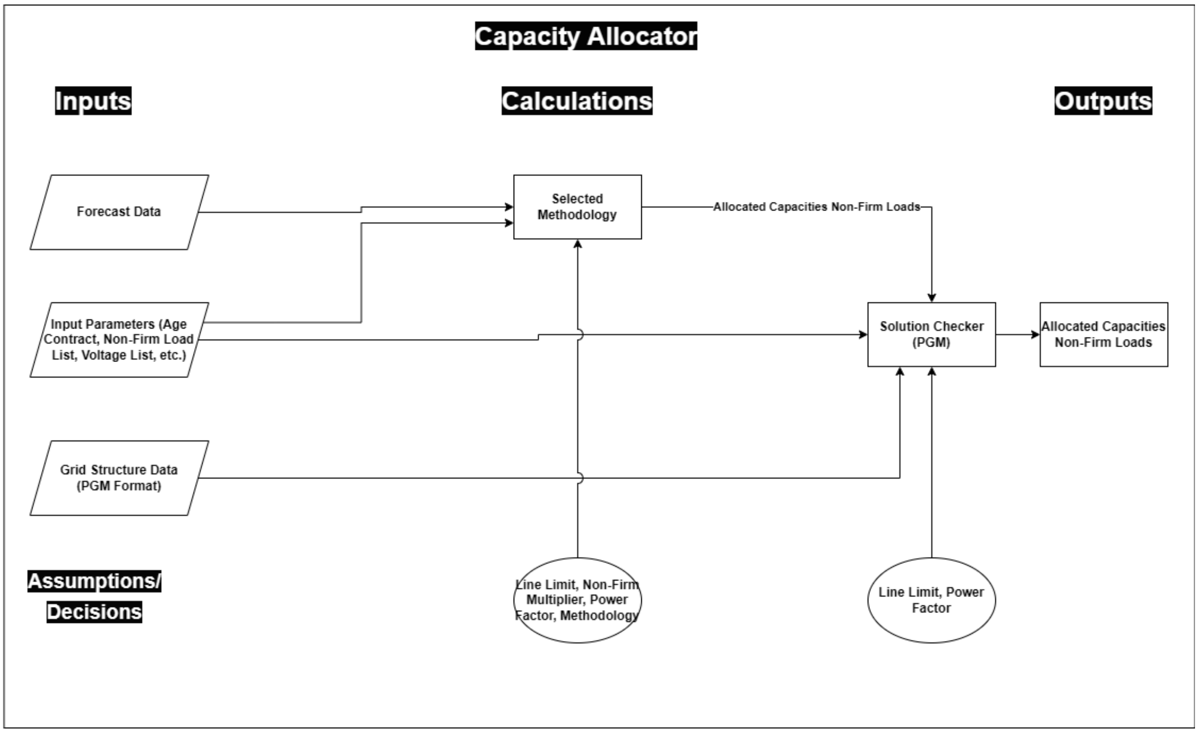

Figure 3.7: A diagram of the allocation phases of our modelling approach.

There are a few key points to notice in Figure 3.7. Firstly, this is where we encounter the first of our important assumptions and decisions. To determine the available capacity, we require the line limit of the grid, the non-firm multiplier and the assumed power factor, as well as the chosen methodology for this specific iteration. We will explain these parameters in Section 3.3. Secondly, it might stand out that the division of capacity in the methodology block does not mention any power flow calculations in Power Grid Model. This is because one of the large limitations of our research was our inability to incorporate the power flow calculations in the optimisation library which varies the allocated capacities until the maximum total allocated capacity is reached. Therefore, the available capacity was calculated using Equation 3.1:

$$C_{Available} = PF * (((2 * I_{Max_{Line}}) * V_{Line} * \sqrt{3}) - P_{Firm}) \tag{3.1}$$

The elements of this formula to calculate the available capacity ($C_{Available}$ (which we calculated in two directions to determine both the capacity for supply and demand) are simple. It is Ohm's law substituted with our variables. The line limit ($I_{Max_{Line}}$) is multiplied by two to ensure our three lines are N-1 secure, whilst the Grid Supply Point voltage (V_{Line} is taken as for the voltage as this is where the limiting factor of the system takes place. We multiply this by the square root of three as we have a three phase system where the voltage is given in line to neutral rather than line to line (ratio equal to square root 3). Finally, we subtract the capacity already taken up by the sum of all of the firm loads, both positive and negative (P_{Firm}). Finally, the whole results is multiplied by the assumed power factor (PF).

Because this equation is an over simplified representation of the actual system, we include the Solution Checker step in our capacity allocation, which is completely external to the the methodologies and can therefore run a power flow simulation in Power Grid Model. This way we ensure that the allocated capacity is always valid for at least the forecast data.

With all of this established, let us now look into how the methodologies were implemented in the model, and what steps they each followed. The full detailed step-by-step implementation can be found in Appendix B. We only discuss the top-level approach here.

Mathematical Optimum

The first methodology is MO, in which we tried to formulate the allocation of non-firm capacity as a convex optimisation which we could then solve. For this purpose, we chose the python library CVXPY, which allows us to formulate our problem in a convex fashion, and then implement a solver to give us our results (Diamond & Boyd, 2016). The extensive step-by-step approach we implemented is explained in detail in Appendix B. For now, we will briefly go through the main points in the process. An import note to add is that the methodology is applied per time step (per 15 minute segment), and not over the whole dataset at once.

- Step 1: We first calculate the total firm capacity (apparent power) forecasted to be used at this time step.
- Step 2: We then combine this with Equation 3.1 to calculate the capacity in both the LDN (demand) and ODN (supply) direction [1,2].
- Step 3: For each of the non-firm load, the requested capacity is split into requested LDN capacity and requested ODN capacity. Each of the two is taken to be an optimisation variable, with a range from 0 to the requested capacity as constraints.
- Step 4: An additional constraint is formulated that specifies that the sum of the allocated capacities in the LDN direction may not exceed the LDN capacity calculated previously, and similarly the sum of the ODN capacities that are allocated may not exceed the ODN capacity calculated previously.
- Step 5: We then formulate the objective statement, which is split into two equally weighed maximize objectives, one trying to maximise the sum of the LDN capacities and one trying to maximise the inverse of the ODN capacities[3].
- Step 6: We can then finally specify our problem, with the constraints and objectives as discussed, and solve this problem with a discrete solver. We used the MOSEK solver as it was more robust and faster than the default ECOS solver normally used by CVXPY. The output of this optimisation are then the allocated capacities for each of our non-firm loads, specified as a range between the maximum LDN and ODN capacity available for that load.

As we mentioned above, we do not incorporate power flow calculations to more accurately estimate the available capacity here, not even in an iterative manner. This was done because the optimisation library only allows users to incorporate built-in atomic functions but not external functions like the power grid model functions that we use (Diamond & Boyd, 2016). This detracts from the accuracy of our results, and to mitigate some of the drawback of this, we incorporated the solution checker mentioned previously, which does check the allocated capacities in a power flow calculation once to ensure it is at least within the limits of the system. However, this means that we were never able to fully 'optimise' the system, which is a significant limitation in our research. With this limitation in mind, power flow calculations were not incorporated into any of the other methodologies, and the same Equation 3.1 was used to determine the available capacity.

LIFO

The implementation of the LIFO methodology is significantly simpler than MO, and is very similar to the other two list-based priority schemes (Adapted LIFO and Carousel). The process is split into two parts: the generation of the priority-list, and the allocation of capacity based on this priority-list.

[1] It should be noted that the total firm capacity can actually increase the capacity of the system in the opposite direction, e.g. a large amount of firm demand means we can allocate more supply as this will be consumed locally rather than having to go upstream through the limiting cables.

[2] A second point to note is that if the available capacity is negative for LDN or ODN, all of the requested capacities in that respective direction are required to be set to zero.

[3] This split was necessary to cope with the requirement to formulate our problem as a convex optimisation. More information is available at Diamond and Boyd (2016)

This second part is re-used in the other two list-based priority schemes. Once again, the full step-by-step process can be found in Appendix B. The process for the generation of the priority-list is very straightforward: the priority order is generated based on the ages of each contract. This priority-list is then passed to the list-to-allocation converter, which then follows the steps below.

- Step 1: Similarly to the MO methodology, first we calculate the total firm capacity (apparent power) forecasted to be used at this time step.
- Step 2: This is then combined with Equation 3.1 to determine the available capacity in the LDN and ODN direction.
- Step 3: Then for every load in the priority-list, in the order of the priority-list, the requested capacity (both in LDN and ODN direction) is allocated. If insufficient capacity is available, the allocated capacity is equal to the remaining capacity. If no capacity is available, the allocated capacity is equal to 0.

In addition to the allocated capacities, the sign of the forecasted capacity is passed to the solution checker, which uses the positive or negative allocated capacity maximum based on the sign in its power flow calculation.

Adapted LIFO

Adapted LIFO is similar to LIFO but creates a separate priority-list for every voltage level. These priority-lists are then combined in order of descending voltages. The allocation of capacity happens in an identical manner as with the LIFO methodology described above.

Carousel

The Carousel method is different from the two other priority-list based methodologies in that it does not remain fixed throughout the run. It takes a rotating priority-list, which shifts one position for every fixed number of time steps. For our baseline run we set this time step equal to 1, i.e. the priority-list shifted every 15 minutes. We also investigated the effect of changing this variable, which we discuss in chapter 4. The allocation of capacity happens in an identical manner as with the LIFO and Adapted LIFO methodology described above.

Pro Rata

Similarly to the Mathematical Optimum methodology, Pro Rata tries to formulate the division of capacity among the non-firm loads as a convex optimisation problem. The main difference between Pro Rata and MO is the addition of one more constraint: the ratio between each load's allocated capacity and its requested capacity needs to be equal. In practice this could not be implemented exactly, as the optimisation library was unable to find a solution for this constraint. Therefore the constraint was formulated as presented in Equation 3.2.

$$\forall n \in non\_firm\_ids : Cap_{allocated_n}/Cap_{requested_n} - Cap_{allocated_{n+1}}/Cap_{requested_{n+1}} <= 0.0001 \tag{3.2}$$

Where $Cap_{allocated_n}$ is the allocated capacity for the nth load, and $Cap_{requested_n}$ is the requested capacity for the nth load. Thus, instead of having to be exactly zero (which is something the library cannot deal with (Diamond & Boyd, 2016)), the difference between the ratios (which should be somewhere between 0 and 1) should be small. The effect of this exact value is analysed in chapter 4.

Following the same constraint, if there is no available capacity in one of the directions that power may flow (LDN or ODN), no capacity can be allocated at all, since all of the ratios still need to be equal or very small. This was hard coded into the optimisation, where the requested capacities were set equal to 0 if either of the available capacities were equal to or smaller than zero.

Aside from these limitations, all of the other steps are identical to the ones performed in the MO methodology, after which the allocated capacities are passed to the solution checker, which subsequently outputs the allocated capacities to the next stage in the modelling process, the power flow calculations with measurement data.

3.2.4. Power Flow Calculations & Key Performance Indices (KPI's)
This brings us to the last part of Figure 3.4: the power flow calculations with the allocated capacities and measurement data to determine our KPI outputs. From the previous phase, we receive the allocated capacities for the non-firm loads. This is then combined with the measurement data as described in Section 3.2.1. This final calculation input data is then passed to Power Grid Model together with the grid structure to output the relevant power flows. This allows us to then calculate each of our KPI's, as well as collecting additional data that might be of interest. The KPI's are measured as follows.

- % of Requested Capacity: This KPI was obtained by taking the average of the ratio of the allocated capacity over the requested capacity.
- % Difference in Allocated Capacity: The percentage difference was derived from the difference between the percentages of the highest allocated load and the lowest allocated load.
- Standard Deviation of Allocated Capacity: The Standard Deviation was taken of the percentages of requested capacity.
- Allocated Capacity per % Line loading": The total allocated capacity was divided by the line loading.
- Total Load Unable to be Allocated: The difference between the requested capacity and the allocated capacity was summed over the whole run.
- # of Exceedances: The number of exceedances was determined from the output of the Power Grid Model, where a line loading larger than 2/3 was considered an exceedance (to maintain N-1 security).
- Average Size of Exceedance: The average size of the exceedances followed the same line as above, taking the average exceedance where the line loading was higher than 2/3.

In addition to these KPI's, we also collected the following data for the baseline run:

- Total Load Unable to Be Used: This was the sum of the time steps where the measurement data was higher than the allocated capacities.
- Number of Voltage Exceedances: The amount of times that the node voltages exceeded their limits (higher than 22.2kV or lower than 19.4 kV for the 20kV bus and higher than 11.1 kV or lower than 9.7 kV for the 10kV busses).
- Number of Times Measurement Data was Higher than Allocated Capacities: The amount of times that the allocated capacity was smaller than the measurement data.
- Average Line Loading: The average line loading from the output file of the power flow calculations.
- Free Space Average: The average amount of unused capacity left on the lines, obtained by multiplying the voltage times the difference between the line limit and the actual line loading.
- Free Space Peak: Similar as above, except the highest value.

For the forecast sensitivity runs we collected the averages and the variances of the KPI's rather than the values for every run. For the line limit run, the average of the variance between the different methodologies per KPI's was measured, as well as the averages and the variances per methodology across all of the line limits.

3.3. Assumptions and Limitations
To round-off this chapter, we can now discuss the various assumptions and limitations that we made in our research. We have split this section into two parts: Section 3.3.1 covers the assumptions and limitations of our more general research approach, whilst Section 3.3.2 details the assumptions that were made in our modelling implementation of our research as well as the limitations that we encountered. In both of these sections, we will only touch upon the most significant assumptions and limitations, whilst the comprehensive list of assumptions and limitations can be found in Appendix A.

3.3.1. Assumptions and Limitations in Research Approach

The following assumptions and limitations apply to our more general research approach and what problem we sought to investigate.

The first major assumption concerns our selected case study. The issue of grid congestion is a rather complex one, as we discussed in chapter 1, which means that for different parts of the grid, congestion will present itself in different ways. Therefore, whilst we might be able to achieve an acceptable answer to our research question for the characteristics and features of our current case study in our research, the wider applicability of these findings is uncertain. For example, we represented the source of congestion in our case study as insufficient capacity of the upstream lines towards the GSP. However, as we discussed in Section 3.1, we achieved this limitation by lowering the actual limits of the system, which implies that the same might be done by for example lowering the limits for voltage fluctuations, or even the tolerance of the transformers connecting the different busses. Moreover, the limited applicability of our findings will be even more significant if the topology of the grid changes, e.g. when the system includes another line to which multiple loads are connected. It is therefore paramount for our findings to be properly contextualised, based on which we might explore which of them would still be applicable if a different topology or limitations was of relevance when implementing non-firm gird connections in a real grid situations.

Secondly, and perhaps even more importantly, we must consider that even the answers to our research question, i.e. which methodologies are optimal for the considered case study, are very dependent on which KPI's are held to be the most important or relevant. If for example one of the methodologies is found to be significantly more 'fair' than the others, it might be more attractive for potential customers and grid operators (for whom it would increase acceptance among customers) but might be less interesting from a societal perspective, where the less efficient usage of the grid might be a more relevant drawback. Therefore, although we assume that our research can yield a recommendation for which methodologies are optimal under which conditions, we must conclude that the actual 'best' methodology is highly dependent on the priority the grid operator places on the different KPI's.

3.3.2. Assumptions and Limitations in Modelling Approach

For the translation of our research to a specific modelling implementation, we had to make certain assumptions and decisions. The full list of these are presented in Appendix A. In this section, we will further touch upon five of these assumptions and decisions, which we felt deserving of further explanation.

Selection of Non-Firm Loads

The first main assumption that we made was the selection of our non-firm loads. As it stands, the substation that we modelled in our research is a real-life part of the grid, to which there are real, firm loads connected. For our analysis, non-firm loads needed to be included. We chose to convert firm loads into non-firm loads, with their firm capacity forecasts becoming non-firm, requested capacities. However, we also needed to include firm loads, as these would create our 'baseline' load, which would determine how much available capacity there was.

In the end, we based this decision on the grid topology that we were provided by Liander. Namely, the decision was made to make all of the loads that were individual, discrete customers non-firm, and all of the loads that were aggregated loads connected to a downstream line to be firm. This meant that out of the 11 loads connected to the substation as illustrated in Figure 3.2, 4 would be considered non-firm, whilst the other 7 were considered firm.

Selection of Line Limit

Next, we have the selected line limit. As we discussed in Section 3.2.1, the grid that we are modelling is appropriately sized in real life, with sufficient capacity to accommodate all of the loads connected to it. To simulate congestion therefore, we needed to lower one of the limits of the system, depending on which type of congestion we wanted to simulate. We chose to lower the upstream line's limits (thus creating congestion), which normally have a limit of 575 Amperes (times 3 for the three lines as illustrated in Figure 3.2. The reason for this decision was that this would require the least amount of changes to the system, and would not require us to change any of the other associated parameters (which would be required when changing the limits of the transformers for example).

However, deciding what level of line limit would give us a case study with sufficient variation in our outputs to perform an analysis was more difficult than it initially seemed. We started out by calculating the line limit based on the total firm load, i.e. removing all of the non-firm loads and doing power flow calculations with ever decreasing line limits until the line loading was equal to or smaller than our requirement (2/3, thus N-1 compliant). This gave us the results presented in Table 3.1 for our measurement and forecast data.

Table 3.1: Table of Recommended and Average Line Limit

	Recommended Line Limit (Amperes)	Average Line Loading (%)
Measurement Data	243.8244	0.1987
Forecast Data	103.7951	0.2891

As can be seen in Table 3.1, the average line loading is significantly lower than the peak values. This means that except for in the rare cases where the firm loads peak, there will never be congestion in the system. We therefore had a choice between the firm peaks sometimes exceeding the limits, but having congestion or the peaks staying within the limits of the system but no congestion and therefore no possibility to compare methodologies. We chose the former, but to support our decision we performed a sensitivity analysis for this parameter. The outcome of these runs, which ran from a line limit of 75 all the way to 225 Amperes, are presented in Figure 3.8.

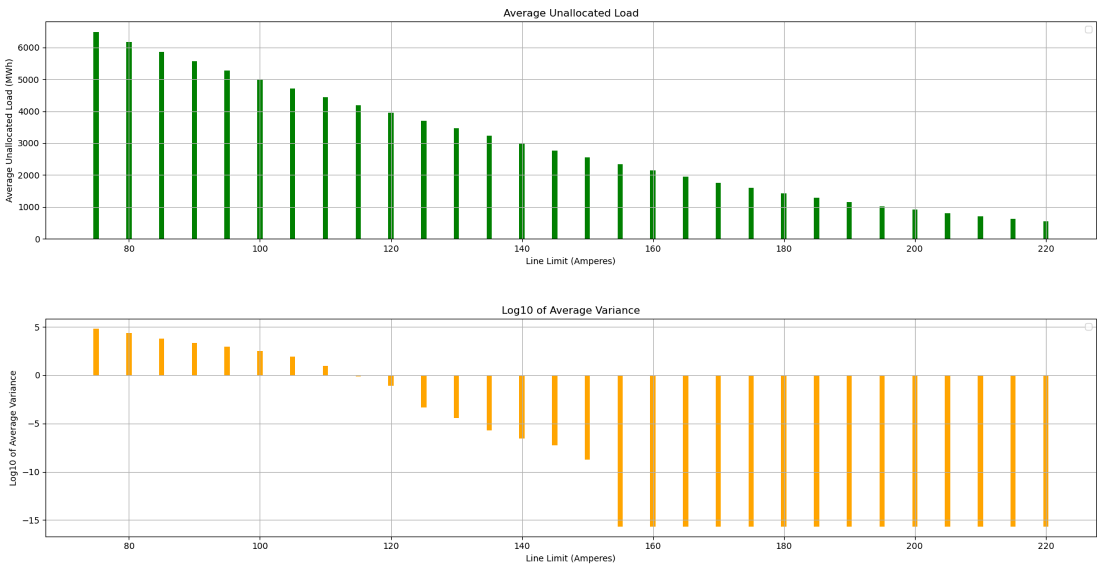

Figure 3.8: A comparison between the average unallocated load (in MWh) and the Log10 of the average variance of all of the KPI's both as a function of the line limit in Amperes.

From Figure 3.8, it was apparent to us that the ideal line limit was somewhere in the range between 80 and 120 Amperes line limit, to have sufficient differentiation between the methodologies. If the line limit is too high, although the unallocated load (the requested load that could not be allocated) quickly goes down, so does the difference between the KPI's, whilst a line limit that is too high will mean a high average unallocated load. In the end, we chose to go forward with a line limit of 100 Amperes. which would give us a sufficient amount of difference between our methodologies whilst still being able to allocate a significant amount of the requested capacity.

Non-Firm Multiplier

Next, we included a parameter called the non-firm multiplier. This parameter, which multiplies both the forecast and measurement data for the non-firm loads, was included because of the relative difference between the firm and non-firm load. This is illustrated in Figure 3.9, where the purple graph indicates the non-firm load, the teal graph is the firm load and the green and yellow give the loading respectively in terms of relative loading (as a percentage of the line capacity) and absolute loading (in MVA).

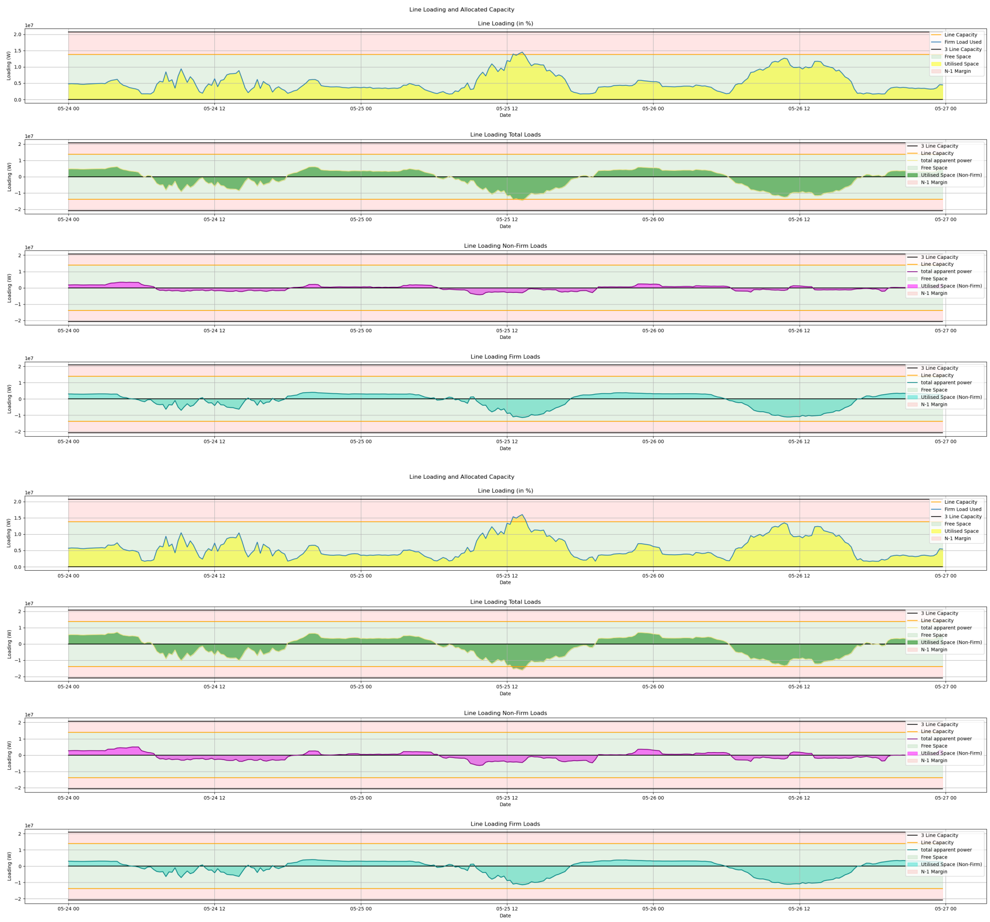

Figure 3.9: A comparison between non-firm multiplier value 1 (Top) and 1.5 (Bottom) with a line limit of 200 Amperes.

As is apparent from the figure, the difference between the non-firm and firm loads is very significant. To determine exactly how big this difference was, we wrote a short script to compare both the peaks between the two as well as the averages, which can be found in Appendix A. We found the ratios to be as presented in the output in Table 3.2.

Table 3.2: The output of the non-firm multiplier script.

Variable	Value
Max Firm	8280000.0
Max Non-Firm	5666666.666666666
Desired Ratio Peaks	1.4611764705882355
Desired Ratio Sums	1.549969550453075

We therefore chose a value for the non-firm multiplier between the two: 1.5. The effect of this assumption is twofold. Firstly, the unused capacity available will have to be divided between a larger amount of requested capacity, which should lead to more marked results as we discussed above about the line limit. Secondly, this will lead to the non-firm loads also contributing to the peaks as opposed to this behaviour only originating from the firm loads, once again as we discussed above.

Symmetrical Capacity Requests

Another important consideration that we ran into in our research was the need for symmetrical capacity requests. Symmetrical capacity requests means that if the forecast data (which we stated to be the 'request' for capacity by the load) is negative, it is matched by an identical positive request and vice versa. This means that instead of a request being for capacity from 0 to 2 MW LDN, the request now becomes from -2 (ODN) to +2 (LDN). Thus for every methodology, a request now meant a reduction in the available capacity in both the LDN and ODN direction.

The underlying issue that led to the need for this assumption was the inability of the forecast to adequately predict when the loads would be requested LDN or ODN. This is apparent in Figure 3.10, where we did not include symmetrical capacity requests, but correctly merged the allocated capacities and the measurement data.

Figure 3.10: Non-symmetrical capacity requests with proper merging of allocated capacities and measurement data.

It is clear from Figure 3.10 that very little capacity is actually used with this implementation, as the forecast consistently fails to predict the direction of the load flow. To ensure our analysis would actually focus on the comparison of the methodologies rather than on the shortcoming of the forecast, we therefore made the decision to move to symmetrical capacity requests.

Iterative Capacity Allocation

The final key assumption that we made concerns a concept we dubbed 'iterative capacity allocation'. In short, iterative capacity allocation would entail that capacity allocation in one direction (LDN or ODN) would mean increased capacity in the opposite direction (ODN or LDN). Take for example a solar installation which has requested a certain amount of transport capacity from the grid operator. This could then be matched with a capacity request by for example a factory that is on the same busbar or substation as this solar installation, even if there might be no capacity available for this request (or if there is capacity available not take up this capacity). In short, iterative capacity allocation could potentially allow for higher utilisation of the grid without risking increased congestion. However, as is probably obvious, iterative capacity allocation would also bring some risk with it. Namely, when capacity allocated by the grid operator, this is framed not as an obligation to use but rather an opportunity or even a possibility to use this capacity. Therefore, if the solar installation outputs its full allocated capacity but, for whatever reason, the factory does not use its full allocated capacity, this will lead to increased loading on the system, perhaps even beyond what it can accommodate, leading to a significant risk for grid operators. This is not even taking into account that customers are not always sure about their requested capacity, like for example with the solar installation. The operator of this installation cannot predict when exactly a cloud might pass by reducing their generation, thus leading to risk that is passed on to grid operators unnecessarily. The concept of iterative capacity allocation is therefore one that could be valuable to investigate, but serious tolerances in this allocation would be necessary to accommodate the increased risk.

To translate this to our specific modelling implementation, however, we noticed in our first implementation of the model (i.e. no symmetrical capacity requests as mentioned above), that the mathematical optimisation methodology was using this concept to distribute more capacity than could be purely allocated based on the available unused capacity. This was found to be significantly excessive due to the uncertainty in the forecast, leading to exceedances far above expectations. We there chose to not allow iterative capacity allocation, and to allocate capacity one time only per time step (and thus not going back after allocating all of the capacities to determine if there was more unused capacity left). This issue was also resolved with the addition of the symmetrical capacity requests mentioned above, as there would be no possibility to compensate two loads if both loads already had identical mirrors in the LDN or ODN direction. Therefore, no additional restriction had to be imposed.

4

Results & Discussion

This now brings us to the results of our research. We have split this chapter into three major parts, followed by a final discussion in Section 4.4. In Section 4.1 we make a comparison of the methodologies under the baseline scenario, and rank them for the various KPI's. In Section 4.2 we discuss the effects of the forecast on these results, as well as analyse what the impact is on our methodology comparison. Finally, in Section 4.3 we do the same for our selection of line limit.

4.1. Baseline Results & Discussion

Let us now discuss the set of results that we obtained. The baseline results were run with a line limit of 100 Amperes and a forecast uncertainty quantile of 99/01 (LDN/ODN). The effect of these parameters are further explored in the next sections. The input parameters that were used for these runs are as follows.

- Non-Firm Multiplier: 1.5.
- Length Simulation: 23516 Time Steps.
- Age Contracts: {102: 0, 105: 1, 106: 2, 111: 3, 113: 4, 114: 5, 115: 6, 116: 7, 117: 8, 118: 9, 202: 4}.
- Line Limit: 100 Amperes.
- Forecast Quantiles: 99th LDN, 01st ODN.
- Power Factor: 0.85.
- Carousel Time Steps Per Shift: 4.
- Pro Rata Equality Maximum Difference: 0.0001.
- N-1 Requirement: True.

With these parameters established, we can now look at the results for the various KPI's.

4.1.1. Baseline KPI's

The first set of results of interest are the Key Performance Indices of each methodology. In Table 4.1 the results of our simulation are shown in terms of the KPI's. We have highlighted the scores from best to worst per KPI in colour.

Table 4.1: A Table of the Baseline KPI's (Line Limit 100 Amperes, 99/01 Forecast Quantile)

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average Size of exceedance (Lower is Better)
Adapted LIFO	0.5157	0.3533	0.2420	0.1858	4806.7918	8267	0.8403
Carousel	0.5897	0.1891	0.3018	0.1559	5229.0888	8502	0.8269
LIFO	0.6287	0.5770	0.2345	0.1374	5297.6330	9039	0.8197
MO	0.5636	0.0898	0.1116	0.1896	4431.5073	8906	0.8313
Pro Rata	0.5267	1.9885e-05	0.2242	0.1651	5132.5879	10531	0.8537

The methodologies have been ranked in Table 4.1 according to the ranking outlined in Table 4.2.

Table 4.2: The colour ranking from best to worst used in the presentation of our results.

Best	Second Best	Middle	Second Worst	Worst

However, we should not purely look at these rankings to gain an overall 'best' methodology, as there are two major considerations when taking these rankings as scores:

- It assumes that all of the KPI's are equally weighted, i.e. being the best at one category is considered equal to being the best at another.
- It assumes that the differences on a per KPI basis between methodologies is negligible. For example, the fact that Pro Rata has practically no difference in its allocation is assumed to be the same as a relatively small difference in the average size of the exceedance.

Instead, we will discuss these outcomes on a per KPI basis to analyse what might cause a certain ranking and what the implications of this are.

% of Requested Capacity

The first, and one of the most important KPI's, is the average allocated percentage of requested capacity. This KPI kept track of how much a load, on average, will be allocated of its requested capacity (as a percentage). This is an important measure of how attractive non-firm ATO's are to potential customers, and is therefore paramount when considering the effectiveness of this flexibility option next to others like market-based and curtailment based flexibility contracts.

The best methodology for this KPI, with a small but significant lead over the others, is LIFO. Even when varying the forecast quantiles and line limit as will be shown in the next sections, this remained true for LIFO which continued to score the best on the requested capacity KPI. What is more, to our surprise the Adapted LIFO methodology scored the worst for this metric, suggesting that giving priority to the lower voltage levels actually increased the average allocation percentage. Aside from this priority to higher voltage levels for Adapted LIFO, the two methodologies are identical, which suggests to us that the lower voltage loads were consistently being under-allocated in the other methodologies.

With respect to the other methodologies, the differences between them are relatively small, on the order of a 5 to 10% percent difference in allocated capacity. Surprisingly however, MO is only third, which suggests that the priority-list based methodologies can be more efficient in achieving higher allocated percentages. Pro Rata scored second lowest, which was within our expectations for this methodology, as the additional equality constraint imposed upon it means that it will not always be able to allocate the maximum capacity available.

% of Relative Allocated Capacity

Next we have the % of Relative Allocated Capacity. This KPI measured the average difference between the highest and lowest allocated load, reflecting how relevant the non-firm connection becomes as more loads are connected and how 'fair' the allocation is.

As expected, the average difference in allocation for Pro Rata is close to zero (but not exactly zero, due to the way we implemented the equality constraint, as discussed in Section 3.2.3), putting it on top for this KPI. More interestingly, we see that MO scores well on this KPI too, with only an average difference in allocation of around 9%. This is significantly lower than the other three methodologies, indicating that the most efficient allocation can also be a fair one.

Next, we see a slight increase in percentage to around 19% for the Carousel methodology, which combined with its excellent score on the previous KPI indicates once again that it is also possible to have a high average allocation percentage whilst still achieving relative fairness. Thus both the Carousel and Mathematical Optimum methodologies show a lot of promise here.

Following up after this, we see the Adapted LIFO and regular LIFO methodology, which score worse on this metric. For the former, this lackluster score combined with the very low KPI score for average allocated percentage shows that in our chosen case study, prioritising higher voltage levels fails to noticeably improve the allocated capacity. For the latter, we must consider that on average this methodology allocated almost 60% more to the highest allocated load. This underlines the effect that using such a methodology will have on the adoption of non-firm contracts in a specific part of the grid: for the first few connections the non-firmness will not be an issue at all, with high average allocated capacities, and a guarantee of future preference. But as soon as there are a few in place, no more new non-firm grid connections can be expected, as the attractiveness of the contract drops perilously.

Standard Deviation of Allocation

In addition to these two straightforward measures of the effectiveness of each methodology we also have the standard deviation of allocation. This measure, although less apparently relevant at first, does give another indication of how potential customers would perceive a non-firm grid connection. A low standard deviation, even with a low average allocated capacity percentage, means a low uncertainty for customers, and therefore a lower risk to adopting such a contract.

Just like before, there is one clear winner here: the Mathematical Optimum methodology, having a deviation half as large as the runner-up. This means the MO methodology performs well as a jack-of-all trades with respect to the average allocated capacity and fairness, whilst doing so in a predictable and regular fashion. As we will discuss later however, using such a methodology in practice does come with a few trade-offs.

Next, we have the Pro Rata, LIFO and Adapted LIFO methodologies in order which all score quite close to each other, indicating that although the predictability is slightly different between them, the variation in allocation is probably subject to external factors, like the firm load, rather than their exact allocation methodology.

Surprisingly, Carousel comes in last with a significant difference compared to the next one up. We suspected this might be due to one of the key parameters of the Carousel methodology: the amount of time steps before the priority-list shifted. To investigate this, we ran the same run for five different amounts of time steps: a single time time step per shift, the baseline at 4 time steps per shift (an hour), a daily shift at 96 time steps per shift, a weekly one at 672 time steps per shift, and a monthly one at 2880 time steps per shift (30 days/month). The results of this can be seen in Table 4.3 below:

Table 4.3: A Comparison of the Carousel Methodology Across 5 Different Time Steps (Line Limit 100 Amperes, 99/01 Forecast Quantile)

Time per Shift in priority-list (Time Steps)	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
15 Minutes (1)	0.5834	0.1524	0.3032	0.1578	5176.0472	8658	0.8289
1 Hour (4)	0.5897	0.1891	0.3018	0.1559	5229.0888	8502	0.8269
1 Day (96)	0.5825	0.1526	0.3028	0.1570	5179.2377	8591	0.8316
1 Week (672)	0.5832	0.1414	0.3036	0.1578	5172.8781	8681	0.8274
1 Month (2880)	0.5849	0.1586	0.3035	0.1603	5166.7991	8469	0.8256

From table Table 4.3, it is apparent that the impact of the time per shift in priority-list parameter on the standard deviation is negligible. It seems that the Carousel methodology by itself simply has a high standard deviation in its load allocation. Looking at the other KPI's, we see that these do not show a clear pattern either, further underlining the lack of impact this input parameter of time per shift in priority-list has on the output.

Allocated Capacity /% Line Loading

The allocated capacity per unit of line loading KPI takes a step away from the load focused metrics and gives us an idea of how efficiently the system is used by each of the methodologies. Although a higher line loading is acceptable (as long as it is within limits), allocating as much capacity per unit of line loading gives us an indication how each of these methodologies handles the distribution of capacity.

Once again, we see the Mathematical Optimum methodology get the highest score, with 0,1896 MW allocated capacity per percent line loading. The difference between it and the runner-up Adapted LIFO is very small however, with that one achieving a close 0,1858 MW per percent line loading. This shows us that giving preference to the higher voltage loads does actually positively influence the efficiency of the allocation, as the LIFO methodology only allocates a meager 0.1374 MW per percent of line loading. Finally, we find the Carousel and Pro Rata methodologies hovering in the middle, with acceptable efficiencies but failing to reach the high levels of the top two.

Total Load Unable to Be Allocated

We now arrive at the most important of the 'societal' KPI's: the total load that was unable to be allocated. This gives us an indication of how effectively each methodology was able to allocate the available capacity, and allow us to compare it to the first KPI to determine which of the methodologies achieves both the highest average allocation percentage and the lowest load unable to be allocated.

As expected, the Mathematical Optimum methodology scores the best here, as this was specifically its design purpose. It significantly outperforms the other methodologies, and combined with the scores it has achieved on the previous KPI's, it is hard to disagree that, in theory, this methodology provides the most consistent performance across the board.

It is once again followed by the Adapted LIFO methodology, which shows that the prioritisation of higher voltage loads when distributing capacity allows for more efficient usage of the system.

Behind it, we find the Pro Rata methodology, which once again is in the middle of the pack, due to the additional constraint that is put upon it by the equality requirement.

At the bottom we find the Carousel and LIFO methodologies, which both fail to allocate almost 800MWh more than the MO methodology, underlining the inefficiency associated with a simple priority-list based allocation mechanism.

# of Exceedances

We then end up in the third dimension of KPI's, namely those of interest to the grid operator. The number and the size of exceedances is a great metric to determine how well a methodology deals with peak in the firm load, and the big difference between them shows that even when the firm load is high, some methodologies still perform better than others.

At the top here we find the Adapted LIFO methodology, which, through its prioritisation of the higher voltage levels clearly sidesteps a lot of the peaks in firm load. Following it closely behind is the Carousel methodology, which seems to get it right some of the times. In the middle we find the LIFO and MO methodologies, which perform noticeably worse than the other two, but still achieve similar levels of exceedance. All the way at the bottom we find the Pro Rata methodology, which exceeds the line limits almost 45% of the time. This indicates to us that the # of exceedances is not purely connected to the load unable to be allocated, but is also dependent on the methodology of distributing capacity and the assumed firm and non-firm loads.

Average Size of Exceedances

This now brings us to our last KPI: the average size of the exceedance. The importance of this metric is twofold: firstly, any exceedance that is curtailed needs to be paid for by the grid operator (when this exceedance falls within the firm or non-firm capacity available to a load), and an associated cost is incurred in balancing the larger grid, both of which are dependent on the size of the exceedance. Secondly, the average size of the exceedance also acts as an indicator, in conjunction with the # of exceedances, to which extent grid reinforcements are needed, where once again the size of the exceedance is a key parameter.

In our results, we see that the difference between the methodologies is relatively small, but noticeable. The LIFO methodology scores the best here, which aligns with the fact that is has the highest load unable to be allocated. This pattern follows with the other methodologies, which score better or worse depending on how they score in the Total Load Unable to be Allocated KPI. The difference between them is small enough for us to conclude that this KPI does not clearly favour one methodology over the other.

One thing we noted after reviewing these results is that because these Average Size of Exceedance KPI's were so close, increasing the line limit by this amount should lead to a marked decrease in the exceedances (unless of course these averages were strongly influenced by extreme values). To investigate this, we determined that an exceedance of around 0.85 MW (or around 1 MVA) at 20kV would require an increase in the line capacity of around 50 Amperes. We therefore increased the line limit by 17 Amperes per line, and ran our simulation again, resulting in the results presented in Table 4.4.

Table 4.4: Output results for the exceedances and average size of exceedance KPI (Line Limit 117 Amperes, 99/01 Forecast Quantile).

117 Ampere LL 99/01 Quantile	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	5101	0.8052
Carousel	5130	0.7855
LIFO	5557	0.7851
MO	5900	0.7948
Pro Rata	7409	0.8039

As we can see in Table 4.4, the increase of the line limit led to a significant decrease of the # of exceedances equal to about 3000 for each methodology. However, the average size of the exceedances only changed by about 0.04 MW, leading to the conclusion that this average is very significantly influenced by extreme values. We further investigated this in Section 4.3, where we experimented with line limits up to 225 Amperes, allowing us to determine that at that point the averages have started trending down.

4.1.2. Baseline Additional Outputs

Aside from the KPI's, there are some additional outputs of interest that we believe to be valuable to include in our discussion. Firstly, we would like to visualize the difference in allocation of the various methodologies across a few representative weeks. Secondly, we included a visualisation of a full run to show what the output loading actually looks like. Finally, we also include a discussion on the measurement load that is curtailed by the allocated capacities.

Visual Comparison of Methodologies

For our visualisation of the different methodologies, we included representative four representative weeks. For spring, we included Figure 4.1. For summer, we have Figure 4.2. For fall we have Figure 4.3 and for winter we included Figure 4.4. In each figure, the different methodologies from top to bottom are LIFO, Adapted LIFO, Carousel, Mathematical Optimum and Pro Rata. In Orange we find the firm load at that time step. Please note that both the positive and negative allocated capacity is included. Each caption also mentions how many time steps from the beginning the simulation start date was shifted.

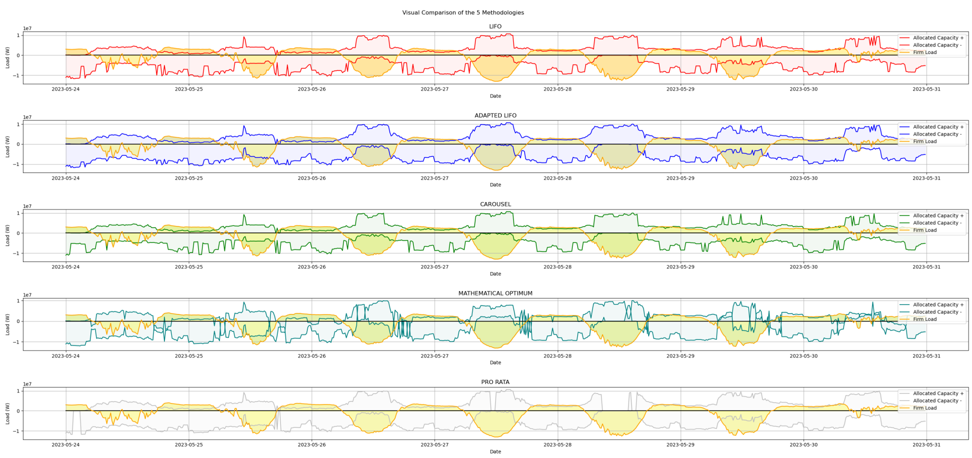

Figure 4.1: A visual comparison of the different allocated capacities per methodology for a week in May (Shifted 0 Time Steps).

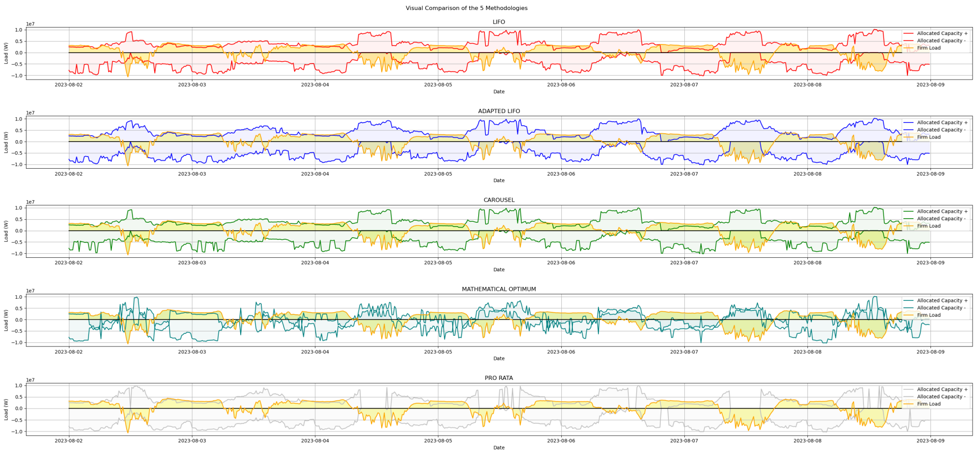

Figure 4.2: A visual comparison of the different allocated capacities per methodology for a week in August (Shifted 6720 Time Steps).

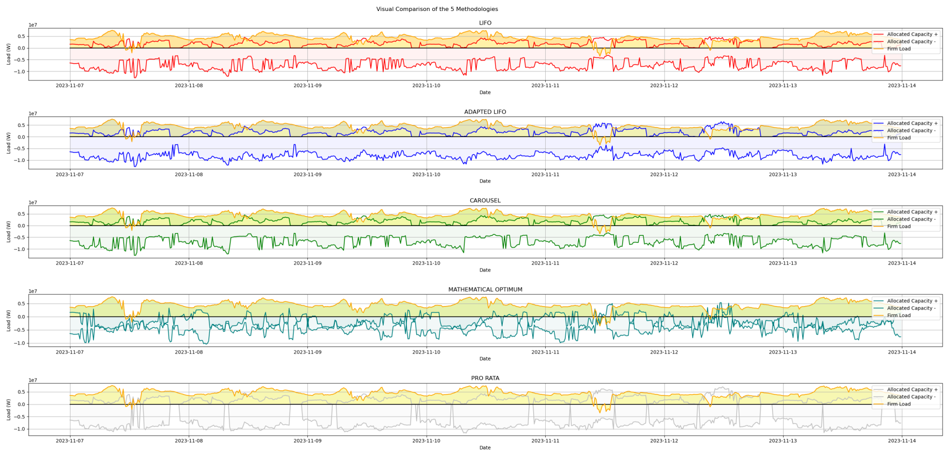

Figure 4.3: A visual comparison of the different allocated capacities per methodology for a week in November (Shifted 16032 Time Steps).

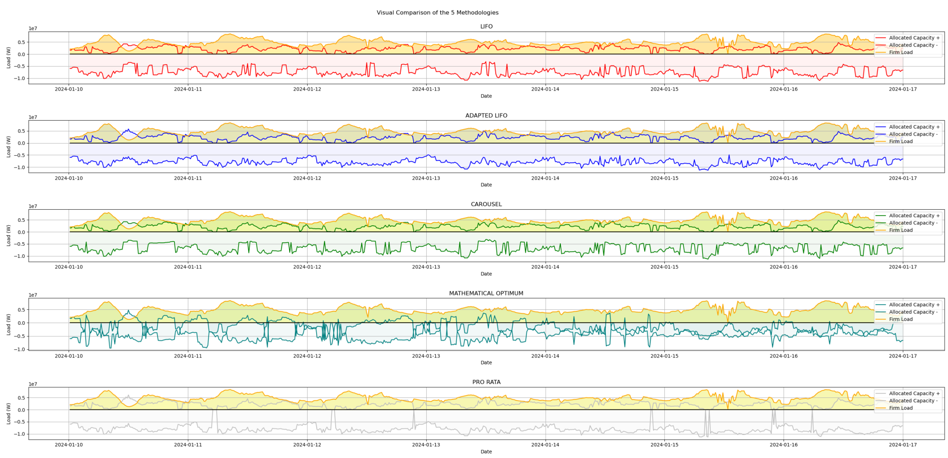

Figure 4.4: A visual comparison of the different allocated capacities per methodology for a week in January (Shifted 22177 Time Steps).

It can be seen in these figures that the differences in allocation between the various methodologies is rather significant, but all follow the pattern of the firm load. Where the latter increases in the LDN direction, we see increased allocation in the opposite ODN direction by the methodologies, some more than others. What also stands out here, is the effect the temporal aspect has on the allocated capacities. Until now, we have only spoken of the 'unused capacity' in abstract terms, not considering the fact that the available capacity might vary dramatically throughout the year. To investigate this, we collected the KPI's for the January and August run which, theoretically should be most different due to their respective distance to each other in the year. The results of this are presented in Table 4.5 and Table 4.6.

Table 4.5: Output results for a week in August (Line Limit 100 Amperes, 99/01 Forecast Quantile).

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	0.5259	0.3930	0.2339	0.2036	125.6387	33	0.7510
Carousel	0.6570	0.6410	0.2129	0.2092	146.9859	39	0.7160
LIFO	0.6528	0.5849	0.2271	0.2114	140.6505	39	0.7202
MO	0.5765	0.0949	0.1083	0.2351	117.8533	32	0.7387
Pro Rata	0.5340	2.0141e-05	0.2314	0.1857	138.6975	108	0.7684

Table 4.6: Output results for a week in January (Line Limit 100 Amperes, 99/01 Forecast Quantile).

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	0.5345	0.3610	0.1683	0.2065	122.5744	264	0.7611
Carousel	0.6388	0.6297	0.1515	0.1303	140.7072	425	0.7782
LIFO	0.6376	0.5550	0.1684	0.1523	130.5606	401	0.7775
MO	0.5816	0.0949	0.0758	0.2057	117.3692	345	0.7747
Pro Rata	0.5943	2.1479-05	0.1097	0.1939	120.4372	385	0.7743

Comparing these two tables, it becomes apparent that the number of exceedances is an order of magnitude higher for the January run. However, when comparing the rest of the KPI's, the difference between Summer and Winter seems very limited: the unallocated loads are similar, the average percentage of requested capacity are nigh identical, and the differences in allocation are also aligned. The only other noticeable difference in KPI's seems to be the standard deviation of allocation, which was consistently higher across the board in August. It is hard to draw a conclusion from these two KPI's though, as all the other parameters seem similar. We therefore find that the season, although it will influence in which direction the capacity will be primarily allocated, will not influence the KPI's across the board. We further confirmed this by running the simulation for the week before the August week shown above. This gave us the results in Table 4.7

Table 4.7: Output results for week - 1 in August (Line Limit 100 Amperes, 99/01 Forecast Quantile).

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	0.5325	0.2633	0.2613	0.1983	134.6912	241	0.8464
Carousel	0.6542	0.5630	0.2270	0.1836	150.3531	213	0.8276
LIFO	0.6492	0.5332	0.2342	0.1850	147.4474	209	0.8306
MO	0.5620	0.0955	0.1150	0.1854	124.8707	236	0.8373
Pro Rata	0.4669	2.0425e-05	0.2784	0.1279	162.4514	379	0.9103

We see that with a shift of just one week, the exceedances are similar to the ones for January in Table 4.6. We also see a significant, but smaller, shift in the standard deviation. We thus find that the influence of the time of year is not significant enough to warrant being considered an important factor in the comparison of the methodologies. This could be attributed to the methodologies all reacting similarly to increased or decreased supply and demand in the firm loading as a result of differences throughout the year.

Another point that stands out here when considering all of the tables presented above, is that the ranking of the methodologies per KPI changes quite significantly between the different runs. In Section 4.1.1 we argued that purely looking at a ranking of the methodologies based on their scores in the KPI's was insufficient. This is further reinforced now by the fact that these rankings vary significantly from week to week, making a purely quantitative analysis of which methodology is 'best' unsuitable, and underlining the need for a qualitative analysis.

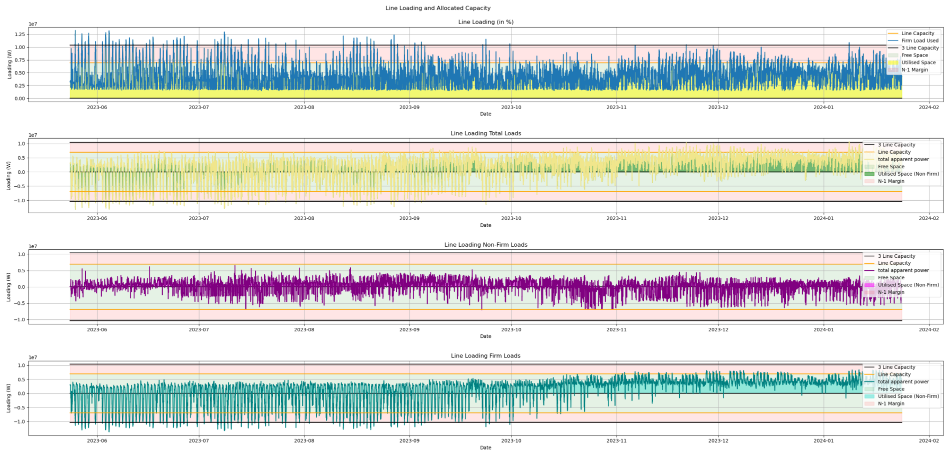

Figure 4.5: Output of a full run (Carousel) with the inputs as specified in Section 4.1.

Visualising a Full Run

In addition to zooming in on a few representative weeks, we also looked into a visualisation of the full run. The visualisation of the run is presented in Figure 4.5. This run uses the Carousel methodology, and the input parameters as specified in Section 4.1. The top graph gives the line loading as a function of the maximum capacity of the lines. The second graph takes into account the directionality of the load. The third graph is the non-firm load whilst the bottom is the firm load. The figure is also repeated in a larger format in Section A.3.

There are two key observations that can be taken from Figure 4.5. Firstly, the amount of exceedances that overshoot not only the N-1 requirement, but also the line limit that we imposed for these runs. These types of exceedances are widespread across the run, and when comparing these exceedances to the firm and non-firm load it becomes apparent that they are predominantly the result of preexisting peaks in the firm load (which already exceeded the limits of the system). This underlines one of the main limitations of our research, as we discussed in Section 3.3.2, namely that if there is sufficient capacity to accommodate these peaks in the firm load, the comparison between the methodologies is rather limited. This is because the peaks of the load are four to five times larger than the averages, leading to a lack of congestion in the system except during those extreme peak moments. Another point of note with respect to these peaks is that almost all of the exceedances above the system limit happen during the late spring, summer and early fall, where there are peaks in, what is most likely, supply from solar based generation.

Secondly, it can be observed that even with the non-firm loads in the system, there is still a significant amount of capacity available, especially if the line limits were raised to accommodate the peaks currently observed. Thus, introducing more load into the system through the use of a non-firm connection is still a real possibility, especially if it is in the form of load that is flexible i.e. an e-boiler or battery storage system.

Load Unable to be Allocated versus Load Unable to Be Used

Finally, there was one additional parameter that we believed to be valuable to discuss before we move on to the general baseline discussion. This is the Load Unable to Be Used metric, which keeps track of how much of the measurement data is cut off by the merging of the allocated capacities with the measurement data as discussed in Section 3.2.1. It thus gives us an indication how much 'real' load is curtailed because the allocated capacities were limited. Moreover, it also gives us an indication of how good the forecast is at predicting when the measurement data will be high or low, which is also a key consideration when evaluating the implementation of non-firm connection agreements. In Table 4.8 we have compared the two metrics for the five methodologies in the baseline scenario. It should be underlined that these are two separate metrics, and they can therefore not be compared one to one, rather it is important to consider that load unable to allocated is a limitation of the methodology, whilst load unable to be used is a limitation of the methodology combined with the uncertainty of the forecasts.

Table 4.8: Output results for the Load Unable to Be Allocated KPI and the Load Unable to Be Used metric (Line Limit 100 Amperes, 99/01 Forecast Quantile).

	Total Load Unable to be Allocated (MWh) (Lower is Better)	**Total Load Unable to be Used (MWh) (Lower is Better)**
Adapted LIFO	**4806.791787923881**	**1317.691038052671**
Carousel	**5229.0888**	**1308.3578916522267**
LIFO	**5297.632975419951**	**1272.3143002733113**
MO	**4431.507289008601**	**984.2069562637543**
Pro Rata	**5132.587867551674**	**1037.51370558713**

The first thing that stands out in this table is the difference between the rankings. Take for example the Adapted LIFO methodology. Whereas in the Load Unable to be Allocated column it is second best with it allocating more than 300MWh more than the next methodology, in the Load Unable to Be Used column it is last, curtailing almost 350MWh more than the Mathematical Optimum methodology. In general, we see that the priority-list based methodologies have to curtail significantly more load in the merging of the allocated capacities with the measurement data than the optimisation methodologies. This suggests to us that the latter are better at allocating capacity closer to the measurement data than the former. Furthermore, when considering that an important drawback of the Pro Rata methodology was its inability to allocate as much capacity as the rest of the methodologies, it is apparent here that the capacity it does allocate closely aligns with the measurement data. It does this with a small difference of only around 50MWh from the top methodology, Mathematical Optimum. Mathematical Optimum remains the most effective at both allocating the maximum capacity and minimising the curtailment of the measurement data.

We find that all of the points discussed above are important to consider when comparing these methodologies, as purely looking at the KPI's might not lead to the conclusions if these considerations are not taken into account. Both the effect of the temporal variation and the load unable to be used are important secondary parameters that we should consider in our final recommendations.

4.1.3. Evaluating the Baseline Results

Having reviewed all of the results we presented in this section, let us go through the key points that we should take forward.

Firstly, from the KPI's we found that the Mathematical Optimum methodology scored the most consistently, but only excelled in its ability to minimise the load that was unable to be allocated. The other methodologies all had their advantages and drawbacks, scoring better on some of the KPI's than others. When considering the three dimensions, the customer focused KPI's preferred the Mathematical Optimum and Pro Rata methodologies. For the societal oriented KPI's, Mathematical Optimum and Adapted LIFO were the top methodologies, both significantly outperforming the rest and being quite close to each other. For the grid operator relevant KPI's, the methodologies were quite close across the board, except for Pro Rata, which came in last for both KPI's.

Aside from these scores, we also reviewed four representative weeks and determined that the allocation of capacity rather closely followed the firm load, indicating a close match between the forecasted values and the measurement data. We also found that the time of year was not an important factor in our comparison of the methodologies, and that the ranking of methodologies did indeed change on a per week basis. Finally, we looked at the Load Unable to be Used metric, and found that the optimisation methodologies are a lot better at allocating capacity close to the measurement data than the priority-list based methodologies.

Concluding this section, we thus find that the Mathematical Optimum methodology provides the most consistent performance, but that each methodology provides its own set of useful traits. The comparison of methodologies based on the baseline results tells us that the 'best' methodology is significantly influenced by how one ranks the different KPI's in terms of importance and relevance.

4.2. Forecast Sensitivity Results & Discussion

As we discussed in Section 3.2, for our baseline results we relied upon the 99/01 quantile forecast, which can be argued to be a 'worst case scenario', as it will assume that both the non-firm as well as the firm loads would be significantly larger than can be reasonably expected. This decision was made because it added a degree of margin to cope with the uncertainty associated with allocating capacity based on forecasts.

However, it is therefore important to determine the effect the selection of forecast has on the output KPI's as this might significantly influence the final recommendation. The output of the sensitivity analysis, with the setup as described in Section 3.2.2 will be discussed in the next sections. In each methodology's section, we compare the average and the variance of the KPI's over the whole range of forecasts to the baseline results. The whole set of outputs will then be discussed in Section 4.2.6.

4.2.1. Forecast Sensitivity Adapted LIFO

Starting off with Adapted LIFO, Table 4.9 presents the average and variance of the set of outputs over the whole range of forecasts.

Table 4.9: Forecast sensitivity results (average and variance) Adapted LIFO (Line Limit 100 Amperes).

ADAPTED LIFO	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7416	0.3071	0.1948	0.1646	1440.4105	9475.52	0.8541
Variance	0.0121	0.0067	0.0002	0.0006	1199269.7925	382627.8896	6.4218e-05

We find that the average percentage requested capacity is significantly higher than for the baseline results, with a variance of 0.0121 % (STD ≈ 0.11%) indicating a rather low spread as well. For the difference in allocation, standard deviation and allocated capacity per unit of line loading KPI's we only see relatively small changes from the baseline results, with the former two improving slightly and the latter experiencing a minor decrease. All three have low variations indicating that these results are relatively stable across the forecasts, matching with the small difference between the average and the pessimistic forecast in our baseline.

For the Load Unable to be Allocated KPI however, a very large decrease can be seen, with the average being around 70% lower than the baseline. The variance of this result is quite significant however, which suggests that this parameter is strongly influenced by the selection of forecast. We will go into more detail on this in Section 4.2.6. The opposite effect can be seen for the # of exceedances, which are higher on average although the difference when compared to baseline is not as large as for the Load Unable to be Allocated) than the baseline results. This makes sense as the quantiles that were used to obtain the baseline results are a worst case forecast, whereas the sensitivity analysis forecasts were more optimistic on average. With respect to the spread of the exceedances, we can observe that although the variance is still large when compared to the more consistent KPI's, it is still significantly smaller than the spread of the Load Unable to be Allocated KPI, with the # of exceedances having a STD of around 600. Finally, we have the average size of the exceedance, which is quite similar to the baseline results, and a variance which is almost negligible. This indicates that although the number of exceedances is higher on average across the sensitivity analysis, the actual average size of exceedances change very little, leading us to conclude that exceedances remain relatively small.

4.2.2. Forecast Sensitivity Carousel

The Carousel results can be found in Table 4.10.

Table 4.10: Forecast sensitivity results (average and variance) Carousel (Line Limit 100 Amperes).

CAROUSEL	% of Requested Capacity (Higher is Better)	% Difference in Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7945	0.0731	0.2297	0.1514	1510.3730	10195.96	0.8451
Variance	0.0084	0.0012	0.0014	0.0003	1448569.8104	305641.7983	3.6345e-05

Similarly to Adapted LIFO, we see that the average value over the forecast for the first 3 KPI's is improved over the baseline results for the Carousel methodology. The variance is even smaller for the average allocated capacity and relative allocated capacity, whilst the variance for the standard deviation is slightly higher. As will be seen from the next methodologies, this pattern will hold true across the board, with significant improvement in the first three KPI's and low variances. Carousel also sees the same dip in the allocated capacity per unit of line loading, which we attribute to the additional allocated load being transported upstream as opposed to meeting demand or supply locally, which we found to be the case in the baseline. Finally, the same pattern with respect to the Load Unable to be Allocated is also true here. A significant increase, but with a high variance, suggesting this KPI to be very sensitive to the forecast quantiles. The # of exceedances for Carousel are actually significantly higher compared to both the baseline Carousel value as well as the Adapted LIFO value, indicating that this methodology is less capable of allocating capacity around peak firm load moment then Adapted LIFO. The average size of the exceedance, remains very close to the baseline, and has a low variance indicating this KPI to be relatively stable across the forecasts.

4.2.3. Forecast Sensitivity LIFO

Once again, we find the results of the sensitivity analysis for LIFO in Table 4.11.

Table 4.11: Forecast sensitivity results (average and variance) LIFO (Line Limit 100 Amperes).

LIFO	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.8104	0.3607	0.1669	0.1461	1533.9141	10501.82	0.8425
Variance	0.0065	0.0127	0.0006	0.0002	1537839.7575	165298.1076	4.2877e-05

The same findings as previously described for Carousel and Adapted LIFO hold true here, with improvements across the board, except for the number of exceedances and the allocated capacity per unit of line loading KPI's. What is interesting to note however, is that the variance of the difference in allocation is an order of magnitude larger for LIFO than for the other two priority-list based allocation schemes. This variance translates to a STD of around 0.11 percent, indicating that the difference in allocation for LIFO (which is already the worst performing methodology for this KPI to start with) is also rather sensitive to the selected forecast. The opposite is true for the number of exceedances, where the LIFO variance and associated STD ($\approx$ 400 exceedances) is lower and thus more predictable across the forecasts. Finally, whereas in the baseline LIFO scores the worst on the Total Load Unable to be Allocated KPI, the average value seems to be trending closer towards the other methodologies, as the forecast becomes more optimistic.

4.2.4. Forecast Sensitivity Mathematical Optimum

The results for the forecast sensitivity analysis for the Mathematical Optimum methodology can be found in Table 4.12.

Table 4.12: Forecast sensitivity results (average and variance) Mathematical Optimum (Line Limit 100 Amperes).

MO	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7906	0.044	0.1378	0.1567	1388.5058	10292.64	0.8454
Variance	0.0098	0.001	0.0002	0.0006	1024193.3317	261015.9104	4.1562e-05

Aside from the same finding that could be made about the previous three methodologies, a couple of things stand out for the Mathematical Optimum methodology in the sensitivity analysis.

Firstly, we can see the gap between it and the top values for the average allocated capacity percentage KPI closing significantly. This suggest to us, as the forecast becomes more optimistic. the methodologies start reaching a plateau, where the differences between them start to reduce. This is in line with the assumption we made about the line limit in Section 3.3.2, where we found that as the congestion in the system reduced, so did the difference between the methodologies. This same line of thinking also hold true for the Total Load Unable to be Allocated KPI, where the Mathematical Optimum methodology held a significant advantage in the baseline, the advantage start to diminish across the forecasts.

Secondly, as opposed to the other three methodologies already discussed, MO actually sees an increase in its standard deviation of allocation. The cause of this increase seems unclear, as the other methodologies' improvement in this KPI are also significantly larger when compared to the baseline. From this, we conclude that the MO methodology finds itself at the bottom of the possible values for this KPI. This can also be observed in Table 4.16 below, where we presented the results of the 45/55 (LDN/ODN) forecasts, and where it can be seen that all of the methodologies start reaching these bottom values of this KPI.

4.2.5. Forecast Sensitivity Pro Rata

Finally, we have the results of the Pro Rata forecast sensitivity analysis in Table 4.13.

Table 4.13: Forecast sensitivity results (average and variance) Pro Rata (Line Limit 100 Amperes).

Pro Rata	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7794	9.7689e-06	0.1936	0.1492	1537.6538	10972.84	0.8569
Variance	0.0104	3.8024e-11	0.0005	0.0004	1327586.2655	179984.3344	0.0002

We once again see the same results as described for the other methodologies, with improvements for all the KPI's but the allocated capacity per unit of line loading and the # of exceedances KPI's. With respect to the latter, it can be observed that the same pattern that was mentioned above on the plateauing of the results is especially apparent here. Whereas the other methodologies see a significant increase in their # of exceedances, the average # of exceedances for Pro Rata across the forecasts is only slightly higher than in the worst-case scenario we simulated for the baseline results. Although Pro Rata still performs the worst, the difference between it and the other methodologies is significantly smaller, mitigating the detriment this has to its position in the comparison. Once again, this is also reflect in its variance, which is rather low when compared to the other methodologies, except for LIFO, which also has the same low spread in its # of exceedances. LIFO does this with a difference between the average and the baseline that is twice as high as that for Pro Rata, underlining the latter's relative improvement in this KPI for our comparison.

4.2.6. Evaluating the Forecast Sensitivity

Bringing the results from all of the methodologies together, we compiled Table 4.14, which gives the average values of the KPI's for each methodology over the range of forecasts simulated.

Table 4.14: Forecast sensitivity results (averages) for all methodologies (Line Limit 100 Amperes).

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	0.7416	0.3071	0.1948	0.1646	1440.4105	9475.52	0.8541
Carousel	0.7945	0.0731	0.2297	0.1514	1510.3730	10195.96	0.8451
LIFO	0.8104	0.3607	0.1669	0.1461	1533.9141	10501.82	0.8425
MO	0.7906	0.044	0.1378	0.1567	1388.5058	10292.64	0.8454
Pro Rata	0.7794	9.7689e-06	0.1936	0.1492	1537.6538	10972.84	0.8569

Reviewing these results, and comparing them to Table 4.1, we can observe that although the values changed, the rankings stayed identical for the most part. The only major change occurred in the Total Load Unable to be Allocated KPI, where we now find Pro Rata at the bottom of the rankings, but the differences between them are a lot smaller.

As discussed extensively now, the results of the forecast sensitivity analysis can be summarized as a positive improvement for most KPI's, with a slight deterioration for the Allocated Capacity per unit of Line Loading and # of exceedances KPI's. Although the number of exceedances was significantly higher than for the baseline results, the total load unable to be allocated was around 70% lower, indicating that our worst-case forecast gave a significant over-estimation of the loads. Therefore, we generated outputs for two more forecast quantiles: an optimistic forecast, with 45th and 55th quantile (LDN/ODN) and a more balanced 70/30 quantile forecast. The outputs of these runs are presented in Table 4.15 and Table 4.16 below.

Table 4.15: Outputs for the 70 LDN / 30 ODN forecast for all methodologies (Line Limit 100 Amperes).

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	0.7697	0.3100	0.2093	0.1585	969.2504	9463	0.8444
Carousel	0.8189	0.2295	0.2295	0.1493	973.7193	10477	0.8379
LIFO	0.8246	0.3485	0.1782	0.1473	972.5967	10778	0.8359
MO	0.8191	0.0341	0.1569	0.1498	951.6272	10218	0.8370
Pro Rata	0.7948	7.7773e-06	0.2331	0.1426	1085.0600	10982	0.8552

Table 4.16: Outputs for the 45 LDN / 55 ODN forecast for all methodologies (Line Limit 100 Amperes).

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	0.9158	0.1323	0.1612	0.1192	232.0383	10482	0.8480
Carousel	0.9365	0.0352	0.1531	0.1130	232.0385	10845	0.8437
LIFO	0.9438	0.1439	0.1168	0.1125	232.0383	10501.82	0.8449
MO	0.9395	0.006	0.1125	0.1108	231.7576	10876	0.8433
Pro Rata	0.9383	3.0524e-06	0.1277	0.1101	240.1426	10933	0.8456

When comparing these results to the outputs in Table 4.1, we see a significant improvement in most KPI's, with higher scores for the requested capacity percentages, lower differences between the loads as well as more consistent and predicable allocation. Most of all, the total load unable to be allocated is significantly lower for all of the methodologies, indicating that as the forecasts get more optimistic, more and more capacity can be allocated. The only two KPI's that seem to be lower across the board on average are the # of exceedances and the allocated capacity per unit of line loading. For the latter, this might indicate the system was allocating capacity which would have been used to balance out local demand or supply with the pessimistic forecast, whilst now the lines are being used more intensely leading to a reduction in the relative efficiency. With respect to the former, we believe that this increase for the most part can be attributed to the fact that the increase in allocated capacity is distributed evenly over the run, leading to certain time steps, which previously were very close to the limit, now being over the limit. This is supported by the fact that average size of the exceedance barely increased for the various methodologies, as this suggests that the average is still strongly influenced by extreme values rather than an overall increase in the exceedances across the board.

However, the reduction in unallocated load might only be occurring because the load was being curtailed at the merging of the allocated capacities and the measurement data. We therefore also investigated the Load Unable to Be Used metric, resulting in the outputs presented in Table 4.17. This table could then be compared to Table 4.8 to determine how much additional capacity had to be curtailed with the more optimistic forecast.

Table 4.17: Output results for the Load Unable to Be Allocated KPI and the Load Unable to Be Used metric for the 45/55 (LDN/ODN) quantile (Line Limit 100 Amperes).

	Total Load Unable to be Allocated (MWh) (Lower is Better)	Total Load Unable to be Used (MWh) (Lower is Better)
Adapted LIFO	232.0383	1238.9168
Carousel	232.0385	1201.9620
LIFO	232.0383	1201.7835
MO	231.7576	1187.5424
Pro Rata	240.1426	1192.4259

Surprisingly, the total load unable to be used is actually lower for all methodologies priority-list based methodologies, and only around 15-20% higher for the optimisation based methodologies. This indicates that the higher allocation occurring with the more optimistic forecast run, is taking place for the most part at time steps where there was still available capacity left. Even the increase in load unable to be used for the optimisation based methodologies is relatively little when considering that they were able to allocate between 4000 to 5000 MWh more, making the increase of around 150 to 200 MWh relatively minor.

From the forecast sensitivity analysis we can thus take away the following conclusions. Firstly, because the baseline simulation uses a worst-case forecast, it significantly overestimates the firm load, leading to an excessive reduction in the allocated capacities. This was further confirmed by the fact that the merging of the allocated capacities with the measurement data for the most optimistic scenario included (45/55 LDN/ODN) led to a Total Load Unable to be Used that was actually lower across all methodologies. This improvement in results was also true for the allocated percentage of requested capacity, difference in allocation percentage and standard deviation of load allocation KPI's, which saw significant, but smaller positive changes. The only KPI's which were lower on average were the allocated capacity per unit of line loading and the # of exceedances KPI's. With respect to the latter, this increase made sense as the more optimistic forecast led to increases in allocation across the board, pushing certain time steps which were near to the limit over. However, an important consideration to add to this was the lack of significant change in the average size of the exceedance, suggesting that this value was mostly the result of extreme values.

Secondly, with respect to the comparison of the methodologies, the rankings changed very little, with Mathematical Optimum still being the most consistent methodology across the board. The other methodologies further solidified their positions in excelling at certain KPI's whilst achieving underwhelming results for others. One thing that should be noted is that the relative position of the Pro Rata methodology did improve as its KPI's were much closer to the other methodologies, especially in those areas were it previously scored insufficiently like the # of exceedances and the allocated percentage of requested capacity KPI.

4.3. Line Limit Sensitivity Results & Discussion

Just like with the forecasts, the selection of line limit is an important parameter when comparing the methodologies. As we discussed in Section 3.3.2, we selected the line limit on the basis of retaining sufficient variation between the different methodologies, whilst keeping the load that is unable to be allocated, as well as the number of exceedances within reason. To determine the effect of this choice, we performed a sensitivity analysis of the line limit input parameter, the results of which we can now review in this section.

Once again, the average and variance per KPI is discussed in each methodology's subsection, followed by a general discussion of the rankings in Section 4.3.2. The sensitivity analysis ran from a line limit of 75 Amperes all the way up to 220 Amperes, in steps of 5 Amperes.

4.3.1. Line Limit Sensitivity Results

Below, we find the limit results for the five methodologies. First, we have Adapted LIFO in Table 4.18, followed by Table 4.19 presenting the Carousel results, after which we have LIFO in Table 4.20. Next there is Mathematical Optimum in Table 4.21 and finally we have Pro Rata in Table 4.22.

Table 4.18: Line Limit sensitivity results (average and variance) Adapted LIFO (Forecast Quantiles 99/01).

Adapted LIFO	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.6900	0.3330	0.2040	0.2791	2851.7749	3969.3667	0.7813
Variance	0.0230	0.0056	0.0012	0.0071	3030450.7092	16943463.6322	0.0041

Table 4.19: Line Limit sensitivity results (average and variance) Carousel (Forecast Quantiles 99/01).

CAROUSEL	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7465	0.1041	0.2455	0.2615	3055.2371	4150.8667	0.7723
Variance	0.0198	0.0052	0.0029	0.0088	3600708.3206	21039037.2489	0.0031

Table 4.20: Line Limit sensitivity results (average and variance) LIFO (Forecast Quantiles 99/01).

LIFO	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7588	0.4338	0.1755	0.2550	3121.7956	4379.5333	0.7683
Variance	0.0151	0.0153	0.0022	0.0107	3718753.8022	24782891.6489	0.0026

Table 4.21: Line Limit sensitivity results (average and variance) Mathematical Optimum (Forecast Quantiles 99/01).

MATHEMATICAL OPTIMUM	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7308	0.0727	0.1231	0.2764	2698.8431	4402.7333	0.7768
Variance	0.0232	0.0005	0.0001	0.0063	2522721.4265	19463822.8622	0.0032

Table 4.22: Line Limit sensitivity results (average and variance) Pro Rata (Forecast Quantiles 99/01).

Pro Rata	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Average	0.7223	1.1733e-05	0.1751	0.2635	3031.3557	5146.3333	0.7824
Variance	0.0322	3.5611e-11	0.0022	0.0078	3699147.3451	25880515.6889	0.0049

We once again see that the average value of the allocated percentage of requested capacity KPI is on average higher than in the baseline results. The relatively high variation (e.g. STD ≈ 0.15 for Adapted LIFO) does indicate that this parameter varies significantly depending on the line limit. The difference in allocations is also slightly lower, and has a low variation associated with it as well, indicating that the difference between the average and the baseline values are relatively insignificant. For the standard deviation of allocation, we also see a minor improvement, with a very low variation, indicating that an increasing line limit should also slightly improve the predictability of allocation. All three of these KPI's were found to improve on average with more optimistic forecasts, but do so to a lesser extent with an increasing line limit.

What is in contrast to the forecast sensitivity results is the noticeable uptick in the average allocated capacity per unit of line loading, which was lower on average for the forecasts. This KPI is almost 50% higher on average when compared to the baseline results, with a STD of only 0.08. Thus, as the line limit increases, the allocated capacity increases even quicker. This is in contrast to our findings from the forecast sensitivity analysis, where we speculated the decrease there might be attributable to more of the load going upstream. We now find that the more likely explanation is that as the forecast becomes more optimistic, the allocated capacity goes up without an equivalent capacity improvement of the lines, leading to increased loading. This is not true when raising the line limit as, inherently, the increased available capacity of the system is matched by an increase in the capacity of the lines. We can therefore hypothesize that this KPI is not only a measure of how efficiently the system allocates capacity, but also of how much capacity the lines still have available.

With respect to the next KPI, the Total Load Unable to be Allocated, we see a similar improvement as for the other KPI's., but with a high variation (e.g. STD ≈ 1750MWh for Adapted LIFO). This makes sense as the increase in line capacity is directly correlated to how much capacity can be allocated. We also note that is improvement is smaller than the one we saw in the forecast sensitivity analysis, suggesting that both parameters are key when evaluating the most efficient way of allocating capacity.

With respect to the # of exceedances, we see a large drop of over 50%, which is sizeable, especially when compared to the result we found for the forecast sensitivity analysis. This result has a very high variation however, with a STD ≈ 4000. This suggests that the low value of the average number of exceedances is significantly influenced by extreme values at the ends of the line limit range, which is in line with our findings in Section 3.3.2. There we observed that the difference between the methodologies tended to peter out after increasing the line limit beyond around 150 Amperes, indicating that at this point, the number of exceedances was very low. The same can be concluded when reviewing a full run in Section A.3, where the exceedances all seem to be of relatively equal magnitude. We thus find that the low number of exceedances found here are caused by the segment at the upper limits of the line limit range, which significantly drop the averages. This is reinforced by the average size of the exceedances KPI, which has remained quite close to the baseline value. The exceedances in our line limit sensitivity analysis are therefore mostly present in the lower line limits, which pull down the averages, as the higher line limits have fewer exceedances to contribute to the average.

4.3.2. Evaluating the Line Limit Sensitivity

Taking the averages of the different methodologies together, we arrive at the resultant rankings as presented in Table 4.23.

Table 4.23: Line Limit sensitivity results (averages) for all methodologies (Forecast Quantiles 99/01).

	% of Requested Capacity (Higher is Better)	% of Relative Allocated Capacity (Lower is Better)	Standard Deviation of Allocation (Lower is Better)	Allocated Capacity /% Line Loading (Higher is Better)	Total Load Unable to be Allocated (MWh) (Lower is Better)	# of exceedances (Lower is Better)	Average size of exceedance (Lower is Better)
Adapted LIFO	0.6900	0.3330	0.2040	0.2791	2851.7749	3969.3667	0.7813
Carousel	0.7465	0.1041	0.2455	0.2615	3055.2371	4150.8667	0.7723
LIFO	0.7588	0.4338	0.1755	0.2550	3121.7956	4379.5333	0.7683
MO	0.7308	0.0727	0.1231	0.2764	2698.8431	4402.7333	0.7768
Pro Rata	0.7223	1.1733e-05	0.1751	0.2635	3031.3557	5146.3333	0.7824

When comparing these rankings with Table 4.1 and even Table 4.14, it stands out that the rankings remain very similar. Compared to the baseline, the Adapted LIFO and MO methodologies switch places in the Allocated Capacity per Unit of Line Loading KPI and the LIFO and MO methodologies switch places in # of exceedances, but due to the small difference in both these instances we would argue this change to be negligible.

Overall, the findings of the baseline results still stand therefore, with Mathematical Optimum remaining the most consistent performer on average across the different line limits. We also find that the sensitivity of the KPI's to the line limits is markedly less than their sensitivity to the selected forecast for the most part, with only the average size of the exceedances and the allocated capacity per unit of line loading KPI's seeing a larger shift. This indicates that even in a part of the grid with high congestion, selection of the appropriate forecast probability quantiles for allocating capacity is critical.

4.4. General Discussion

Now that we have presented all of the results, and discussed them one by one, we will reflect on the meaning of these results, and what the main takeaways are.

Firstly, we compiled multiple rankings of the methodologies and observed that the differences between them varied significantly depending on the input parameters, as well as across the KPI's. We would like to call back to our discussion in Section 3.3.1, where we argued that there is no such thing as the 'best' methodology, but rather that the selection of methodology is heavily influenced by the preferences of KPI's that one takes. For example, although the Mathematical Optimum methodology was mentioned to be the most consistent repeatedly, it also scored consistently average on both the average allocated percentage of requested capacity, as well as the number of exceedances. Both of these KPI's are important to multiple stakeholders in this system, with the problem owner, the grid operator, being heavily invested in keeping the latter of the two as low as possible. Furthermore, as we already touched upon earlier, these non-firm connections cannot be considered in a vacuum, and must always be compared to the alternatives that are available. In Figure 2.1 in chapter 2, we already identified the plethora of alternative congestion management methods, all of which have their own advantages and trade-offs. Therefore, leaning into one of the aspects of non-firm grid connections, like for example the proportionality of Pro Rata or the guarantee of future preference of LIFO, can be the difference between a non-firm ato being an attractive product, and being an edge solution looking for a problem. Thus, when evaluating the various KPI's, we should remember to also evaluate them individually, rather than abstracting them into the 'best' or 'worst' across all KPI's.

Secondly, in this chapter, we found a host of interesting results which did not seem readily apparent at the beginning of the research:

- The number of time steps of the Carousel methodology does not significantly influence its standard deviation of allocation.
- The average size of the exceedances KPI was significantly influenced by extreme values.
- The variation of the allocated capacities across the different seasons matches the variation in firm load.
- The variation of the KPI's between different seasons is negligible however.
- We found that some of the exceedances that can be observed during a full run exceed even the system limit, whilst still having a large amount of unused capacity in the system between peaks.
- We also found that the priority-list based methodologies' advantage in total load unable to be allocated is largely nullified by their inadequate performance on the Total Load Unable to be Used metric, indicating that the capacity they might have allocated more actually remains unused after merging with the measurement data. The optimisation based methodology on the other hand score significantly better here.
- We initially speculated that the decrease in the average scores for the allocated capacity per unit of line loading KPI in the forecast sensitivity analysis to be due to a less efficient matching of demand and supply inside the system as the Total Load Unable to be Allocated went down.
- In the line limit sensitivity analysis we found that this was only partially true however, as the decrease in Total Load Unable to be Allocated that was matched with an increase in line limit actually led to an improvement in the Allocated Capacity per Unit of Line Loading.
- We also found that the average number of exceedances was significantly lower than the baseline results, suggesting a consistent decrease with increasing line limit. However, the large variance of this KPI suggest that this was not the case but rather that the number of exceedances was relatively constant up till a certain line limit, at which point they dropped greatly to a very low value leading to a lower average. This was confirmed by the visualisation of the full run, where it could be seen that most of the exceedances were rather similar in magnitude.
- Another supporting result to this conclusion was the fact that average size of the exceedances barely dropped when compared to the baseline results, indicating that there were a lot of line limits where the number of exceedances were next to zero.

Finally, as mentioned above we also performed sensitivity analyses for both the forecast inputs as well as the line limit parameter.

From the forecast sensitivity analysis we concluded that the pessimistic forecast that was used in the baseline scenario led to a significantly lower score for most of the KPI's, with the only exception being the allocated capacity per unit of line loading, as well as the number of exceedances. The latter of which was relatively stable across the forecasts however, indicating that this was not so much a feature of the optimistic forecasts but rather that the pessimistic baseline forecasts was able to slightly reduce the number of exceedances. For all of the other KPI's, performance improved significantly. This was most noticeable in the Total Load Unable to be Allocated KPI, which saw an average value across the forecasts which was around 70% lower than the baseline, a marked improvement. To ensure this improvement was not at the expense of the Total Load Unable to be Used (which would indicate that the extra allocated capacity was actually just curtailed during the merging of the allocated capacities and the measurement data) we also investigated that metric for the most optimistic of our forecasts (which should have the highest values). To our surprise, this metric was also on average lower than in the baseline, indicating that the use of a pessimistic forecast consistently lead to an under allocation of capacity whilst only slightly reducing the number of exceedances.

Aside from this consideration, we also found that the ranking of the different methodologies did not change noticeably. The only major difference of note was that the methodologies on average laid closer to each other than in the baseline results.

For the line limit sensitivity, a similar analysis was performed. Just like with the forecasts, we found that the average values of most KPI's were improved when compared to the baseline results. However, the high variance of the various KPI's indicated that these did change significantly as the line limit changed. Furthermore, the improvement for all KPI's but one was smaller than the improvement for the forecasts. The one except was the number of exceedances, which was heavily influenced by extreme values as mentioned above.

Similarly to the forecast sensitivity analysis, the ranking of the methodologies did not change appreciably, with the differences between the methodologies becoming smaller.

Our overall takeaways from the sensitivity analysis therefore were that our baseline results are relatively sensitive to these input parameters, but that our comparison between the methodologies still holds water across the board.

5
Conclusions & Recommendations

We now arrive at the final chapter of this thesis, where will discuss the conclusion and recommendations of our work. In Section 5.1 we will revisit our research gap and the associated research question, after which we discuss the relevant answers that we identified in our research. This is then followed in Section 5.2 by a discussion of the relevant recommendations that we identified with regards both to our own work as well as implications with respect to the larger topic of grid congestion. Finally, we will also reflect on our work and try to identify the limitations and shortcomings of our research, as well as discussing recommendations for future research.

5.1. Conclusions

In the beginning of our work, we introduced how the current energy transition is leading to increasing levels of grid congestion on the Dutch electricity network. As a consequence of this congestion, we discussed how many important societal projects like the electrification of industry and the expansion of the housing stock are being significantly hindered. To deal with this congestion, grid reinforcement was identified as the most straightforward and effective long-term solution. However, due to the large investment as well as the long throughput time required to implement grid reinforcement, this solution would not become effective in the near future, requiring other avenues of alleviating congestion. An important way of achieving this was through the use of flexibility, allowing for more efficient grid utilisation and the adjustment of consumption and supply to the available capacity on the network. We found four way of achieving this flexibility: a rules-based approach, network tariffs, market based procurement and finally through the use of non-firm connection agreements. Our research focused on non-firm connection agreements, where the grid operators dynamically allocates capacity to these connections based on the available capacity in the network. One of the key aspects of this method of procuring flexibility however is the manner in which the available capacity is divided among the non-firm grid connections. This brought us to our research gap:

There is a lack of exploration into the implication of different priority schemes for the allocation of capacity among non-firm connection agreements in the context of distribution grid congestion.

From this followed our research question:

“What strategies and mechanisms can be employed by grid operators to efficiently allocate and distribute the available capacity among non-firm grid connection agreements (ATO) in the distribution grid, ensuring fair treatment of customers whilst improving grid utilisation?”

We split this research question into five sub-questions, as formulated below:

- SQ1: What mechanisms have been devised for allocating capacity in the context of non-firm grid connection agreements?
- SQ2: How can we measure the performance of these different mechanisms to ensure fair treatment of customers and improving grid utilisation?

- SQ3: How do the different mechanisms score on these measures when compared to each other?
- SQ4: What is the effect of the forecast uncertainty in these results?
- SQ5: What are the implications of this comparison for grid operators when selecting their approach to dividing non-firm capacity among connected parties?

The answer to the first two sub-questions were obtained from our review of the state-of the art literature. For the first sub-question, we found a host of methodologies for distributing the available capacity among non-firm grid connections. From these, we selected the following five.

- **Mathematical Optimum (MO:** The Mathematical Optimum methodology formulates the capacity allocation as an optimisation problem and tries to allocate highest possible total capacity.
- **Last In, First Out (LIFO):** The LIFO methodology allocates capacity in order of the age of the connection. The longer a non-firm grid connection has been connected, the higher in the allocation order it will be.
- **Adapted LIFO:** Adapted LIFO is similar to LIFO but takes into account the topology of grid as an additional factor combined with age, prioritising higher voltage connections.
- **Rota/Carousel:** A similar priority-list based methodology which rotates the priority order on a fixed time schedule, ensuring all connections are at the front of the list at least some of the time.
- **Pro Rata/Proportional:** An adaptation of the MO methodology, Pro Rata also tries to optimise the allocated capacity but adds the additional constraint that the allocated percentages are proportional.

These five methodologies were selected based on their real-life application and their feasibility in being implemented in our model. Each of these methodologies is formulated with a specific goal in mind, with for example LIFO being the most effective at keeping the non-firm grid connection effective for existing customers when more are added, whilst Pro Rata prioritises the ’fairness’ of the allocation.

To determine the effectiveness of these methodologies in order to compare them, we once again drew on the available literature and came up with three primary dimensions of relevance for these methodologies. These are customer-focused (fairness), societal focused (grid utilisation) and grid operator focused (grid performance) measures of effectiveness. Based on these three dimensions, the following Key Performance Indices (KPI’s) were obtained:

- **Fairness**
  - How much do the connected parties get to use their requested capacity (as a % of requested capacity)
  - How much do the connected parties get with respect to each other (difference in % of highest allocated vs lowest allocated requested capacity)
  - How predictable is the allocation of capacity (the variance of the allocation of capacity)
- **Grid Utilisation**
  - How much is the total capacity of the grid used more when compared to the base scenario per allocated unit of capacity (average load allocated (MWh) per % loading increase of lines)
  - How much total load/demand is unable to be allocated (sum of capacity unable to allocated in MW/MWh)
- **Grid Performance**
  - How regularly does the allocated capacity still have to be curtailed in the real time operation of the grid (# of exceedances)
  - And to what extent does the allocated capacity need to be curtailed (average size of exceedance (MW))

With this combination of methodologies and KPI's, we then performed an experimental case study on a substation operated by the DSO Liander in order to answer the other three sub-questions. In our case study, the source of congestion was a lack of capacity on the upstream lines to the grid supply point. The core components were as follows:

- A 20kV bus, to which one customer is connected.
- 3 lines from the 20kV bus to the upstream network grid supply point, which is considered the 'source' in our case study.
- Two 10kV busses (A and B), with 6 and 4 customers connected respectively.
- 2 Transformers, which each connect one of the 10kV busses to the 20kV bus.

Four of these customers were considered non-firm, and the other 7 were considered firm connections. The amount of capacity in the system was determined based on the line limit that was chosen for the three upstream lines. The allocation of capacity was based on forecasts generated based on the measurement data for the loads in the period from May 2023 to January 2024.

We found that the Mathematical Optimum methodology scores the most consistently across the KPI's, but that each of the methodologies excels at a set of KPI's, leading us to the conclusion that the 'best' methodology is highly dependent on the priority one gives to the different KPI's.

We found that the Adapted LIFO methodology balanced the societal and grid operator dimensions, scoring a low 'load unable to be allocated' and '# of exceedances' KPI and a high 'allocated capacity per unit of line loading' KPI. Carousel on the other hand scored highly on the '# of requested capacity' KPI whilst having a significantly lower difference between the allocation of different loads KPI when compared the other two priority-list based methodologies. LIFO scored the highest on the average percentage of requested capacity, indicating its effectiveness for existing non-firm connections even with more non-firm loads connected. Mathematical Optimum scores the most consistently across all KPI's and is able to allocate the highest amount of total capacity. Finally, Pro Rata ensures the 'fairest' outcome, and does this in a predictable fashion with a low standard deviation of allocation.

Furthermore, we observe that the differences between the methodologies is rather small at times, indicating that other methodologies could achieve similar performance for certain KPI's. We found that these rankings did stay relatively similar throughout the year, indicating that, at least for the baseline conditions, the results are relatively consistent.

Aside from these main findings, we also investigated the impact of our selection of baseline conditions. Namely, we performed a sensitivity analysis for the selected forecast probability, as well as a sensitivity analysis of the line limit of the upstream lines.

We found that although the average values of the KPI's across the sensitivity analyses are significantly higher than in the baseline conditions, the actual ranking between the methodologies remain quite consistent, and each methodology scores well on their own respective set of KPI's.

We thus conclude that although our baseline conditions assume a worst-case scenario both with regard to the forecasted loads as well as the capacity available on the system (line limit), the comparison and the associated analysis still hold true.

Aside from these primary findings, we also found the following secondary findings:

- The number of time steps of the Carousel methodology does not significantly influence its standard deviation of allocation.
- The average size of the exceedances KPI was significantly influenced by extreme values.
- The variation of the allocated capacities across the different seasons matches the variation in firm load.
- The variation of the KPI's between different seasons is negligible however.
- We found that some of the exceedances that can be observed during a full run exceed even the system limit, whilst still having a large amount of unused capacity in the system between peaks.

- We also found that the priority-list based methodologies' advantage in total load unable to be allocated is largely nullified by their inadequate performance on the Total Load Unable to be Used metric, indicating that the capacity they might have allocated more actually remains unused after merging with the measurement data. The optimisation based methodology on the other hand score significantly better here.
- We initially speculated that the decrease in the average scores for the allocated capacity per unit of line loading KPI in the forecast sensitivity analysis to be due to a less efficient matching of demand and supply inside the system as the Total Load Unable to be Allocated went down.
- In the line limit sensitivity analysis we found that this was only partially true however, as the decrease in Total Load Unable to be Allocated that was matched with an increase in line limit actually led to an improvement in the Allocated Capacity per Unit of Line Loading.
- We also found that the average number of exceedances was significantly lower than the baseline results, suggesting a consistent decrease with increasing line limit. However, the large variance of this KPI suggest that this was not the case but rather that the number of exceedances was relatively constant up till a certain line limit, at which point they dropped greatly to a very low value leading to a lower average. This was confirmed by the visualisation of the full run, where it could be seen that most of the exceedances were rather similar in magnitude.
- Another supporting result to this conclusion was the fact that average size of the exceedances barely dropped when compared to the baseline results, indicating that there were a lot of line limits where the number of exceedances were next to zero.

To return to the research question then, we can then finally answer the last sub-question. Our findings suggest that the methodology used by the grid operator to allocate the available capacity across non-firm connections does actually significantly influence the outcome of the system, and depending on which metrics the grid operator values, the most effective methodology will vary. This conclusion remains true across different levels of congestion in our considered system, as well as the forecast uncertainty that is accepted.

This conclusion does need to be put in its proper context however, as these findings were developed for a very specific case study. There are therefore a few considerations that need to be taken into account when evaluating which methodology works best.

Firstly, in the selected case study the primary limitation of the system leading to congestion was the capacity of the lines to the grid supply point, which was selected with an eye to achieving a relatively simple system limitation. However, in reality the limitation on congested system can be due to a host of reasons, ranging from voltage constraints to transformer overloading to even limitations in the circuit breakers or other safety equipment in the system. Thus, whereas in our research we were able to optimise or design towards a single limitation, in a real system, there would be multiple boundaries which need to be taken into account, which could significantly influence how each methodology performs. To give a specific example of this, in a system where voltage constraints lead to a specific line consistently being unable to be allocated capacity, a methodology like Pro Rata would need to be significantly adapted or risk being useless. Therefore, we argue that the comparison methodologies is primarily functional in its analysis, and that any holistic takeaways need to be avoided.

Secondly, we noticed in our research that the forecast has a significant effect on the performance of the methodologies. Due to the way we designed our research, our forecasts were generated based on back-casting measurement data, which by definition is impossible for real life grid operations. We noticed in our results that the forecasts had a significant impact on the outputs, and that the selection of a more optimistic or pessimistic forecast could significantly affect the differences between the methodologies (although, as mentioned above, the ranking remained similar). In reality, generating a forecast that matches the average loading on the system seems feasible, however generating a forecast that accurately predicts the peaks in the loading on the system is a lot harder. Predicting these peaks is important for the allocation of capacity among non-firm loads, as these moments are the primary instances in which little, if any, load can be allocated. It is thus important to consider when reviewing our conclusions that these were found in a system where the forecasts were generated based on the measurement data, leading to an improved ability to forecast the peaks in the system loading.

Finally, we performed our research on a simplified case study, which consisted only of busbars and a couple of transformers. In reality, substations where these methodologies might be applied will consist of more components, which will have an effect on how the methodologies perform. For example, there might be lines with multiple loads connected to them (think of a street for example), which requires the methodologies to take into account spatial location and additional constraints. Furthermore, as substations get more complex, methodologies which are simpler (like Carousel or LIFO) might become more attractive due to their straightforwardness and transparency, both to customers and to grid operators. It is therefore important to underline once again, that our conclusions apply to our specific case study with our specific selected set of KPI's. Extrapolating these conclusions should be done with caution.

5.2. Recommendations & Future Work

Throughout this document, we have underlined specific points of note for grid operators. We have compiled these points here, which serve as a recommendation for specific considerations should be taken into account when implementing both the methodologies discussed in our research and non-firm ATO's in general. At the end of each recommendation we summarise the key takeaway in a box.

The first of the key recommendations from our research lays with one of the more fundamental aspects of the non-firm connection agreement: the request for capacity. In our research, we modelled these requests based on the forecast values of the non-firm loads. For every 15 minute segment/time step, we assumed that the forecast value for the load was equal to the requested capacity by the load. This is not possible (or at least not feasible) in real operations for a couple of reasons. Firstly, the forecast is a prediction by the grid operator, not by the customer, of the expected capacity that is required by a specific load at that moment. It being a forecast by the grid operator however, means that the prediction is subject to serious assumptions. We believe, as confirmed by the first implementations of the non-firm ATO's, that it would significantly more effective if the customer estimates their required capacity and passes this as a request to the grid operator. This brings us to the two prongs of this specific recommendation however: how would the customer do that, and with what resolution. With regard to the former, we recommend that grid operators evaluate if existing (or planned) infrastructure can be adapted to enable these requests, like for example the real-time interface currently under development by Netbeheer Nederland. The second sticking point where we recommend the grid operator to investigate possible solutions, is the resolution of the requested capacity. As we mentioned, in our research we used a resolution of 15 minutes, the standard time step in most electricity market processes. However, the ability of a customer to estimate their requested capacity to such an extent is probably dependent on the nature of the customer. We therefore recommend grid operators to investigate what kind of resolution (e.g. an hour, a quarter of a day, etc.) would provide the most balanced trade-off between easy of use and optimal performance. This specific choice is also significant for the methodologies, as the resolution will significantly impact how efficiently the grid can be utilised by maximising the available capacity.

The resolution of requests (how many time blocks per day a customer needs to request) should be carefully chosen such that customers can properly predict their needed capacity without having too be excessively detailed.

Following this line of thinking, we also recommend that the forecast used by grid operators to allocate non-firm capacity is further investigated. As we found in our research, the selection of forecast has a significant impact on the effectiveness of different methodologies but also on the value of non-firm connections as a whole. It is therefore paramount that the choice of forecast is carefully weighed to balance the risk and uncertainty of more optimistic forecasts with the higher efficiency of lower forecasts. Generating more accurate forecasts is also of great value, especially if those forecasts are better at predicting the peaks in the firm capacity in the system. We determined in our research that although the forecasts could reliably match the average utilisation of the system, predicting the peaks was still difficult. This is especially critical for non-firm capacity allocation as it exactly these peaks that require the methodologies to deny some loads their requested capacities. Furthermore, being able to determine the exact location of the limiting constraints in peak situations would also be highly beneficial to a methodology like Adapted LIFO, as well as optimisation methodologies like Mathematical Optimum. In short, we recommend improving forecast accuracy, especially with regards to the peak moments and the location of the limiting constraints, to further improve the comparison between methodologies.

Generating accurate forecasts of the firm loading is paramount to making the use of non-firm grid connections feasible.

An another important recommendation, which we touched upon multiple times throughout our research, and which connects to the above two recommendations is the balance between making the flexibility option of a non-firm grid connection attractive enough and preventing gaming/excessive costs for other grid users. As we discussed in our state-of-the-art chapter, non-firm grid connections are only one of the plethora of options to creating flexibility in the electricity grid. Making it sufficiently attractive for customers to be used should therefore be an important consideration when implementing this option. Of course, the current draw for this option is the lack of alternative in the form of a firm grid connection for new connections or existing connections which wish to scale up. However, the use of such a non-firm grid connection is still a significant change, potentially deterring otherwise perfectly adequate connections which could actually contribute to grid stability. On the other hand, we also discussed that one of the risks with implementing non-firm grid connections is the possibility for gaming by connections. One of the major advantages of a non-firm grid connection is the reduction in the grid tariffs that customers have to pay, which for large connections can be a very significant financial advantage. However, when implementing grid tariffs for these connections, the structure should be so to disincentivise excessively large capacity requests where they are not needed, as well as minimising requested capacity that is not utilised. There are multiple ways to achieve this, by for example putting a tariff on 'wasted' capacity that is not utilised, or perhaps basing grid fees purely on requested capacities. Regardless, we recommend further research into this topic, to determine how this delicate balance between creating an attractive flexibility option whilst ensuring it is financially feasible and does not pass grid operation fees onto other customers.

In our research, ensuring the attractiveness of non-firm connections was important. Further research should be done on determining what measures could be adopted to ensure this attractiveness without risking negative side-effects like for example gaming by connected parties.

To further build on this point, we also recommend that the interaction between non-firm grid connections and other congestion management tools is carefully evaluated. As we determined in our research, the firm grid capacity that is utilised sets the stage for the different methodologies. Other flexibility options, like for example connections which offer flexibility to grid operators on platforms like GOPACS, should therefore be considered when allocating capacities. Determining the behaviour of these flexibility options can be quite difficulty at times however, as their activity primarily takes places during real-times grid operation, whilst the allocation of capacity should occur before the closing of the day-ahead market. Evaluating the effects that this might have on the performance of the different methodologies as well as non-firm grid connections in general is therefore key to ensuring these different flexibility options do not hinder each other and perform in cooperation rather than competition.

The interaction between non-firm grid connections and other flexibility options should be carefully studied to ensure that they do not interfere with each other's operations.

This need for careful evaluation shows up in another important parameter of a grid that contains non-firm grid connections: the maximum amount of non-firm grid connections or the scope at which the methodologies are applied. We found in our results that for methodologies like LIFO, their performance is heavily dependent on the number of loads that it has to divide the available capacity over. As more non-firm grid connections appear in a specific part of the grid, the less attractive the connection will become if all other factors remain constant. Thus, when implementing these methodologies, it should be considered how many loads should be taken into account when dividing the available capacity. If one were to subdivide the grid into smaller parts, each with their own respective available capacities, a methodology like LIFO might still work effectively. Other methodologies, like Mathematical Optimum are better at dealing with this, as their allocation can take into account multiple constraints and balance the capacities around that. However, it should be considered that as more non-firm loads are added to the optimisation, or as the scope grows larger (thus leading to more possible constraints) the difficulty of finding an optimal solution will increase. We therefore recommend further investigation into the optimal scope upon which methodologies are applied, as well as how many loads should be included in this division of capacity.

The scope at which the methodology for allocating capacity is applied can play a significant role in the effectiveness of that methodology.

One further consideration that we encountered in the methodology section of our research, was the concept of iterative capacity allocation. Iterative capacity allocation meant that an allocation of capacity in one direction (supply or demand) could be matched by an equivalent allocation of capacity in the opposite direction, leading to a compound increase in allocated capacity without exacerbating grid constraints. In our research, we decided to disallow this, as our allocation was based on forecasts rather than requests. However, in reality, if the tariff structure is effective in ensuring requested capacity is close to used capacity, iterative capacity allocation could potentially be effective. We thus recommend further research in this direction, to determine the possible effects this might have, both positive as well as negative.

Iterative capacity allocation could potentially increase grid efficiency but the increased risk needs to be offset by an effective tariff structure or other framework to ensure allocated capacities are matched closely by the used capacity of non-firm grid connections.

For the final recommendation, we would like to touch upon the outcome of our research, that we presented in the conclusions above. As we mentioned there, there is no objectively 'best' methodology for allocating capacity among non-firm grid connections. Rather, the best methodology depends on which KPI's are found to be the most important. We recommend that this choice of what aspects are important when evaluating ways to allocate capacity is further investigated, in the context of our methodologies but also in the wider context of non-firm grid connections. Namely, we recommend that grid operators evaluate how non-firm grid connections fit into the larger framework of creating a sustainable and future-proof electricity grid, and use this as a basis to determine what aspects are key for this flexibility option which cannot be provided by alternatives. This would be a strong foundation to inform a selection of which KPI's are the most important, thus aiding in selecting the most appropriate methodology for the allocation of capacity among non-firm grid connections.

The 'best' methodology is highly dependent on which metrics are most relevant to the stakeholders involved in their implementation.

Finally,let us reflect on our research and its outcomes. As we mentioned in Section 5.1, the answer to our main research question is not straightforward. In short, there are several ways of allocating non-firm capacity, each with their own respective advantages and disadvantages. We investigated five of these methodologies in a case study consisting of a relatively simple grid topology and using a set of KPI's to determine their performance.

As was apparent, each of the methodologies has their advantages and drawbacks, and our research has identified them for the specific case study under consideration. Extrapolating our findings to a wider context, we expect the following:

- Adapted LIFO will probably become more effective than the other priority-list based methodologies as the grid topology becomes more intricate, as it is able to allocate capacity based on the location of the grid constraints.
- Carousel's variable 'time steps per priority list shift' might become more relevant with a larger grid topology with more components and loads, as the constraint might then be located somewhere between loads.
- LIFO on the other hand is expected to deteriorate in performance based on our results, as its simple prioritisation scheme will quickly fall apart as the system becomes more intricate due to its inability to dynamically alter its priority preferences.
- Mathematical Optimum will quite likely remain the most consistent scorer across the board, but finding an optimal solution might become more difficult as more complexity and additional constraints are added, as well as increased numbers of non-firm grid connections.
- Pro Rata will face these same issues, but will also become less effective as more non-firm connections are added, as these all need to be proportional.

From all of this, we recommend further investigation into the effectiveness of these methodologies. We do believe that such a deeper exploration would benefit from examining only one or two of these methodologies at a time, as this would allow for more fine-grained analyses. In our own research, we found that the combination of seven KPI's and five methodologies lead to significant complexity already, so balancing this complexity with the relevance of the research would be paramount.

Furthermore, we recommend further investigation into the recommendations that we outlined above. Although these recommendations were mostly framed in terms of relevance to grid operators, further research into aspects like balancing flexibility option attractiveness and internalising the costs of the system or improved peak forecast generation would be worthwhile.

Bringing all of these findings together would ensure that this important avenue of stimulating and reinforcing the energy transition is properly implemented, to the benefit of all.

A

Appendix A

A.1. Table of Assumptions and Decisions

In Table A.1, we have presented the full list of assumptions and decision variables in our research. In the right column we have also included our rationale behind these values.

Table A.1: A Table of the assumptions made in our research.

Assumption\Decision	Value	Rationale
Time Period Run	2023-05-24 00:00:00+00:00 2024-02-23 23:45:00+00:00	This was the time period that was available at the beginning of our simulations.
Non-Firm Load Multiplier	1.5	Multiplier added to increase non-firm load to proportionality with firm load.
Baseline Forecast Quantiles	99th LDN, 01st ODN	Worst-Case Scenario for allocation of capacity.
Non-Firm Loads	105,116,117,202	Choice made based on which loads were individual customers rather than aggregated lines.
Ages Contract	102: 0, 105: 1, 106: 2, 111: 3, 113: 4, 114: 5, 115: 6, 116: 7, 117: 8, 118: 9, 202: 4	Arbitrary.
Baseline Line Limit	100 Amperes	Value based on variation in outputs across different line limits. Sufficiently low to ensure difference between methodologies, but sufficiently high to ensure capacity unable to be allocated is not excessive.
Power Factor	0.85	Worst-Case Scenario for allocation of capacity.
Forecast Quantiles for Sensitivity Analysis	[['01','99'],['02','98'],['03','97'],['05','95'],['06','94'],['07','93'],['08','92'],['09','91'],['10','90'], ['11','89'],['12','88'],['13','87'],['14','86'],['16','84'],['17','83'],['18','82'],['19','81'],['20','80'], ['21','79'],['22','78'],['23','77'],['24','76'],['26','74'],['27','73'],['28','72'],['29','71'],['30','70'], ['31','69'],['32','68'],['33','67'],['34','66'],['36','64'],['37','63'],['38','62'],['39','61'],['40','60'], ['41','59'],['43','57'],['44','56'],['45','55'],['46','54'],['47','53'],['48','52'],['49','51'],['50','50'], ['51','49'],['52','48'],['53','47'],['54','46'],['55','45']]	Randomly sampled forecat quantiles between 0 and 100.
Line Limit Range for Sensitivity Analysis	75 to 225 Amperes	Range within which there was a noticeable difference between values.
Carousel Time Steps Per Shift	4	Every hour shift.
Pro Rate Equality Maximum Differenc	0.0001	Trade-off between accuracy and computation time.
Line Voltage	20000 Volts	Assumed to be fixed due to grid supply point creating stability.

A.2. Forecast Sensitivity Analysis Quantiles

For our sensitivity analysis of the forecasts, we drew a random sampling of forecast quantiles as shown in the snippet from our code shown below in Figure A.1.

```
forecast_quantiles = [['01','99'],['02','98'],['03','97'],['05','95'],['06','94'],['07','93'],['08','92'],['09','91'],['10','90'],['11','89'],
                      ['12','88'],['13','87'],['14','86'],['16','84'],['17','83'],['18','82'],['19','81'],['20','80'],['21','79'],['22','78'],
                      ['23','77'],['24','76'],['26','74'],['27','73'],['28','72'],['29','71'],['30','70'],['31','69'],['32','68'],['33','67'],
                      ['34','66'],['36','64'],['37','63'],['38','62'],['39','61'],['40','60'],['41','59'],['43','57'],['44','56'],['45','55'],
                      ['46','54'],['47','53'],['48','52'],['49','51'],['50','50'],['51','49'],['52','48'],['53','47'],['54','46'],['55','45']]
```

Figure A.1: A code snippet of the range of percentiles used in our forecast sensitivity analysis.

A.3. Full Run Output

A full run is presented in Figure A.2 below. This run uses the Carousel methodology, and the input parameters as specified in Section 4.1. The top graph gives the line loading as a function of the maximum capacity of the lines. The second graph takes into account the directionality of the load. The third graph is the non-firm load whilst the bottom is the firm load.

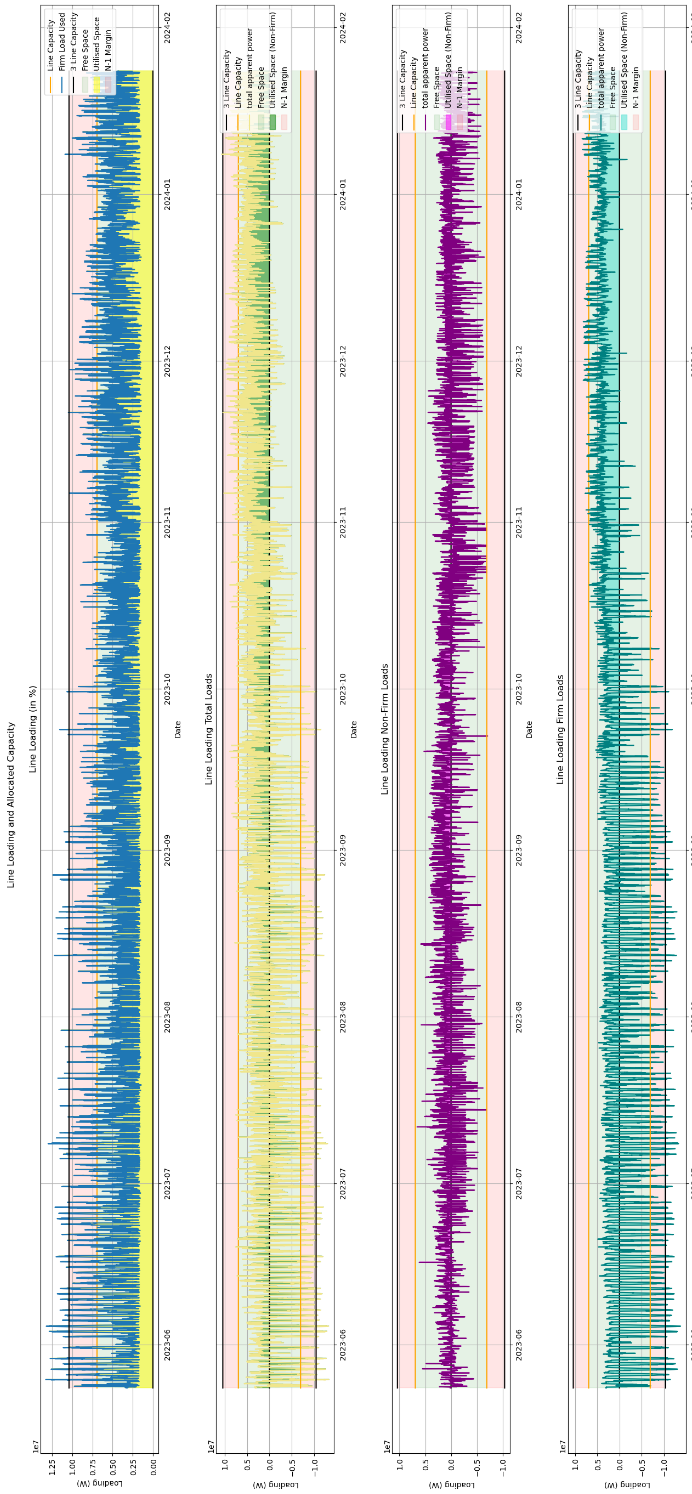

Figure A.2: Output of a full run (Carousel) with the inputs as specified in Section 4.1.

B

Appendix B

In this appendix, we will go through each of the methodologies, and discuss the step-by-step process that they follow in their allocation procedure.

B.1. LIFO

Inputs:

- Non-Firm Ids
- Age Contract
- Grid Structure Data
- Forecast Data
- Firm Ids
- Limits
- Power Factor

Process

The process consists of two parts: the generation of the priority-list, and the allocation of capacity using that priority-list.

1. The priority-list is generated by sorting the non-firm ids in the order of the ages of the contract.
2. This priority-list is then passed to the allocation of capacity process.
3. In this process, first the current firm capacity is calculated from the forecast data's firm ids.
4. This is then multiplied by the inverse of the power factor to get the apparent capacity as opposed to only the active capacity.
5. The available capacity is then calculated in both the LDN and ODN direction using Equation 3.1.
6. If the LDN capacity is smaller than 0 or the ODN capacity is larger than 0, they are set to 0 (these conditions check if there is not already an exceedance).
7. The requested capacity for the non-firm ids is then obtained from the forecast data, and symmetrically mirrored (as discussed in Section 3.3.2).
8. Subsequently, in order of the priority-list, the following nested-if loop is followed:

9. (a) If the current requested capacity is smaller than the current available capacity (in either direction), the allocated capacities is set to be equal to the requested capacities in both the LDN and ODN direction. The available capacities in both directions have the requested capacity subtracted from them.
   (b) Else if the current requested capacity in the LDN direction is smaller than the available LDN capacity, but the requested ODN capacity is larger than the current available ODN capacity, the allocated capacity in the LDN direction is set equal to the current requested LDN capacity and the allocated capacity in the ODN direction is set equal to the available ODN capacity (thus not the requested capacity). The available capacity in the LDN direction has the requested capacity subtracted, and the available ODN capacity is set equal to 0.
   (c) Else if the current requested capacity in the LDN direction is larger than the available LDN capacity, but the requested ODN capacity is smaller than the current available ODN capacity, the allocated capacity in the LDN direction is set equal to the current available LDN capacity (thus not the requested capacity) and the allocated capacity in the ODN direction is set equal to the requested ODN capacity. The available capacity in the ODN direction has the requested capacity subtracted, and the available LDN capacity is set equal to 0.
   (d) Else if the current requested capacity is larger than the current available capacity in both directions, the allocated capacity is set equal to the available capacity in both directions. Both available capacities are set to zero.
10. This set of allocated capacities for this specific time step is then passed back to the main process.

B.2. Adapted LIFO

Inputs:

- Non-Firm Ids
- Age Contract
- Voltage of the Non-Firm Ids
- Grid Structure Data
- Forecast Data
- Firm Ids
- Limits
- Power Factor

Process

The process consists of two parts: the generation of the priority-list, and the allocation of capacity using that priority-list.

1. The priority-list is generated by sorting the non-firm ids in the order of the ages of the contract per voltage level and then sorting by voltage level (higher voltage is higher in the priority-list)
2. This priority-list is then passed to the allocation of capacity process.
3. In this process, first the current firm capacity is calculated from the forecast data's firm ids.
4. This is then multiplied by the inverse of the power factor to get the apparent capacity as opposed to only the active capacity.
5. The available capacity is then calculated in both the LDN and ODN direction using Equation 3.1.
6. If the LDN capacity is smaller than 0 or the ODN capacity is larger than 0, they are set to 0 (these conditions check if there is not already an exceedance).

7. The requested capacity for the non-firm ids is then obtained from the forecast data, and symmetrically mirrored (as discussed in Section 3.3.2).

8. Subsequently, in order of the priority-list, the following nested-if loop is followed:

9. (a) If the current requested capacity is smaller than the current available capacity (in either direction), the allocated capacities is set to be equal to the requested capacities in both the LDN and ODN direction. The available capacities in both directions have the requested capacity subtracted from them.

   (b) Else if the current requested capacity in the LDN direction is smaller than the available LDN capacity, but the requested ODN capacity is larger than the current available ODN capacity, the allocated capacity in the LDN direction is set equal to the current requested LDN capacity and the allocated capacity in the ODN direction is set equal to the available ODN capacity (thus not the requested capacity). The available capacity in the LDN direction has the requested capacity subtracted, and the available ODN capacity is set equal to 0.

   (c) Else if the current requested capacity in the LDN direction is larger than the available LDN capacity, but the requested ODN capacity is smaller than the current available ODN capacity, the allocated capacity in the LDN direction is set equal to the current available LDN capacity (thus not the requested capacity) and the allocated capacity in the ODN direction is set equal to the requested ODN capacity. The available capacity in the ODN direction has the requested capacity subtracted, and the available LDN capacity is set equal to 0.

   (d) Else if the current requested capacity is larger than the current available capacity in both directions, the allocated capacity is set equal to the available capacity in both directions. Both available capacities are set to zero.

10. This set of allocated capacities for this specific time step is then passed back to the main process.

B.3. Carousel

Inputs:

- Non-Firm Ids
- Current step
- Steps per priority-list shift
- Grid Structure Data
- Forecast Data
- Firm Ids
- Limits
- Power Factor

Process

The process consists of two parts: the generation of the priority-list, and the allocation of capacity using that priority-list.

1. The priority-list is generated by dividing the current step by the steps per allocation variable. The number of steps to shift is then the integer value of this ratio. The priority-list is then shifted by this result.

2. This priority-list is then passed to the allocation of capacity process.

3. In this process, first the current firm capacity is calculated from the forecast data's firm ids.

4. This is then multiplied by the inverse of the power factor to get the apparent capacity as opposed to only the active capacity.

5. The available capacity is then calculated in both the LDN and ODN direction using Equation 3.1.
6. If the LDN capacity is smaller than 0 or the ODN capacity is larger than 0, they are set to 0 (these conditions check if there is not already an exceedance).
7. The requested capacity for the non-firm ids is then obtained from the forecast data, and symmetrically mirrored (as discussed in Section 3.3.2).
8. Subsequently, in order of the priority-list, the following nested-if loop is followed:
9. (a) If the current requested capacity is smaller than the current available capacity (in either direction), the allocated capacities is set to be equal to the requested capacities in both the LDN and ODN direction. The available capacities in both directions have the requested capacity subtracted from them.
   (b) Else if the current requested capacity in the LDN direction is smaller than the available LDN capacity, but the requested ODN capacity is larger than the current available ODN capacity, the allocated capacity in the LDN direction is set equal to the current requested LDN capacity and the allocated capacity in the ODN direction is set equal to the available ODN capacity (thus not the requested capacity). The available capacity in the LDN direction has the requested capacity subtracted, and the available ODN capacity is set equal to 0.
   (c) Else if the current requested capacity in the LDN direction is larger than the available LDN capacity, but the requested ODN capacity is smaller than the current available ODN capacity, the allocated capacity in the LDN direction is set equal to the current available LDN capacity (thus not the requested capacity) and the allocated capacity in the ODN direction is set equal to the requested ODN capacity. The available capacity in the ODN direction has the requested capacity subtracted, and the available LDN capacity is set equal to 0.
   (d) Else if the current requested capacity is larger than the current available capacity in both directions, the allocated capacity is set equal to the available capacity in both directions. Both available capacities are set to zero.
10. This set of allocated capacities for this specific time step is then passed back to the main process.

B.4. Mathematical Optimum

Inputs:

- Non-Firm Ids
- Grid Structure Data
- Forecast Data
- Firm Ids
- Limits
- Power Factor

Process

The Mathematical Optimum methodology goes through the following steps.

1. Firstly, the total firm load is calculated based on the forecast data and the firm ids list.
2. This is then converted to apparent power by multiplying by the inverse of the power factor.
3. The available power in both the LDN and ODN direction is then calculated using Equation 3.1.
4. Then the optimisation parameters are specified as follows.
5. (a) The number of variables is equal to twice the amount of non-firm loads, with each non-firm load having a LDN variable and an ODN variable associated with them.

(b) The first constraint for every variable is that their value must lie between 0 and their respective requested capacity (be it LDN or ODN)
(c) If the available capacity in the LDN or ODN direction is smaller than zero (indicating that there is already an exeedances in that direction according to the forecast), all of the variables that have a requested capacity in that direction (be it LDN or ODN) will be constrained to be equal to 0.
(d) The final constraint is that the sum of the LDN variables should be smaller than the available LDN capacity and vice versa for the ODN variables and the available ODN capacity.
(e) The objective statement is then split into two, and is formulated as a weighted sum of two objective statements with equal weights.
(f) • The first objective is to maximise the sum of the LDN variables.
  • The second objective is to maximise the sum of the ODN variables.

6. The optimisation is then ran with the problem statement containing the objectives and constraints discussed above with the MOSEK solver.
7. This set of allocated capacities for this specific time step is then passed back to the main process.

This splitting between two objective statements is due to the fact that ODN capacity is formulated as a negative value in the formulation of Power Grid Model. This means that a maximisation of these variables would be equal to 0.

B.5. Pro Rata

Inputs:

- Non-Firm Ids
- Current step
- Steps per priority-list shift
- Grid Structure Data
- Forecast Data
- Firm Ids
- Limits
- Power Factor

Process

The Pro Rata methodology goes through the following steps.

1. Firstly, the total firm load is calculated based on the forecast data and the firm ids list.
2. This is then converted to apparent power by multiplying by the inverse of the power factor.
3. The available power in both the LDN and ODN direction is then calculated using Equation 3.1.
4. Then the optimisation parameters are specified as follows.
5. (a) The number of variables is equal to twice the amount of non-firm loads, with each non-firm load having a LDN variable and an ODN variable associated with them.
   (b) The first constraint for every variable is that their value must lie between 0 and their respective requested capacity (be it LDN or ODN)

(c) Secondly, the equality constraint is formulated. It specifies that the difference between the ratio of the allocated capacity and the requested capacity for every variable and the ratio between the allocated capacity and the requested capacity for every next variable with a similar direction (be it LDN or ODN) must not be larger than the equality value. This equality value is set to be equal to 0.0001.

(d) If the available capacity in the LDN or ODN direction is smaller than zero (indicating that there is already an exeedances in that direction according to the forecast), all of the variables will be constrained to be equal to 0.

(e) The final constraint is that the sum of the LDN variables should be smaller than the available LDN capacity and vice versa for the ODN variables and the available ODN capacity.

(f) The objective statement is then split into two, and is formulated as a weighted sum of two objective statements with equal weights.

(g)
- The first objective is to maximise the sum of the LDN variables.
- The second objective is to maximise the sum of the ODN variables.

6. The optimisation is then ran with the problem statement containing the objectives and constraints discussed above with the MOSEK solver.

7. This set of allocated capacities for this specific time step is then passed back to the main process.

This splitting between two objective statements is due to the fact that ODN capacity is formulated as a negative value in the formulation of Power Grid Model. This means that a maximisation of these variables would be equal to 0.

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