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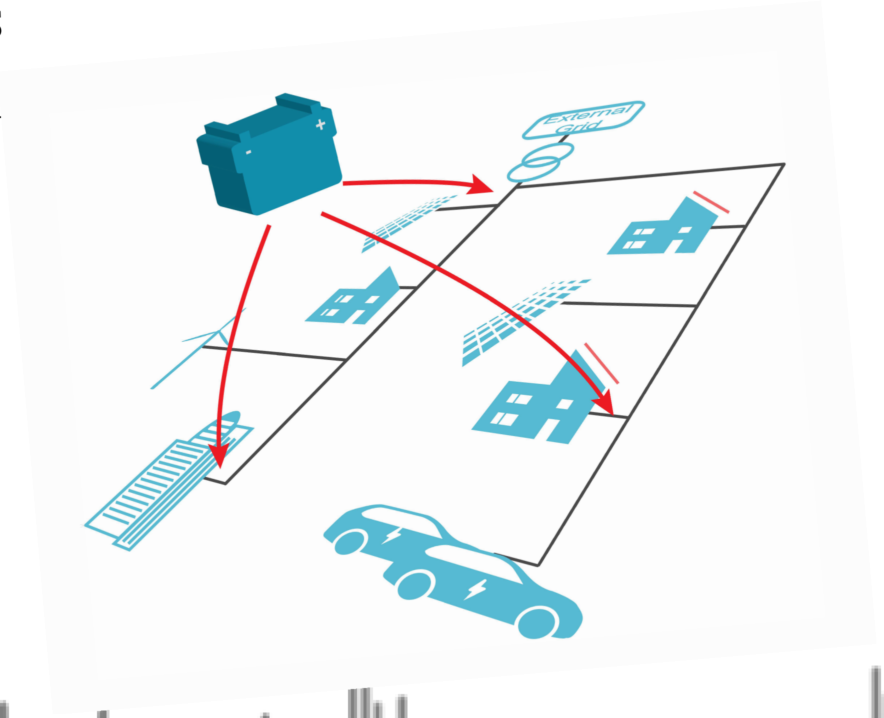
Complex System Engineering and Management
Master's Thesis

Duncan Sieval

Delft University of Technology



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by

Duncan Sieval

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First University Supervisor:	Prof. dr. Martijn Warnier
Second University Supervisor:	Dr. Ir. Kenneth Bruninx
Company Supervisor:	Ir. Rick Dijksman
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Preface

This thesis is the grand finale of my academic endeavor as a student. It marks the end of my Master's degree in Complex System Engineering and Management. Not only have I applied the interdisciplinary insights from this program, I also used knowledge of my bachelor's programme at Utrecht University and previous experiences within the field of energy storage. I am glad that I was given the opportunity to dedicate my thesis to this subject, while being provided with the freedom to incorporate my own creativity. It felt good to contribute to societal and scientifically relevant research. I hope that my contributions help to reduce climate change through efficient integration of renewables. The severity of the exponentially growing climate change problems really helped me to stay motivated throughout this extensive project.

To be honest, I underestimated the cognitive and mental load of such a large individual project. Especially at moments when things did not go as planned and became time-consuming, for example during debugging of programming errors. For the first time, I spend more than six months full-time on one project, while being self-reliant. This caused some sort of emotional attachment, from which I learned a lot. One of the big lessons that I learned is that imaginary and optimistic thinking in opportunities helps for motivation and creativity. However, doing this endlessly, without defining boundaries slows progress and caused me to sometimes be lost in the details. It is important to finalize decisions and commit to a direction.

I am proud that I completed this project while also accomplishing my personal preset goals. Next to writing this thesis, I learned new skills on the extensive AC load flow application. Additionally, I gained knowledge in both the fields of electrical engineering and complex system engineering. Furthermore, I expanded my programming skills within Python. I also gained knowledge on the qualitative aspects of enablers for energy flexibility, and got the chance to further develop my own ideas on business opportunities. Lastly, I am glad that I had the chance to further expand my social network in the field of congestion, grid integration, energy storage and innovation. Within these fields, I hope to further collaborate and accomplish future goals.

Without the help of a lot of people, this research would not have been realized. First of all, I want to express my gratitude towards the persons in my personal environment, especially my girlfriend and parents for their support and patience, both during this time-consuming research, as well as during the course of my academic journey.

Furthermore, I want to thank Prof. dr. Warnier for his extensive guidance throughout the whole project. I especially appreciate the space and time for debate and discussions. The flexibility throughout the project is also much appreciated. I would also like to thank Dr. Ir. Bruninx for his sharp and analytical questions, which contributed to the analytical quality of this research.

And last but not least, I want to thank all the people at Stedin in providing a professional and analytical environment with powerful resources and models in which I was able to perform my research. I especially want to thank Rick, Emma, Albert and the members of the New Energy System sub-team within the Innovation department for their continuous support, alongside their ability to make my thesis days more bearable.

Finally, I hope that this thesis will contribute and serve as a foundation for exciting developments in the future, both for my own career as well as for society!

Duncan Sieval
Delft, January 2026

Executive Summary

Problem situation

To support the energy transition, society is electrifying. This however, puts pressure on electrical distribution grids. It leads to insufficient electrical transport capacity that results in grid congestion, which has major consequences for society and limits economic growth.

Flexibility from distributed energy resources can be used to shift electrical transportation peaks with demand response, which mitigates congestion. Additionally, various additional measures and resources can be deployed throughout the system to mitigate congestion. Such resources are limited and should be placed congestion-efficiently. However, there is no alignment in the congestion solving capabilities of already existing distributed flexibility and other upcoming congestion measures. This lack of alignment is caused by lack of insight in the potential from distributed flexibility to solve congestion. Research on this topic is limited, lacks detail and does not focus on local differences, while these differences drastically influence the system. The potential depends on uncertain factors, including continuously developing regulatory frameworks, congestion management methods and incentive structures, as well as user-preferences, technological capability and various other influences. These result in lack of insight in the potential of distributed flexibility to mitigate congestion, which restrains the electricity system and thereby the integration of renewables in the energy transition.

Research question

To assess the potential of distributed flexibility to mitigate congestion, this research bridges the transparent integration of heterogeneous local and autonomous user-specific flexibility into quantifiable mathematical flexibility reactions, to assess remaining congestion in distribution grids. Therefore, the following research question is answered: *”How can the potential impact of incentivized, location-specific distributed flexibility on congestion locations in Dutch distribution grids be evaluated?”*

Research approach

To provide an answer, a power-flow model is co-simulated alongside a stochastic state evolution model with Monte Carlo sampling, to shape flexibility reactions. To perform this co-simulation, the following 4 steps are sequentially performed:

- First, modeling the reference power-flow is performed in the first model. Congestion without the influence of distributed flexibility reactions is identified through an AC power-flow model simulation within an existing case-study grid.
- Secondly, congestion and relevant strategies to incentivize distributed flexibility are identified. The identified congestion is coupled to distribution substation entity agents that represent the aggregated prosumers. These distribution substations than act on the congestion via implicit financial incentive that encourage flexibility reactions. To assess the robustly remaining congestion, maximal financial incentives are used that are differentiable at specific timesteps and locations. This step elaborates that resulting flexibility reactions after this incentive reveal where severe and robust congestion remains.
- Thirdly, incentivized flexibility reactions are modeled. The flexibility reactions are developed in the stochastic state evolution model, which is the second model of the co-simulation. Multiple factors combine into hourly flexibility state reactions of the agents. In the approach, a split of four factors is made, including the previously described incentive factor. The flexibility states incorporate uncertainty within flexibility envelopes that incorporate probability distributions. From these stochastic envelopes, flexibility reaction states are drawn through Monte Carlo sampling. In the reactions, the magnitude of the effect of the incentive factor, is varied within scenarios.
- Lastly, the influence of spatial correlation is applied on the stochastic state evolution model. Hereafter, the flexibility reaction states are compared with the required flexibility to solve congestion

from the power-flow model. The influence of spatial correlation is studied and deployed on the flexibility reaction states within a scenario, to account for regional differences in the ability to provide flexibility.

Results

Distributed flexibility providers can contribute with demand response for mitigation of current congestion and thermal overloading. Still, the results show that congestion might remain after encouraging distributed flexibility reactions with implicit financial incentives, caused by local differences in 4 combined factors. Technically, the available physical flexible capacity factor is usually large enough to mitigate congestion. However, combined with the factors of capability, incentive structure and behavior, the reactions might be inadequate to solve congestion currently. The scenario results show that the congestion solving capability of the modeled flexibility reactions depend on the magnitude of the incentive structure, and the size of the remaining congestion area is also dependent on the incentive. Additionally, spatial correlation that results in spatial clustering of flexibility reactions also negatively influences congestion, especially once congestion areas are small.

However, policy analysis has shown that small distributed flexibility providers are not incentivized or activated to deploy their flexibility for demand response to explicitly target congestion caused by voltage fluctuations instead of congested caused by current. However, the power-flow results show that voltage congestion differs locally and occurs only at specific distribution substations under the overarching sub-transmission voltage distribution transformer. This shows the potential of distributed flexibility to as explicitly target voltage-congestion, for example via Volt-VAR adjustments.

The remaining current congestion after flexibility reactions can typically be linked to specific parts of the topology. In the larger congestion areas, congestion is caused by overloaded sub-transmission voltage transformers that supply the multitude of distribution substations. There are typically enough flexibility providers in these larger sub-regions that can solve congestion once financial incentives are high enough. Relative undershoots of flexibility can certainly be compensated by overshoots of other flexibility providers, and in total enough flexibility can typically be provided. Even when regional disparities within these larger congested areas are present, congestion can be resolved once the geographical congestion area is large enough and contains enough flexibility providers with spare capacity.

However, the results show that congestion can be more local and caused by a component lower in the radial distribution hierarchy than the overarching sub-transmission voltage distribution transformer. Sometimes congestion caused by a specific line or component low in the distribution hierarchy is only caused by and impacting a few distribution substations. In these local areas, there is a higher chance that there might not be enough flexibility to locally solve congestion. Although overall flexibility provision throughout the whole network might be high, flexibility provision in the specific congestion region might be low. Here, the sample size or number of flexibility providers is small and sensitive to sampling outliers. This effect might already occur once financial incentives are high and spatial correlation is low, but especially occurs once low financial incentives apply.

The level of the financial incentive is dependent on the spatial and temporal focus of the applied congestion management mechanism. Even under the most incentivizing mechanisms, congestion might remain as flexibility is locally unavailable. Additionally, higher spatial correlation also adds to the severity of this effect. Once there is a lot of spatial correlation between flexibility providers in such a small and highly local congested area, flexibility reactions are less evenly dispersed, and outlying undershoots might be more common, causing inability of the participants in the area to compensate and solve congestion together. The results show at what areas flexibility provision is currently inadequate to mitigate congestion, and where additional flexibility might be needed.

Recommendations

It is important to realize for industry experts, researchers and policy makers, that the four factors influence flexibility reactions in such a way that local differences in the ability to solve congestion might arise under the conditions at present. Even under high financial incentive scenarios, congestion might remain. However, the influential factors are under continuous development, and especially factors related to capability and incentive structure might positively influence flexibility reactions in the future. Upon deciding where to strategically place upcoming flexibility assets, grid operators should take the combined effect of different congestion management mechanisms into account. These drastically influence the activation of other flexibility assets and influence congestion-efficient alignment.

Especially congestion in components low in the radial distribution hierarchy is likely to remain once financial incentives are low and once flexibility endowments are highly unevenly spatially dispersed. Congestion can be highly local for both voltage congestion and current congestion. Therefore, it is recommended to DSOs and flexibility providers create insight in the uneven distributions and concentrations of existing distributed flexibility, to strategically place and coordinate new flexible assets where flexibility is disproportionally inadequate. Only specific distribution substations need additional flexibility. The magnitude of the incentive and the amount of spatial correlation among already existing flexibility providers should be taken into account upon deciding where additional flexibility should be located. To more accurately see what specific distribution substations are useful to provide with additional flexibility, the probabilistic envelopes from the framework can be further narrowed by adding more and location specific information. Furthermore, more knowledge on the extent to which and at what granularity spatial correlation occurs, might reveal insights in where additional flexibility is needed.

Once assessing locations where congestion robustly remains to complementarily place additional flexibility and storage, financial incentives that are focused at specific timesteps and places are put forward as relevant in this research. These targeted and differentiated mechanisms are able to offer the highest magnitudes of financial incentives for reactions and reveal where the most persistent congestion remains. To increase distributed flexibility and engagement of storage operators, it is therefore recommended to DSOs to make a more reliable and active platform for such congestion management services, in which more of theses local congestion problems are requested. Only then does it becomes attractive for flexibility providers to systematically engage in such services. Nevertheless, recent developments show that other congestion management mechanisms, such as the time-off-use-tariff, will also be implemented in the future. This might lower the impact from incentives that are focused on specific timesteps and locations, as there is less remaining congestion to be solved. The extent to which these mechanisms, that are less detailed and not so much focused on specific locations and timesteps, impact congestion is unknown and dependent on the magnitude of the incentive. Therefore, it is recommended to DSOs to investigate the impact on physical congestion from these different congestion management mechanisms, so that they can be aligned complementarily.

For storage operators, congestion service providers and all sorts of other flexibility providers, it is recommended to exploit the differentiated and local congestion problems in an efficient manner. The provided framework creates insight in where congestion remains after deployment of already sited distributed flexibility. Once such insights are increasingly signaled and made available to storage operators, it can be used to exploit flexibility at exactly the right places and times, so that additional congestion revenues can be generated under the mechanisms that differentiate incentives through time and space.

The code that was used to answer the research questions can be accessed at:
https://github.com/developerDuncan/Assessing-congestion-patterns-and-flexibility-reactions.git

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Nomenclature

Abbreviations

AC	Alternating Current
ACM	Authority for Consumers and Markets
BEMS	Battery Energy Management System
BESS	Battery Energy Storage System
BRP	Balancing Responsible Party
CM	Congestion Management
CMM	Congestion Management Mechanism
CRC	Capacity-Restrainment Contract
CSP	Congestion Service Provider
(D)LMP	(Distributed) Locational Marginal Pricing
DER	Distributed Energy Resource
DR	Demand Response
DSO	Distribution Service Operator
EMS	Energy Management System
EV	Electric Vehicle
FACTS	Flexible AC Transmission Systems
HEMS	Home-Energy Management System
HVAC	Heating, Ventilation, and Air Conditioning
OLTC	On-load Tap Changer
TSO	Transmission Service Operator
V2G	Vehicle-to-grid

Glossary

Demand response	Voluntarily and temporarily adjustment of electricity consumption or production by customer-sited energy resources in response to price signals or incentives
Distributed flexibility provider	Prosumer or end-user that performs demand response actions at a specific location in the grid
Distribution substation	Medium-voltage substation stepping down medium-voltage (3–25 kV) to low voltage (400 V–3 kV), also known as middenspanningsruimte (MSR) in Dutch
Sub-transmission voltage transformer	Transformer that steps down voltage from the sub-transmission voltage (25–100 kV) to medium-voltage (3–25 kV)
Probabilistic flexibility envelope	Mathematical representation of the range of flexibility a resource can provide, expressed with probability distributions instead of fixed bounds
Granularity	Degree of detail or resolution in a system or process, referring to how finely information is divided across dimensions such as time and space. In this research it refers to the spatial and temporal detail at which congestion management measures are applied
Congestion signal	An indicator communicated within power systems that reflects the presence and severity of congestion, typically to be translated and used to trigger or coordinate actions to relieve network constraints, for example with transactive values

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Introduction

1.1. Problem statement

Global warming is occurring at unprecedented pace, with its negative consequences increasing exponentially [1]. In the Paris agreement it was therefore agreed upon to limit the rise of temperatures by decreasing greenhouse gas emissions [2]. Electrification is an important part of the strategy to reach net-zero emissions, with the purpose to increase the share of electricity in the total energy consumption. This transition is currently happening, which puts an enormous pressure on electricity grids [3]. Both supply and demand of electricity are growing, through adoption of for example solar-photovoltaics, electric vehicles (EVs) and heat pumps [4].

In the Netherlands, this has already led to insufficient electrical transporting capacity, a phenomenon also known as grid-congestion, which has severe consequences [5]. The intermittency of renewables and demand makes it difficult to efficiently integrate and transport renewable resources in the grid. One of the main consequences is the curtailment of valuable green electricity, while conventional generators with harmful emissions are still in operation [6]. Additionally, new grid-connection applications are often refused, with major setbacks for businesses and society. Regular grid expansion to mitigate congestion faces technical, regulatory, economic, environmental and workforce-related difficulties [7]. A promising solution to these challenges is energy flexibility through storage, which stores excess electricity and smoothens fluctuations in electricity flowing through the grid [3]. A diverse array of storage technologies exists, fulfilling various functions, among which congestion management [8].

Nevertheless, the deployment and congestion-relevant integration of storage systems and other flexibility assets, both centralized and decentralized, remains limited. Key barriers that interfere further integration include unclear and evolving regulatory frameworks, rigid market structures and location-specific as well as technological grid constraints. All of these affect the economic viability of potential business cases. Additionally, the congestion-relevant integration remains limited because of the missing markets problem [9]. The flexibility providers have incomplete insight of congestion information. The congestion value for the grid operator is unknown to the asset owner, as the grid operator cannot easily monetize and signal this. Contrasting is that current regulations require storage systems and other sources of flexibility to be operated and owned by private entities, and not by grid operators themselves. These private entities tend to prioritize profit maximization through energy arbitrage, while congestion reduction and grid performance might be unprioritized and uncompensated objectives [10]; [11]; [12]. However, to fulfill these objectives and mitigate congestion, the compensation mechanisms, possibly financial, have to be organized accordingly. This is currently not happening sufficiently, as the individual strategic behaviors of private actors in combination with current regulatory and market structures influences the deployment of storage and flexibility in grid-capacity inefficient ways, leading to congestion. There is no alignment between different levels and types of flexibility in solving congestion, as valuation and incentives that tune, coordinate and cause complementarity are lacking. This results in unaligned incentives and unnecessary flows of electricity in such a way that congestion prevails, causing losses for society and high costs for system operation [13]. For distributed flexibility specifically, the incentives, interactions and operations for grid-performance are often ignored or misunderstood, while the quantity of flexible assets and their potential in solving congestion is growing drastically, especially once aggregated [14]. Properly assessing and deploying the potential value of existing flexibility not only decreases congestion, it also supports and creates insight in the integration of renewables.

Network operators on the other hand, are equipped by the Dutch regulator (ACM) with various tools to influence power flows and congestion. For example dynamic network tariffs and various forms of capacity managing solutions. Combined with such congestion management mechanisms, the additional features of flexibility assets can be used for congestion reduction, and flexibility providers can be strategically aligned. Unfortunately, available congestion mechanisms are nowadays barely deployed [15]; [16]. The currently available mechanisms do not use the full potential of distributed flexibility. Furthermore, the combined effects of these different mechanisms on power flows and congestion patterns are largely unknown and hard to optimize [17]; [18]. However, specific mechanisms are more efficient than others with regard to economic allocation or value for society [19]. Knowledge on strategic deployment and combinations of these tools is limited, as the mechanisms are new and continuously developing.

Many other factors cause uncertainty in the valuation of the seemingly advantageous decentralized flexibility for congestion mitigation, and the possible outcomes of flexibility reactions are large. A conceptualization that analyzes the combined effect of mechanisms with flexibility factors is missing. It is hard to understand how prosumer incentives, flexible capacity, preferences and congestion mechanisms align, as they combine in a complex manner [14]. There are no clear market-signals, and a complete and transparent market with real-time grid conditions that allows immediate response of flexibility assets for congestion remains absent to this day, causing the effect of flexibility on congestion to be unclear. In general, the effects of decentralized and local incentives for system-wide grid alleviation are a under-researched topic in current literature with a lot of uncertainty [17]; [20]. However, recent insights show that local developments are becoming increasingly relevant.

To conclude, there is lack of insight on the degree to which distributed flexibility can impact congestion. To successfully integrate local developments in grid planning practices, topological considerations, flexibility, and market-and congestion-structures should be considered simultaneously [21]. As Vizia et al. [22] put it, there is lack of frameworks to assess the socio-technical environment with factors that influence flexibility. Such assessments could ultimately provide insights for design decisions concerning topological and flexible capacity considerations, particularly for applications such as centralized large-scale energy storage, as their complementarity depend on distributed capacities elsewhere in the system [23]. Congestion depends on all sorts of factors such as incentives and consumer behavior. However, no information is currently available on the combined integration and synthesis of these factors, leaving distributed flexibility largely unused.

1.2. Research objectives

The research focuses on congestion-efficient alignment of distributed flexibility. This requires insight on the extent to which already existing and location-bound distributed flexibility might impact Dutch distribution grids, to see where congestion is likely to remain and where additional measures are needed to solve congestion. Creating this insight is the main objective of this research and synthesized in the following main research question: *”How can the potential impact of incentivized, location-specific distributed flexibility on congestion locations in Dutch distribution grids be evaluated?”*.

This question can be answered by the following sub-questions, that are further explained in the research approach:

1. *Where does congestion occur in Dutch distribution grids under current conditions without activation of distributed flexibility?*
2. *How can the effect of a congestion management mechanism that encourages the maximum potential of distributed flexibility be modeled?*
3. *What interplay of factors influences possible reactions of distributed flexibility to mitigate congestion?*
4. *What are the implications of spatial correlation in distributed flexibility reactions on congestion patterns?*

1.3. Scope

1.3.1. Dutch electrical distribution grids

Storage and flexibility can be deployed in both transmission and distribution grids [24]. However, flexibility deployed in high-voltage transmission grids without the right incentives for congestion mitigation and without aligned dispatch, might still contribute to congestion in the underlying distribution grids [25]. The majority of electricity is ultimately used in capacity-lacking distribution grids. As a result, the Dutch distribution grid, operating at voltages below 110 kV, is among the most congested grids in the world [24]. Additionally, distribution-grids are increasing in importance as all sorts of developments are increasingly focused on decentralized operation, including the implementation of smart meters, behind-the-meter solutions, and P2P-energy trading, and distributed demand-response [26]; [27]. Contrary to conventional electricity systems, renewable electricity and flexibility can be locally facilitated in distribution grids. The adoption of assets such as flexible heat pumps and bidirectional EVs will increase fluctuation in and utilization of distribution grids. Overall, distribution grids are relevant for congestion mitigation with such distributed flexibility assets, which is therefore focus of this research.

Within distribution-grids, the medium-voltage (MV) level is among the most congested parts, while being essential in the connection of the transmission network with the low-voltage network [28]. This level includes industrial consumers and large flex-markets such as GOPACS, and has typical maximal power capacities up to roughly 100 MW [29]. Modeling the detailed LV network is computationally intensive due to its high node count, granularity, and regulatory complexity, and is therefore out of scope. Instead, the MV network is modeled at a coarser level, capturing LV prosumers and outputs in an aggregated manner, with the added benefit of better data availability from actively measured MV distribution substations. This research focuses on implications of distributed flexibility reactions within the grid sub-transmission and medium-voltage levels, operating at levels of 3 kV up to everything below 110 kV. Here, congestion analysis for flexibility can still have high volume impacts, while simultaneously being relevant for low-voltage parts.

1.3.2. Distributed flexibility

Besides local generation, these distributed sources also include storage and other types of flexibility enhancing characteristics and assets, among which appliances such as vehicle-to-grid (V2G) EVs that have bidirectional charging capability and residential batteries [30]. Additionally, industry can enable flexibility by assets such as e-boilers, and by shifting production processes. Two types of flexible resources can be distinguished [31]. Firstly are storage-based resources, such as battery energy storage. Secondly are load-based resources such as HVAC, heaters and production processes. These flexible distributed systems distinguish themselves by having the ability to manage variability and uncertainty in both generation and demand, bounded by the ability to maintain a satisfactory level of reliability at reasonable cost over different time horizons [32]. The focus is on distributed flexibility that is inherently location-bound, only able provide congestion relief at specific grid locations where the assets and entities are physically connected. This local flexibility and demand response is uncertain as it is dependent on all sorts of factors such as consumer behavior, as argued by Moradi and Farzaneh [33].

Alongside generation and demand-side flexibility, grid-side flexibility can also be distinguished [34]. This entails flexibility that is achieved using grid-components such as on-load-tap-changers that are able to switch between voltage levels [35]. Nowadays, this solely requires the will of the grid operator to be activated without involvement of other deciding stakeholders. This however, might change in the future, as described in section 2.1.2 [15]. Although congestion is impacted by grid-side flexibility such as reactive power management, existing distributed flexibility in this research only focuses on generation and demand-side flexibility with active power adaptations. Nevertheless, the implications of the research are also relevant for grid-side flexibility through for example reactive power management.

In the remainder of this thesis, these demand and generation flexibility resources at electrical distribution grid end-users are referred to as distributed flexibility providers, that perform demand response actions. All sorts of prosumers and assets aggregate at medium-voltage distribution substations. In the remainder of this thesis, these distribution substations represent the underlying low-voltage aggregated prosumers as one distributed flexibility provider entity at the MV-level. These distribution substations can be represented as both nodes and agents and develop flexibility reactions that shape power flows.

1.4. Link to CoSEM Program

Socio-technical developments

The ability of distributed flexibility to reduce electro-technical congestion comes paired with the fulfillment of all sorts of factors, especially congestion management measures and incentives. There is a system in which the technical components of electrical power assets and grids are combined with social and economic components such as participant behavior and regulatory or DSO policies. These aspects interact and co-shape each other, creating a socio-technical system. The bi-directional interactions form a complex adaptive system with feedback cycles, in which DSOs, aggregators and prosumers shape technical flexibility and congestion through policies, protocols and regulatory frameworks, and vice versa [31].

Complex systems

Specifically two complex aspects of this system are distinguished and each represented in a separate model. Firstly, flexibility reactions are influenced through all sorts of factors. This forms a demarcated part of the complex system. Secondly, these flexibility reactions interact in the system-wide grid. Congestion appears as a result from the combined flexibility reactions by grid participants in the grid. Both of these demarcated models use and impact information from the system. Such a dynamic, decentralized network of parallel individual actors with characteristics that cause collective emergent behavior, creates a typical complex system [36]. Both complex parts of the system are explained below.

- **Flexibility reactions shaped by socio-technical factors**

  Especially the various factors in the development of the demand response reactions of flexibility providers bring complexity. These heterogeneous and interdependent factors interact and combine, to shape flexibility reactions in which a lot of uncertainty is present. The study of Christensen, Ma, and Jørgensen [37] for example mentions technical, economic, social and regulatory factors interchangeable influence each other. For example, technical factors such as residential storage capacity, might be dependent and only lead to flexibility once there economic incentive for which the user-behavior has susceptibility. A plethora of other factors play a role in the combined complex synthesis of factors, such as temporal dynamics, weather developments, politics and more. The exact demarcation of the socio-technical system is substantiated in chapter 4.

- **Flexibility loads in electrical power grid**

  The second complex aspect of this system can be captured through electro-technical power flow models. The flexible loads namely interact indirectly through the grid, which leads to complex congestion as result of various power injections and withdrawals. Changes in one location can affect voltages flows, losses and congestion elsewhere. The loads are distributed, interconnected and adaptive, operating under nonlinear physical constraints with mutual dependencies, makin the system increasingly complex. Furthermore, the spatial distribution of the loads plays a big role, adding to complexity. The result of this complexity is visible in chapter 7.

These systemic issues in electricity infrastructure, markets and the surrounding system require an interdisciplinary approach in policy, technology and market design, as the combined socio-technical flexibility reactions, based on aspects such as preferences, capacities, capabilities and congestion measures produce emergent behavior. This analytical integration makes this a typical Complex System Engineering research.

1.5. Outline

The remainder of this research is structured as follows:

- First, a literature review on the knowledge gaps is provided in chapter 2, in which separate parts are distinguished:
  1. Related concepts in the field of research are first explained in the theoretical background, for general understanding. Especially the congestion and congestion management mechanisms are explained.
  2. Secondly, the 4 research gaps in the literature are described, that subsequently lead to the

  sub-questions. These 4 gaps are converted into sub-questions and steps that are used throughout the remainder of this thesis to to structure most of the chapters.
  3. The third section gives a synthesis on the literature review. Additionally, the real-world societal relevance of the gaps is described.
  4. The fourth section, specifically reviews the modeling methods concerning flexibility. This part zooms in on state-of-the art strengths and weaknesses of modeling frameworks and how these contribute to the knowledge gaps and potential alleviation thereof.

- The research approach is introduced in chapter 3. Here, the approach used to answer the main research question and sub-questions to solve the gaps from the literature review are stated. It is structured in four sequential steps, one for each sub-question.
- The system description is given in chapter 4. First, the stakeholders in the system are elaborated on, and secondly the electro-technical aspects of the system. Thirdly, the socio-technical system aspects that influence flexibility are subdivided into 4 factors, that are used throughout the remainder of the thesis.
- The model is developed in chapter 5. This chapter especially focuses on the conceptualization and modeling assumptions and scope. Each of the 4 sub-questions from the approach are worked out in steps.
  1. In step 1, an explanation on the identification of congestion in a network with historical load profiles through a power-flow network model is given.
  2. In step 2, the previously identified congestion is used to incentivize distributed flexibility and assess robustly remaining congestion through a relevant congestion management mechanism.
  3. In step 3, the distributed flexibility reactions in which multiple factors play a role, among which the incentives from step 2, are shaped. Firstly, the stochastic flexibility state evolution model is clarified to construct flexibility reactions, after which the the model scope is further narrowed. Lastly the Monte Carlo sampling strategy is described.
  4. In step 4, an additional feature to the flexibility state model is included. The effects of spatial correlation between neighbors are accounted for in the flexibility reactions. This leads to the final reactions that can be used to assess congestion, after implementation is performed in the next chapter
- In chapter 6, the model is implemented in the case study. In the first section, the 4 factors as defined in chapter 4 are separately implemented by specifying the formulas. In the end of this section, in 6.1.5, the factors together lead to probability distributions in factorial envelopes, that describe the operationalized flexibility states. In the second section, the influence of spatial correlation of flexibility states between direct neighbors is added.
- The results are analyzed in chapter 7. First, the case study and power-flow results are presented, after which the default model behavior is elaborated on in the second section. The second third section shows and interprets the scenario results.
- In chapter 8, the discussions are given. The implications of the results are discussed first. Secondly, the strengths and weaknesses of the research per step are discussed. At last, a concise section is devoted to strategy to validate the results.
- In chapter 9, the overall conclusions to the to the sub-questions are given, alongside an answer to the main research question. Secondly, the scientific and societal contributions are given, and in the last section the recommendations for stakeholders and for future research are both put forward.

2

Literature review

Literature and advancements in energy storage, flexibility, grid-management and congestion tools are evolving rapidly [38]. To maintain a relevant scope that adds to both scientific and applied knowledge, this review addresses state-of-the-art research gaps in four parts. First, theoretical background related to the problem is given to provide a basis for understanding. Secondly, the individual research gaps that lead to a relevant scope for main research question are described in section 2. This section holds four sub-sections, each with one research gap and sub-question. In section 3, a synthesis is given on these. Additionally, in section 4, research gaps are linked to relevant methods.

2.1. Theoretical background

To understand what plays a role in the assessment of distributed flexibility and its impact on congestion, an explanation is given on electro-technical congestion, congestion management measures and applications thereof in the Dutch electricity sector. However, flexibility providers and possible reactions are introduced firstly.

2.1.1. Flexibility providers and grid services

Large flexibility providers, such as storage operators and flexibility aggregators, serve multiple objectives. For example grid and frequency stabilization, peak shaving, providing backup power and energy arbitrage [39]. Tlexibility providers are typically autonomous in decision-making with regard to output, and allowed to maximize their own objectives [40]. This task can be performed with automated energy management algorithms that are optimizing, updating, and choosing output and storage functions. When considering implicit demand response, which refers to the possibility of users to voluntary respond to signals reflecting network variability without direct control, such automated decision-making is especially relevant [41]. Minimal action from the flexibility providers is needed, other than the load adaptations itself. Such implicit actions can also be performed by small distributed flexibility providers, once aggregated by an intermediary that pools many individual assets into a single controllable flexibility resource [42].

Demand response can also be explicit, when the flexibility is traded on on external markets [41]. This requires active commitment of providers, for example trough bidding mechanisms. The flexibility can be deployed on markets to contribute to congestion relief. Nevertheless, without alignment it can also contribute to congestion via the various markets that exist to trade the electrical energy. However, an additional but separate market that is especially relevant for congestion are the congestion market platforms, such as GOPACS in the Netherlands and the upcoming NODES in Flanders, further elaborated on in section 2.1.3.

Furthermore, flexibility resources such as energy storage systems are capable of providing a diverse array of services next to active power management [43]. This has relevance as new ancillary service incentives and markets for explicit demand-response other than frequency regulation are currently being developed throughout Europe [44]. One of these services is inertia support, for which resources with grid-forming inverters can be used to maintain stable operating conditions. Nowadays, this becomes increasingly relevant as conventional synchronous generation and inertia is dropping with the rise of renewable energy sources [45]; [46]; [47]. Another ancillary service under development that is also relevant for congestion mitigation, is reactive power management and voltage services. In Europe, among others the British National Energy System Operator and GOPACS are exploring options for reactive power markets, which are accessible to flexibility providers via explicit demand-response mechanisms [15];[44]. At present, reactive power is often managed within mandatory provision via grid codes, through annual tenders for grid-connected generators and through usage of grid-operator owned equipment such as Flexible AC Transmission System (FACTS) devices and on-load tap changers (OLTC) [48]; [49] ; [50]. In the future however, private and market-based systems, among which flexible storage systems with rated capacities larger than 1 MW, might also provide reactive power services [51];[48]. Thus, when assessing implications of flexibility on congestion both active and reactive power aspects are relevant, as both can impact congestion and network losses [52].

2.1.2. Electro-technical congestion

To understand the physical nature of the problem, electro-technical congestion is explained. Congestion is announced before acute physical congestion occurs, since grid-operators operate with N-1 considerations. Usually, it is announced when contracted capacity is expected to exceed rated capacity if additional capacity is awarded. Congestion already limits grid capacities, and is expected to increase.

Electrical congestion can be subdivided into three categories. First of all, the most apparent type is thermo-physical congestion, caused by thermal limitations. The other types, voltage and stability congestion, are related to system limitations. The relevance of the three types was cross-checked with informal interviews with DSO experts from the technical innovation and research department, such as Hoogeboom and Fricke [53]. The experts validated the types of congestion, and its relevance for mitigation. These three types, as distinguished by Mahawar et al. [54]; U.S.-Department-of-Energy [55]; Yusoff, Zin, and Khairuddin [56] are introduced below:

- **Thermal congestion**

  Thermal congestion occurs when current flowing through grid equipment exceeds its rated thermal capacity. Large power flows cause the equipment to heat up excessively, caused by resistive thermal power dissipation (I2R) losses, in which the magnitude of current plays a major role. The magnitude hereof is determined by apparent power (kVA), which includes both real and reactive power components. These magnitudes are not allowed to systematically exceed the ratings. However, component limits are defined as rated capacities. This rating implies that most of the equipment can physically withstand short-term current overloads, enabled by thermal inertia. Hence, rated capacities are not always binding, especially when congestion rarely occurs. Still, deterioration increases exponentially at overloads. This is financially detrimental, as it leads to reduced lifetime [57]. Overall, thermal congestion is seen as the main reason for congestion announcement, and is a fundamental physically limiting component.

- **Voltage congestion**

  Voltage congestion occurs when allowable operating limits for static voltage magnitudes are exceeded. This can be caused by large injections of real power, for example by solar PV at feeder ends. Additionally, power quality issues such as sudden changes in non-linear loads influence voltage congestion [58]. Alongside real power control, voltage is influenced by reactive power management. Reactive management is used to manage the power factor, related to the amount of capacitive and inductive components in the system. This influences the magnitude of voltage and therewith congestion. Various tools are available for reactive power management through grid-side flexibility, among flexible resources including smart-inverters with reactive power capabilities. These have advantages over conventional 'grid-side' flexible technologies such as FACTS devices or OLTCs, as they are relatively cheap and require less maintenance [59]. A hard voltage deviation up to 10% is technically allowed in distribution networks, where grid operators aim for 5%. Voltage congestion constrains the operational and control aspects that are embedded policies, grid codes and operating limits. These policies do not physically limit what is technically feasible, as equipment can often withstand higher voltages. Especially during periods with large PV-injections at feeder ends, these operational limits cause congestion.

- **Stability congestion**

  This type of congestion occurs when dynamic stability is lost, such as generator synchronism or voltage collapse. It can be caused by rare but large disturbances trough faults and equipment failures [55]. It is a system-wide and dynamic issue, that is largely determined by the global dynamics of the interconnected system. Although synthetic inertia of flexibility providers might contribute to mitigation, it cannot be solely solved by these. This congestion is highly dependent on operational and regulatory strategies from grid operators, and therefore not focused on.

Components in congestion

Congestion manifests itself in specific equipments. Especially transformers, and distribution and transmission lines, tend to be thermally limited and difficult to replace for example because they are laid underground. Other equipments, such as bus-bars and breakers, are typically oversized. These can be replaced and maintained easier, and are not often a constraining factor. Therefore, this research primarily focuses on congestion in lines and transformers, as a result from apparent power voltage and current overloading.

Demand response implications for congestion from real and reactive power

Real power is seen as the dominant component causing congestion and in the focus for small-scale distributed flexibility providers. This occurs via implicit mechanisms, but possible also via explicit mechanisms through aggregators or CSPs. In contrast, small distributed flexibility providers have only limited capability and incentives for reactive power compensation [48]. Small flexibility providers do typically not participate in explicit reactive power mechanisms for voltage congestion mitigation.

However, state-of-the-art flexibility systems can work with explicit demand-response, such as large-scale storage with advanced inverters above 1 MW [48]. These can contribute to grid-side flexibility and voltage congestion mitigation with reactive power management. The management of such grid-side flexibility aspects is slowly opening up to entities other than the DSO, but still only works via explicit demand-response, thus requires active commitment of providers [60];[15]. So, unlike thermal congestion, voltage congestion and its mitigation is strongly dependent on regulatory frameworks, operational setpoints, and control strategies, making voltage congestion only directly and explicitly addressable through explicit demand-response for providers with capacities above 1 MW [48]. This research primarily focuses on congestion as a result from apparent power overloading and the implications thereof for real power flexibility, in terms of both voltage and current. However, to be complete, this research also takes into account the implications that these current and voltage might have for reactive power flexibility requirements, as it might be relevant for large-scale explicit demand-response.

2.1.3. Congestion management

To provide insight in how distributed flexibility can be activated to mitigate congestion, congestion management mechanisms (CMMs) are explained. There are multiple CMMs for which there is a plethora of literature available. The methods of Yuan, Hu, and Li [61], Yusoff, Zin, and Khairuddin [56] and Mahawar et al. [54] were compared and distinguished to create a non-exhaustive overview, for which the results are shown in table 2.1 below.

In the overview, it becomes apparent that there is general consensus on the CMMs. Differences exist in the level of detail and sub-classifications. Most authors differentiate between direct and indirect control methods and technical and non-technical methods. Direct control uses a centrally controlled entity, usually the DSO or TSO, without relying on decentralized decision-making by other agents. These central entities use network configuration, cutting of loads and reducing distributed power output to mitigate congestion. Indirect control methods use demand response mechanisms. Recent studies reflect the growing importance of distributed control and indirect solutions. The higher-level methods are separately described in bullet-points below.

CM Method	**[61]**	**[56]**	**[54]**
Direct control			
Technical Methods			
Transformer taps	✓	✓	
Outaging of congested lines		✓	
Grid upgrades	✓		
FACTS devices	✓	✓	✓
Network reconfiguration	✓		
Optimal Power Flow (OPF)			✓
Operational Strategies			
Security Constrained Dispatch			
Redispatch / ex post Counter Trading	✓	✓	✓
Load Curtailment	✓	✓	
Distributed Generation		✓	✓
Indirect control / Demand Response			
Pricing-based Methods			
Nodal pricing	✓	✓	
Zonal pricing		✓	✓
Smart tariffs			
Market-based Methods (ex ante)			
Preventative Auctioning		✓	
Local markets		✓	

Table 2.1: Summary and comparison of congestion management methods across different studies

- **Technical methods** These can be distinguished by the electro-technical measures that enable grid-side flexibility, as explained in section 1.3.2. They have the ability to physically alter network characteristics and equipment capabilities, and are controlled by a central entity with direct manipulation of system parameters. For example, FACTS devices can manage power flow by altering line impedance.
- **Operational methods** These measures are related to scheduling and procedural operations and can be distinguished by the ability to operate in the short-term and their dependence on real-time monitoring. Again, these measures are managed by the grid operator. It involves decision-making with situational awareness. For example generation rescheduling and mandatory redispatching are used to nullify congestion, after market-based mechanisms have proven insufficient.
- **Indirect control methods / Demand response** These distinguish themselves by using economic and informational signals to nudge users to change behavior and power plans, rather than issuing mandatory commands or performing physical control actions. This category is typically referred to as voluntary and indirect demand response. This can, but not necessarily, be based on pricing based demand-response programmes. These indirect measures promote system-wide efficiency and encourage usage of distributed resources, while helping balance supply and demand.

Applied congestion management measures and granularity

This subsection elaborates on CMMs that are currently applied within Dutch distribution grids, with a focus on distributed flexibility providers. Additionally, the concept of granularity in CMMs is explained.

For flexibility providers that get dynamic incentives and tariffs, elasticity might be beneficial. A lot of variations of such CMMs that use third parties to provide flexibility exist. Some CMMs are already implemented or near implementation by the TSO and DSOs in the Netherlands [62]. The currently applied mechanisms rely on voluntary participation from the heterogeneous end-users, which makes them especially suitable for mobilizing distributed flexibility. The portion of grid participants that is currently subject to these measures is limited, especially for indirect measures [16]; [63]. Nevertheless, two main types can be distinguished: capacity-restraining contracts and redispatch contracts, which can both be activated via GOPACS [64]. While participation in these schemes is voluntary, the activation of flexibility is decided by the DSO. Usually, flexibility providers are rewarded afterwards [16].

These methods can be characterized as direct, market-based congestion management instruments, rather than purely indirect measures. Nevertheless, a clear market-based element is incorporated, as it requires bidding from market participants that is subject to locational and time-varying compensation [15]. Through flexibility platforms like GOPACS in the Netherlands or the upcoming Nodes from Fluvius in Flanders, activation of local flexibility through such market-based mechanisms is facilitated. In such market-based mechanisms, congestion creates spatially and temporally varying scarcity signals that allow incentives to be targeted toward actual contributors. Such explicit mechanisms might be translated into implicit mechanisms for consumers by aggregators, industrial users and CSPs under future regulatory developments, and therefore are important to take into account [41]; [65].

An important aspect that influences the efficiency of applicable congestion management mechanisms is the granularity. In congestion management mechanisms, granularity refers to how detailed or fine-scaled the control, pricing, or actions are when managing congestion in the power system. It describes the resolution of the mechanism in space and time at which congestion is identified and managed. Once a highly temporally granular mechanism applies, it can explicitly target a specific timestep, without applying to other timesteps. Once a highly spatially granular mechanism applies, it can explicitly target a specific area or a specific congestion contributor, without applying to other areas. In the local flexibility platforms such as GOPACS, spatial and temporal granularity is generally high, as they can be targeted towards specific areas at specific timesteps. Such mechanisms use power transfer distribution factors in their allocation, just like Distributed Locational Marginal Pricing (DLMP) and are therewith congestion-efficient to coordinate the burdens.

Recent developments show growth and relevance for these voluntary demand-response mechanisms that become increasingly granular. A real-world example of a spatially uniform and non-discriminatory CMM is the time-of-use tariff in distribution grids, without locational segmentation, that will be implemented in the future [62]. Although already more temporally granular, this mechanisms does not have the high temporal and spatial granularity that local flex platforms can have. Hence, all kinds of control methods are already used and under development in the Netherlands, also with indirect aspects. More types of capacity restraining contracts are in development, and recent reports of grid operators also emphasize the usefulness and importance of spatially and temporally stimuli and financial incentives to mitigate congestion [7]; [66]; [64].

Apart from this, Dutch CMMs are mainly focused on active power regulation. However, recent developments have shown that participatory reactive power management will be used increasingly for congestion reduction in the future. Nowadays, grid-side flexibility is be opening up to large grid-clients as well. By making use of the capability from smart-inverters from distributed resources, voltage congestion can be managed through absorbing and injection reactive power. Especially GOPACS is exploring options to do so, aimed at large clients [15]. This underlines the relevance of this congestion management option when siting additional and upcoming storage systems and flexibility providers. In contrast, it is not relevant yet for small distributed flexibility agents, who currently have almost no incentive to participate in reactive power management [60]; [48].

2.2. Literature review on research gaps

Through understanding of the previously introduced background concepts, the research gaps are sequentially elaborated on in this section. These gaps further specify, navigate and guide towards the sub-questions. The combination of the sub-questions can be synthesized in the main research questions, which is elaborated on in section 2.3. First, the various research gaps are connected to the sub-questions sequentially. The gaps that correspond with the subsections and steps 1, 3 and 4 below are narrative scoping literature reviews, whereas subsection and step 2 is a systematic literature review on how to model the maximum potential of distributed flexibility under the various CMMs.

2.2.1. Relevance of modeling existing congestion patterns

The relevance of flexibility is undisputed in mitigating and modeling congestion. Flexibility provides the capacity for demand response that the voluntary CMMs rely on to mitigate congestion. It is of key importance to site these flexible systems in a geo-spatially and electro-technically efficient manner [67]. A plethora of literature is available on optimal siting and sizing of storage systems to mitigate congestion in distribution grids. The majority of literature approaches congestion-optimal deployment and siting in energy systems as if there is a coordinating authority that orchestrates to optimize a system-wide objective [54]. There is mutual agreement among the studies of Ortiz et al. [68]; Das et al. [69]; Song et al. [70] that specific algorithms are powerful in doing this, such as genetic algorithms. It has been proven that properly siting flexibility providers through such algorithms, reduces congestion while achieving reliability gains and cost reductions as argued by Su et al. [67] and Ortiz et al. [68].

However, the value for grid operators to solve congestion is largely unknown to the flexible asset owner. There are missing markets for congestion, where the operator is not able to monetize and signal congestion [71]. Therefore, the autonomous and private flexibility providers that act with their own individual sizing, siting and dispatch algorithms, have limited incentive to take consequences for the system-wide grid into account. This results in limited alignment between existing location-bound distributed flexibility and yet-to-be-sited flexibility providers, while these can simultaneously and complementarily relieve grid congestion in an efficient way. Their complementarity is complex. Each solution's ability to ease congestion might affect the other's impact, as the loads are indirectly connected via the grid [70]. Because flexibility and demand response in one area reshape flows and congestion patterns elsewhere, local flexibility continually influences where new flexibility is most profitable and whether CMMs are effective, as [72] argue. Among others the study of Jing et al. [73] argues that existing flexibility is not sufficiently taken into account when placing new flexible systems. Furthermore, the study of Kotthaus et al. [74] also recommends to provide more insight in alignment between distributed flexibility providers, especially since recent growth increases the potential. To assess the potential impact of distributed flexibility on congestion once properly aligned with existing flexibility, insight in where congestion arises in the first place under business as usual conditions should be created. This congestion pattern can be used for alignment, and therewith impacts the potential of distributed flexibility to mitigate congestion. Creating insight in these congested locations shows where existing demand response is inadequate, and where additional measures are necessary to solve congestion.

Such information is fundamental. Once it is known where and to what extent additional measures are required to solve congestion, the ex post effects of additional measures that are deployed in the future can also be assessed. Assessing the effects of the additional flexibility measures on congestion is relevant, as the amount and influence of distributed flexibility assets is expected to increase drastically in the future [75]. The study of ECN [76] expects that around 40% of the total Dutch flexibility requirements can be accounted for with distributed sources of demand response in 2050, whereas other research suggests that the quantitative maximal capacity of distributed flexibility capacity can even amount up to 35 GW, corresponding to 58% of national flexibility needs in optimal scenarios [66]. This however, is the quantitative potential which deviates from the socio-technical reality. As Wang et al. [77] and Oskouei and Gharehpetian [78] put it, activation and incentivation of these local flexibility resources, for example via CMMs, is key to reduce grid congestion. CMMS will be applied more thoroughly in the future, and the impact of location-bound distributed flexibility becomes more relevant to assess.

To conclude, activation of additional distributed flexibility with CMMs should be aligned with existing congestion patterns to assess the potential impact of distributed flexibility. However, information on such congestion patterns is lacking and differs per grid. Therefore, the first sub-question creates this insight by identifying where congestion arises under business as usual conditions, with lack of CMMs and no alignment and encouragement for demand response. It should provide insight in where flexibility is currently inadequate, and where it is relevant to assess the effects of increased flexibility reactions. Only after the effects of additional flexibility at these specific congestion locations have been accounted for, the most severely congestion that still remains can be assessed. Therefore, the following subquestion should first be answered: *Where does congestion occur in Dutch distribution grids under current conditions without activation of distributed flexibility?*

2.2.2. Research gap on implementing CMMs for maximum potential

After providing insight in congested locations and inadequacy of flexibility reactions under the business as usual scenario, the effect of additional flexibility reactions can be assessed. Such additional measures and demand response can be activated via CMMs that create signals and tension to which flexibility providers can respond with flexibility, often while competing for revenues, regulatory attention and market signals. However, only limited information is available on how to align and encourage this upcoming additional flexibility to deploy the maximum congestion solving potential. Especially the role of various CMMs that influence demand response reactions is unknown. The systematic literature review provided below, further assesses the underlying properties of the CMMs that shape and determine the potential of distributed flexibility to solve congestion. It elaborates on the research gaps in modeling the maximum potential of distributed flexibility in solving congestion, under the various CMMs. Firstly, the review strategy is introduced, after which the results of the systematic review are visualized in an overview on which a synthesis is given afterwards.

Systematic review strategy and set-up

During the reviewing process cross-checking was performed using the Scopus database combined with Google Scholar to check potential availability gaps. The Mendeley Reference Manager was used to organize data while ensuring consistency. Informal conversations with DSO experts were also used for exploration and confirmation of the topics. The used search strings are focused on the assessment of CMMs combined with distributed and decentralized flexibility utilization in electricity grids. Large-language AI models were used to find synonyms and closely related concepts, ensuring completeness of the search strings. Search string elements are related to; distributed and local flexibility, congestion management, components, characteristics, demand-response, prosumers, flexible assets, distribution networks, comparison and assessment. The majority of relevant literature was found through backward and forward snowballing. Especially studies that incorporate and compare different CMMs were focused on, as these tend to elaborate on relative positioning and comparison of strengths and weaknesses of CMMs. Selection criteria were also used, as shown in the PRISMA diagram in figure 2.1 below, that includes visual overview of the search strategy. 19 studies were included that mention congestion management characteristics with regard to distributed flexibility, of which the results are included in table 2.2 below, after introduction to the structure of the overview in the next subsection.

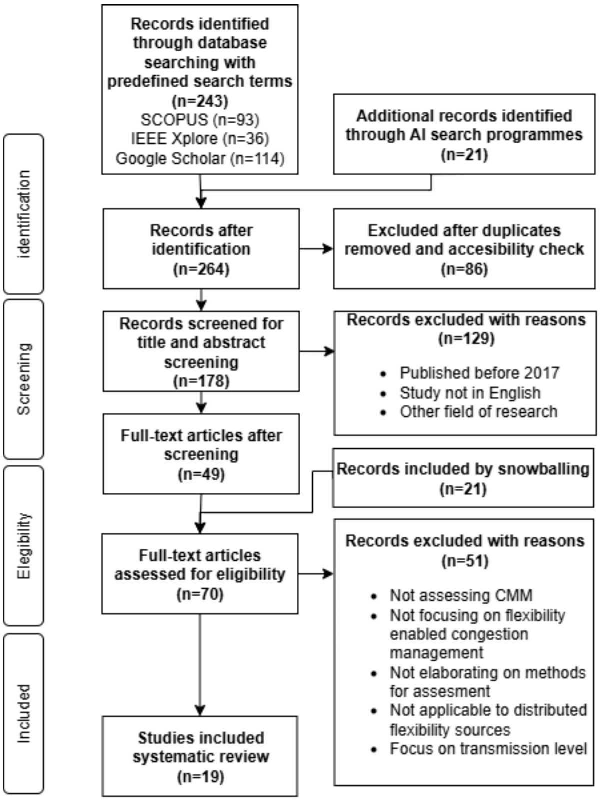


Figure 2.1: PRISMA flow diagram for study selection process

Structure of table with review results

The various studies of the review mentioned in column 1 of table 2.2 below were compared, and the other columns elaborate on the following aspects:

- In the second column, a checkmark for comparison of CMMs is given. This checkmark shows whether CMMs are relatively positioned among each other, and whether strengths and weaknesses are compared. This improves the understandability and validity of CMMs and their proportionality, instead of unilaterally analyzing these in isolation with potential bias.
- The third column is a checkmark that states whether a study elaborates on the elements that provide flexibility and modeling thereof, instead of only assuming general willingness-to-pay, elasticities or cost-minimization objectives, without inclusion of detailed and substantiated information and dependencies on costs and preferences. It assesses whether a study elaborates on the underlying causes or portfolios that induce locally differing flexibility, and which aspects specifically differ.
- The fourth column states which CMM or category is the main focus or is proposed as ultimately relevant and 'best-of-class' for utilizing the full potential of distributed flexibility.
- The last column provides an explanation on what characteristics make the proposed CMM or category relevant to utilize distributed flexibility potential. Additionally, it assesses whether and how the CMM interacts with distributed flexibility, and if this interaction includes detailed information about the underlying components that shape the flexibility.

Study	CMM comparison	Flexibility elaboration	Praised CMM	CMM argumentation and modeling of distributed flexibility reactions
Kulms et al. [79]	✓	✗	Market-based approaches	These allow greater accessibility through uniform economic incentives. Additionally, markets provide more aligned incentives and profits, however communication network costs lower social welfare. The effects of different possible flexibility portfolios are not assessed here.
Papavasiliou [80]	✗	✗	local pricing and DLMP	Provision of location-specific, real-time incentives make it attractive to activate flexible demand. However, these signals are complex and complicated especially for LMP mechanisms and detailed electrotechnical information such as voltage, reactive characteristics, and ancillary services.
Fattaheian-Dehkordi et al. [81]	✗	✗	Indirect and decentralized strategies	These provide scalability, security, adaptability, and data privacy. The combination of agents with abstract transactive values in CMM's, has the advantage that no central controller or optimization has to be performed. In this way the autonomous and differing nature of agent with flexibility for demand response can be modeled. However, the response to this value is not explained.
Zeiselmair et al. [82]	✗	✗	Local flexibility markets	These optimize coordination and give access to multiple markets while increasing economic efficiency through proper allocation, however understanding agent-behaviour is key to understand the market dynamics. The flexibility reaction works with flexibility offers and constrained optimization, however no details on flexibility bids or composition thereof is provided.
Edmunds et al. [83]	✓	✓	Market-based approaches	Provide a way to implement local conditions that are scalable and support price based methods. Besides, aggregation allows for probabilistic and averaged solutions which increases effectiveness of indirect mechanisms. This study elaborates on the aggregator portfolio, which is binding for flexibility constraints and probabilities. The aggregator portfolio is modeled via agents.
Vo et al. [84]	✓	✗	Indirect congestion methods	Direct management can require more investment from DSOs, indirect congestion is financially attractive. Indirect congestion methods however, only work properly when enough capacity is already present in the system. There is no further insight or elaboration in how this capacity influences prices and elasticity however, and in the underlying flexibility capacity and scarcity.
Pediaditis et al. [85]	✓	✗	Indirect congestion methods	Because they are scalable and practical, especially tariffs are efficient at high prices or congestion. Markets are more efficient at low prices, however the relation is complex as efficiency depends on system dynamics, liquidity, and elasticities. No details are given on the qualitative reactions of distributed flexibility.
Hennig et al. [17]	✓	✗	Disfavours market-based approaches	Especially dynamic tariffs are suited for flexible consumers and aggregation is beneficial. In general, mechanisms must be tailored to the problem at hand, and should be assessed simultaneously. Market-based measures are susceptible to strategic behaviour. This study does not focus on the underlying composition of distributed flexibility, it solely focuses on CMM's
Zhan et al. [86]	✓	✗	(non-) technical methods combined	These efficiently coordinate demand-side flexibility while incorporating preferences and fairness with scarcity. Technical methods are especially relevant when combined with indirect methods. The study focuses on applications that facilitate control, but do not go into detail on what exactly is controlled in a qualitative manner.
Oskouei et al. [78]	✓	✗	Price-based DR programs	Provision of local information in incentives is good for financial efficiency, and complexity decreases by aggregation and distributed control in general. Besides, unlocking of consumer-side flexibility for local decentralized asset usage can be supported through financial incentives. The flexibility reaction here is modelled through mathematical optimization, but does not go into detail on the components that shape the flexibility.
Mehinovic et al. [72]	✗	✗	Local flexibility markets	Local sensitivity factors, with for example power transfer distribution factors allow for accurate evaluation of flexibility bids, this improves the efficiency of coordination. The reaction of flexibility is embedded in the bid, but not explicitly modelled or substantiated.
Zhao et al. [87]	✗	✗	DLMP and market-based approaches	DLMP provides accurate, location-specific financial signals that reflect the real operational stresses and losses in the distribution network, thus enabling optimal incentivization, which can resolve issues beyond technical measures. This study however does not go into detail on the reactions of flexibility, rather it focuses on how DLMP should be created to accomplish flexibility.
Attar et al. [34]	✗	✓	Local flexibility markets	These cause balanced and realistic integration with trade-off awareness while being open to future developments. Dependency on size of bidding area and cybersecurity, and relevance has to be measured under multiple measures. This study is bidding based, hence does not use cost minimization or direct willingness-to-pay characteristics, but does specify flexibility activation times, durations and volumes.
Kilthau et al. [14]	✗	✗	Decentral congestion market	A decentralized market approach increases scalability while taking financial incentives into account. This paper proposes distributed management and computing in markets, with a separation of tasks in respectively energy and congestion negotiation. Besides, the congestion agents of different users have a common objective, which does not align with reality. The agents market-decisions are modelled extensively, but the incentives and willingness to pay are not explained.
Holst et al. [21]	✓	✓	Seasonal peak tariff	Power and time-based components make this instrument more robust. However, the efficacy of combinations is dependent on specific conditions. Introducing multiple instruments might be ineffective and inefficient, as it requires more effort. Here, it is assumed that HEMS with cost minimization objectives react to the congestion signals, and specific numbers for specific assets are given, although no substantiation for the techno-economic parameters is given or how this interconnected system interacts.
Gorrasi et al. [19]	✓	✗	Simpler market designs	Simpler market designs, such as static limits and dynamic operating envelopes, are more effective than DLMP in networks with shorter feeders and larger consumers. Locational signals make structures more efficient. However, simpler designs lead to less cost efficient and more conventional investments. The reactions of participants are minimization objectives while incorporating willingness-to-pay for network costs, but do not elaborate on the composition of these.
Hanif et al. [88]	✗	✗	DLMP	Each local agent manages its own uncertainty, which relieves the DSO from the heavy task of predicting centrally, this makes use of the competitiveness of private parties. Robust load dynamics have to be incorporated in the formation of these DLMP answers, however, no information is given on how the DLMP price leads to the flexibility reactions.
Stute et al. [89]	✓	✓	Dynamic tariffs	This study mentions that a variety of congestion signalling mechanisms should be used as diversification is important when combating congestion. Besides, the local characteristics and motivations influence the efficiency of the congestion mechanisms. Unique from this study is the fact that it elaborates slightly on the reactions of prosumers next to price elasticity.

Table 2.2: Structure and evaluation criteria of the literature review, comparing studies based on CMM comparison, treatment of flexibility elements, proposed best-of-class CMMs, and elaboration on their relevance for distributed flexibility.

Synthesis

The results make up a coherent story on what CMMs are relevant when modeling the maximum potential of distributed flexibility in solving congestion. However, this relevance is only validated by a limited amount of studies that compare simultaneous assessment of CMMs, as argued by [17] and visible in column 2 of the table. Nevertheless, studies that assess CMMs in isolation also elaborate and added to the understanding. Remarkably, there is no consensus whether CMMs should be deployed simultaneously. Among others Pediaditis et al. [85], Zhan et al. [86] and Zhao et al. [87] advocate for simultaneous combinations of methods. Not only to assess the full potential, but also because it increases potential if properly aligned. The paper of Stute and Kühnbach [89], adds to this that diversification of CMMs is always advantageous. In contrast is among others the paper of Holst et al. [21], that mentions that multiple mechanisms at once might increase DSO effort and decrease efficiency. Combinations of indirect methods combined with technical methods can also contribute to the potential of distributed flexibility in solving congestion, whereas technical methods without combining non-technical methods are less relevant, according to Zhan et al. [86] and Zhao et al. [87].

Especially the maximum potential of distributed flexibility on physical congestion is focused on in this research, as this shows where the most robust and persistent congestion remains. There is consensus among studies in preferring indirect methods to mitigate congestion in the most impactful way. These methods are less costly for grid operators and shift the burdens towards consumers through implicit behavioral incentives, in which only limited direct and explicit actions from the grid operator are required. Indirect approaches allow greater accessibility for flexibility providers, especially through aggregation as argued by Oskouei and Gharehpetian [78]. Multiple studies mention the importance of aggregation, as it is an enabler of flexibility while reducing costs, and increasing predictability and market readiness. Especially indirect CMMs that provide implicit behavioral incentives for aggregated, autonomous and decentralized flexibility providers are easily scalable and adaptable. Indirect CMMs can use financial and non-discriminatory incentives such as tariffs, but there is no consensus on what indirect measures are optimal.

In general, financial measures are praised when assessing CMMs only on physical congestion mitigation. Studies like Kulms et al. [79] and Papavasiliou [80] stress the role of local congestion pricing and the efficiency for resource allocation that comes with higher temporal and spatial granularity for distributed flexibility activation. In this light, a lot of authors, among which Zeiselmair and Köppl [82], Mehinovic, Suljanovic, and Zajc [72], and Attar et al. [34], emphasize the value of local flexibility markets. These efficiently find the balance of scarce resources for economic allocation by price differentiation among participants at different locations. In general, the inclusion of locational and temporal information through scarcity-and congestion-signals, not only in market-mechanisms, provides significant potential for distributed flexibility to efficiently solve congestion, which is specifically mentioned by Mehinovic, Suljanovic, and Zajc [72]. Additionally, the locality of local pricing and market-based measures can incentivize and signal scarcity in situations that cannot be solved by other measures, as signals can be varied in real-time at specific locations. Holst et al. [21], add to this that financial incentives, possibly highly granular, work best to activate distributed flexibility without requiring bilateral contracts or technical integration for direct control from the DSO. Furthermore, market-based measures have the ability to directly reflect scarcity signals for future developments, without needing additional measures whereas non-financial incentives need additional measures as argued by Attar et al. [34]. Overall, local and temporally detailed financial indirect mechanisms are praised.

However, in markets specifically, as also emphasized by Hennig, Vries, and Tindemans [17] and Stawska et al. [90] strategic behavior might lead to problems. Additionally, for market-based measures there are issues with fairness and unequally endowed system constraints, as Attar et al. [34] mention that the quality of market-based measures is dependent on the size and technical characteristics of the area. When not solely looking at physical congestion in the assessment of CMMs, Papavasiliou [80] mentions that the complexity of implementing such detailed and local pricing structures in distribution networks is high due to issues like practical feasibility and technical feasibility like reactive power and voltage limits. Distributed Locational Marginal Pricing (DLMP) for example, requires advanced metering forecasting and settlement systems for all users, which might lower social welfare. The study of Gorrasi, Bruninx, and Delarue [19] adds to this that simpler and less granular designs might be more effective, especially in networks with short feeders and large participants. For financial incentives, only once uniform prices or incentives apply, participants are treated equally and non-discriminatory, and regulatory complexity is avoided. However, such uniform mechanisms might also result in higher system costs or be locally inadequate, reducing social welfare.

There is consensus on the importance of granularity once assessing CMMs. The effect of financial incentives, both highly granular or non-discriminatory uniform, on critical congestion points will be similar once the same congestion contributors are targeted. However, granular CMMs are more efficient and precise in targeting congestion with regard to system costs and social welfare, instead of applying the incentive everywhere uniformly [34]. Therefore, one can expect the highly granular mechanisms, that sometimes use financial compensation instead of pricing, to be more intense in terms of financial incentive. These highly granular CMMs are ultimately relevant to assess congestion that remains. As they impact social welfare to a lesser extent, they can provide relatively high incentives and therewith cause the most potent flexibility reactions. However, such CMMs might be unfair and discriminatory, as argued by [91]. In contrast, the uniform pricing-based mechanism, is non-discriminatory. It therefore has higher burdens with regard to social welfare, and cannot be as intense. Nevertheless, for both highly granular and uniform mechanisms, the quantification of flexibility reactions and physical congestion itself is dependent on the magnitude of the financial incentive. Granularity of CMMs itself does not play a major role in this reaction, but magnitudes of financial incentives depend on granularity. This magnitude is primarily determined by grid operators, regulatory authorities and modelers.

To conclude, once solely assessing the role of CMMs in modeling flexiblity reactions, indirect highly granular mechanisms such as DLMP are optimal for congestion efficiency. Nevertheless the implementation hereof is complex, and the granularity of different prices might be discriminatory and unfair. Still, the financial aspect of CMMs is praised as it efficiently allocates burdens, and can be relatively non-discriminatory, scalable and fair, especially once prices are uniform. So, there is only partly consensus on what financial indirect congestion mechanisms are relevant for distributed flexibility, but the granularity or uniformity of the mechanism impacts the relevance, which is dependent on the objectives. CMMs with high spatial and temporal granularity would be able to give the highest incentives, and are able to assess the robustly remaining congestion after the most positive flexibility reactions. However, CMMs have to be non-discriminatory and accessible. Overall, it is unknown how the effect of such financial CMMs with high spatial and temporal granularity can be modeled, while simultaneously being non-discriminatory and focused on the maximum potential of distributed flexibility providers to solve congestion. This can be synthesized in the second sub-question: *How can the effect of a congestion management mechanism that encourages the maximum potential of distributed flexibility be modeled?*

2.2.3. Research gap concerning influential flexibility factors

Not only CMMs impact distributed flexibility reactions and the adequacy for congestion mitigation. CMMs interfere with factors of distributed flexibility providers in the electrical network, that also determine the reaction [92];[90]. Together, local flexibility assets and factors, in combination with CMMs and incentivization solve the puzzle and reduce overloading, although significantly more complex [93];[21];[94]. The following section zooms in on these factors and investigates the research gaps.

Direct CMMs such as curtailment and DSO-operational adjustments, do not directly rely on local characteristics and heterogeneity among users. These CMMs are less relevant when assessing flexible reactions, as the effects on congestion are trivial and chosen by the grid operator. However, all voluntary and indirect CMMs depend on incentive based-mechanisms that aim to influence behavior of grid users. These are therewith increasingly dependent on local and heterogeneous user characteristics and elasticities. In existing literature, only little elaboration is given on the underlying flexibility factors and flexibility portfolio that combine into a demand response reaction. However, such information is needed for congestion assessments as Stute and Kühnbach [89] argue. Some studies include information by using prices with elasticities or willingness-to-pay (WTP) principles to assess reactions, without elaborating on the components that make up these values. Although these principles provide a systematic way to represent scarcity and consumer preferences, they do not transparently show the underlying built-up and dependencies of these preferences and do not show how reactions come about. The usage of only these abstract principles such as elasticities is not unexpected. There is no uniform method to model differentiable prosumer reactions to CMM incentives, argued by Holst et al. [21]. Furthermore, mathematical optimization models do often focus on a single objective and also give limited information on the socio-technical background and integration of uncertainty without in-depth causes.

Evaluating flexibility reactions with price-principles only is incomplete, as not all scarcity can realistically be captured by pricing mechanisms and some congestion mechanisms do not use prices and financial incentives at all [95]. In the end, it remains unclear what local component or factor is essential in the local provision of flexibility through such elasticities.

Overall, the transparent overview is lacking or not concrete within existing models. The varying information per participant on integrated profile loads and factors is something that receives little attention or is assumed fixed and exogenous. Especially the factors that cause heterogeneity among end-users is something that not taken into account in a transparent and insightful way in existing analyses. Fattaheian-Dehkordi, Aghaei, and Amjady [81] argue that this is not unexpected as most methods are centralized in decision-making and have limited adaptability to local changes. Additionally, this study argues that centralized methods have scalability issues with growing data. They often lack the capacity for detailed incorporation of different types of components and behavior that influence loads, which is needed to incorporate local characteristics. Also Grover-Silva, Girard, and Kariniotakis [96] argue that fluctuating market-based operational and behavioral considerations are complicated to simulate simultaneously during a computationally extensive grid sizing and placement planning calculation. Furthermore, most studies are coarse in their assumptions and local data input, while outputs and conclusions such as optimal storage dispatch and locations are highly detailed. The precision of these outputs might be misleading because it rests on simplified premises [97].

However, although concise, a limited amount of studies elaborate on the underlying flexibility factors. For example, Edmunds et al. [83] make a distinction between inflexible and flexible components among different agents with EVs, storage systems or renewable energy supply with state of charges, while also distinguishing between fully controllable or price-driven flexibility. To counter their lack of elaboration on the build-up of flexibility, the study mentions that aggregation allows for modeling reactions with abstract values without needing to assess each flexibility provider individually. Aggregation is emphasized by multiple studies as relevant for assessment of the CMM and flexibility compositions, as it allows for using probabilistic data and therewith can be useful in assessing and exploiting the full potential of distributed flexibility as Oskouei and Gharehpetian [78] emphasize. Although limited, other studies that have slightly more detail on the factors include the distinction between agents with or without HEMS and controllable and uncontrollable loads [34]; [21]. The study of Stute and Kühnbach [89] is unique and extensive as it distinguishes per agent the types of technology, alongside WTP and energy-management system differentiation, and the ability to choose between CMMs.

To conclude, only a limited amount of studies do include location-specific and varying information on demand response. There is consensus on the fact that these factors should increasingly be incorporated into future modeling practices, as they have significant impact on the optimal spatial placement of flexible systems [69];[70]. Other literature, among which, Taltavull-Villalonga et al. [93], explicitly suggest future research to create insight in the integration of demand-side flexibility or electric vehicles to alleviate excessive stress on centralized storage. In general, taking congestion management strategies related to local flexibility into account when deciding on locations for flexible systems is pointed out to be important, even though there are lots influential factors and possible outcomes [73]. Therefore, the third research gap that this research addresses is: *What interplay of factors influences possible reactions of distributed flexibility to mitigate congestion?*

2.2.4. Research gap on spatially heterogeneous grid-participants and factors

Where only a limited amount of studies model local agent factors, even less model heterogeneity in these agent factors. Heterogeneity entails that the local flexibility factors and reactions can differ per agent. It is known that this influences distributed flexibility, but only a limited amount of studies model this [98]. Some of the studies mention a specific way to include heterogeneity in modeling flexibility components, although actual implementation is not performed. The papers of among others Edmunds et al. [83], Kilthau et al. [14], Gorrasi, Bruninx, and Delarue [19] and Kulms et al. [79] use agents to represent decision making of flexibility users. It allows for decentralized control, separation of tasks, coordination and negotiation while simulating realistic behavior, where agents can include heterogeneous characteristics. However, more heterogeneous characteristics can be added to such models.

Furthermore, Wüllner et al. [43] emphasize the dependency for congestion mitigation, grid upgrade deferral and reactive power management on network topology and local constraints. Despite not often being done in the literature, expanding static geo-spatial information of underlying components in power system characteristics with more dynamic real-time energy planning is considered as a high priority for institutions and future research [99]. These geo-spatial differences impact congestion differently, and spatial dependencies lead to regional disparities in the ability to manage congestion [100]. So not only is there heterogeneity in flexibility reactions, this heterogeneity also depends on the geo-spatial location in the grid. Especially once grid-participants in close spatial proximity have likewise flexibility behavior, regional disparities become apparent. Such regional disparities are certainly present in the Netherlands, where flexible assets are disproportionally spatially distributed [76]. Overall, limited information is available on the extent to which such amplified locational differences impact congestion, but literature recommends that insight should be created in how varying distributed flexibility developments and components influence flexibility reactions and congestion as argued by Zeiselmair and Köppl [82]. Therefore, the last research gap can be synthesized by the following sub-question: *What are the implications of spatial correlation in distributed flexibility reactions on congestion patterns?*

2.3. Research gap synthesis

To summarize, the research gaps listed below have been found. Together, these lead to the main research question. Afterwards in this section, the application and relevance of these research gaps towards the real-world is elaborated on in a separate sub-section.

- Congestion-efficient placement and alignment of flexibility complementarily to existing flexibility is not prioritized. This lack of alignment is caused by the lack of information, incentives and signals on adequacy of flexibility at congested locations. This is amplified by lack of insight in how to asses the impact of both CMMs and local differences in reactions of flexibility providers.
- Flexibility reactions depend on CMMs. The most severe congestion that remains can be assessed under financial CMMs with high granularities that maximally encourage potential. However, it is unknown how the effect of such mechanisms can be modeled while being non-discriminatory.
- Flexibility reactions depend on heterogeneous flexibility factors that vary per participant and are complex to create insight into. There are no uniform frameworks to transparently evaluate potential of distributed flexibility while showing dependencies that arise in local differences. Existing literature does not focus on the uncertain heterogeneous background factors that might influence distributed flexibility reactions, partially because this is computationally extensive.
- Flexibility reactions differ per location. This has large impacts once system-wide flexibility is concentrated in specific areas, caused by correlation between flexibility providers in spatial proximity. Limited local information is available to model these differences. As a result, existing research does not transparently model such spatial dependencies and regional disparities in the grid.

Overall, there is limited insight in congestion, while needed to identify remaining robust congestion locations after flexibility reactions, for additional and complementary measures. When solely looking at physical congestion, indirect congestion mechanisms rely on voluntary user behavior and elasticities, whereas direct CMMs do not. Therefore heterogeneous local characteristics, that can be nudged by voluntary and passive signals, are of utmost relevance in assessing flexibility reactions and congestion under these indirect CMMs. Granularity of CMMs matters for system efficiency and social welfare, and therewith might influence the intensity of financial incentives. In both highly granular and uniform mechanisms, the impacts on physical congestion depend on the financial incentive. However, the financial incentive of highly granular mechanisms can be more intense and is therefore more relevant to assess the maximum potential of distributed flexibility reactions and the most severe congestion that remains. It remains unclear how such CMMs and their effects can be modeled and implemented in a non-discriminatory way. Furthermore, the congestion impact of indirect financial CMMs cannot be assessed without incorporating the local and heterogeneous flexibility factors that respond to the CMM incentives. These factors can differ substantially, even though the different types of indirect CMMs themselves will remain largely agent-independent and non-discriminatory. Current literature rarely explores these variations or their influence on flexibility behavior. Furthermore, the effect of local differences and regional disparities in these reactions are not taken into account sufficiently. Together, these research gaps can be synthesized in the main research question: *”How can the impact of location-specific distributed flexibility on congestion locations in Dutch distribution grids be evaluated?”*

2.4. Exploration on flexibility modeling methods

The final quantity of distributed flexibility that is ultimately deployed, depends on flexibility factors that are shaped by the underlying socio-technical regime, in which a lot of uncertainty from various sources is present. To accurately model these flexibility reactions, Holst et al. [21] mention that various frameworks can be used to model the composition and quantification of flexibility transfers and capacities, each with different strengths and weaknesses. To create oversight in state-of-the-art modeling methods and gaps, a concise review is given in this section.

Mathematical models for scheduling

First of all, one can distinguish between scheduling models and forecasting models for flexibility, as argued by Raza et al. [101]. Precise scheduling models are prescriptive rather than predictive, and mainly associated with mathematical optimization. In most mathematical models, also known as as white-box models, variables are known exactly and output features can be traced to inputs according to Yuan and Tang [102], ensuring transparency and high interpretability. These models allow for precise modeling of system constraints and identification of optimal behavior, with transparent architecture for system-level design optimization. Furthermore, with techniques such as stochastic optimization, uncertainty can also be incorporated. As argued by Wang et al. [103] and Raza et al. [101], these models do not predict flexibility from data. Rather, they optimize scheduling with an objective function or provide information for decisions while accounting for uncertainties. Such techniques can have high computational burdens, as argued by Hekmat et al. [104]. However, when modeling heterogeneous participant's distributed flexibility reactions, it should be noted that agents are autonomous in optimizing energy flexibility and are not tied to uniform system objectives. This autonomy in decision-making introduces various uncertainties. Uniform system-wide mathematical models are less relevant to model user flexibility reactions, as grid-participants all have their own objectives, preference formulas and scarcity evaluation.

Models for forecasting and data inclusion

Next to purely mathematical models related to flexibility modeling, are data-driven forecasting models. Rather than choosing best outputs in a given set of variables, these studies engage in forecasting flexibility and demand by determining and specifying data-driven variables, as the study of Raza et al. [101] argue. This study argues that there are a multitude of data-driven forecasting techniques available, such as black-box machine-learning models with artificial neural networks, statistical models, probabilistic and stochastic models [102]. Exact physical parameters do not always need to be known here, as these models can produce functional relationships between output and input without needing specifically defined intermediate parameters [105]. However, these models are less useful to create insight in flexibility reactions, as the internal workings are not transparent and clearly interpretable.

Mathematical models for flexibility representation

Next to isolated, transparent mathematical optimization methods or black-box data-driven models, combinations also exist. For example, flexibility envelopes that combine data-driven information in mathematical envelopes. These are graphical and mathematical representations of the range of possible power adjustments that an entity can have over time, both upward and downward. In general, these envelopes are highly interpretable and have guaranteed performance as argued by Nosair and Bouffard [106]. Such envelopes are nowadays used to prescriptively show how upper and lower limits from DER's should dynamically operate, as argued by Lankeshwara et al. [107]. They can be used to signal limits to end-users for network conditions [108]. In contrast however, is that end-users nowadays are largely autonomous in choosing outputs in a non-discriminatory way. This descriptive aspect is not what envelopes are used for in these studies, while it could be beneficial for analysis of potential flexibility reactions and resulting congestion as argued Hekmat et al. [104].

Such an envelope for end-user flexibility might represent a two dimensional surface with flexible power availability. For each timestep the capability and limits of flexibility are communicated in a standardized way, with minimum and maximum power levels. Envelopes are also able to incorporate actions at subsequent timesteps that influence actions at other timesteps. Figure 2.2 below shows a graphical representation of flexibility envelopes, as used in the study from Gasser et al. [109]. In here, the upper and lower energy bounds are shown per timestep. The region between these bounds defines the feasible power possibilities.

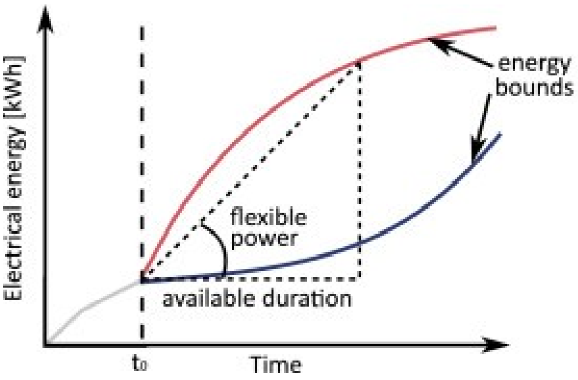


Figure 2.2: Graphical representation of two-dimensional flexibility envelope. The blue bound shows the lower limit, the red bound shows the upper limit. The possible energy states develop over time, represented by the area between the bounds.

Despite providing a range, the region within the envelope does not inform on decisions and only shows feasibility, originally without probabilities. Traditional envelopes only focus on the boundaries with deterministic capability. This makes it useful for analyzing worst-case outcomes and robust-solutions. However, to simulate or forecast output quantities from such envelopes, the envelope method still requires a 'decision layer'. This is needed to determine the actual impact, as the uncertainty regions can be quite large with limited interpretive value. Not only can this be done through individual and computationally extensive explicit optimization frameworks, that require well-defined objectives and constraints as argued by Nosair and Bouffard [106]. Informing such decisions can also be done through statistical and probabilistic models, which are useful when uncertainty regions are large.

The previously described mathematical models and envelopes can be used for interpretable and transparent forecasting, once these are enriched by data as argued by Meer, Widén, and Munkhammar [110]. By being approximate rather than exact, inclusion of probabilistic data can reduce the complexity of flexibility reactions, as argued by Hekmat et al. [104]. Such an approach suits the fuzzy knowledge on uncertainties and unknown unknowns in local distributed flexibility potential. To this end, multiple-sources of uncertainty and various degrees of probabilities concerning data can be integrated in probabilistic flexibility envelopes.

Relevance of modeling grid-participant's stochastic flexibility reactions

To conclude, all sorts of uncertain factors play a role in modeling flexibility potential. Although inclusion of such data can serve as causal input for insightful envelopes, existing research rarely creates complete overviews of data. Such practices would support interpretable modeling and forecasting of; reactions to demand-side programs, market design, aggregation, and all sorts of other factors and their surrounding complex systems as argued by He and Khorsand [111]. Furthermore, as discussed in the literature review, heterogeneity and local correlation plays a big role among agent flexibility reactions, but existing models do not take this into account thoroughly. This heterogeneity, differentiation and uncertainty can be properly represented in enriched probabilistic flexibility envelopes. These can also transparently represent the abundant presence of uncertainty that comes paired with the deployment of indirect CMMs.

In continuation of this Vizia et al. [22] and Kulms et al. [79] mention that existing literature overvalues flexibility potential as these neglect different locally available information and unbundled power systems. They advocate for approaches that consider separate roles and actor-specific information, which can be effectuated through modular frameworks that allow specification and differentiation of coordination schemes with separate agents or entities. Such a model could bridge interrelations between complex participant factors and technical systems, to properly model the varying socio-technical background of flexibility.

3

Research approach

The following main research question was posed: *”How can the potential impact of incentivized, location-specific distributed flexibility on congestion locations in Dutch distribution grids be evaluated?”*. To provide an answer, a multi-sided co-simulation approach is used. This co-simulation holds two model-parts needed to identify and simulate congestion.

As a first part, flexible load profile reactions of all distributed flexibility providers are needed. Therefore, a qualitative and interpretive stochastic flexibility state model is used to define and structure flexibility reactions with Monte Carlo sampling, while showing underlying causal factors that influence flexibility. Secondly, a power-flow model is also used, with two purposes. On one hand, historical congestion in this power flow is needed as input for incentivation of flexibility reactions in the flexibility state model. On the other hand, the results of the power-flow model can be used to assess and compare the impact of the flexibility reactions on congestion in the old and new situations. In the end, this co-simulation can be used to compare the modeled flexibility reactions with the needed flexibility from the congestion power flow assessment. Herewith, system-wide conclusions can drawn for congestion and adequacy of flexibility provision.

To bridge the quantitative flexibility reactions needed for congestion assessment from the power-flow model with the qualitative factorial influences in the flexibility state model, the mathematical concept of flexibility envelopes is introduced in section 3.3, with additions for stochastic probability distributions in chapter 5. However, a specific order with additional steps is used to answer the main research question. Therefore, in the remainder of this approach, the co-simulated models are divided via 4 steps that respectively correspond with the 4 sub-questions. This process flow is shown in figure 3.1 below.

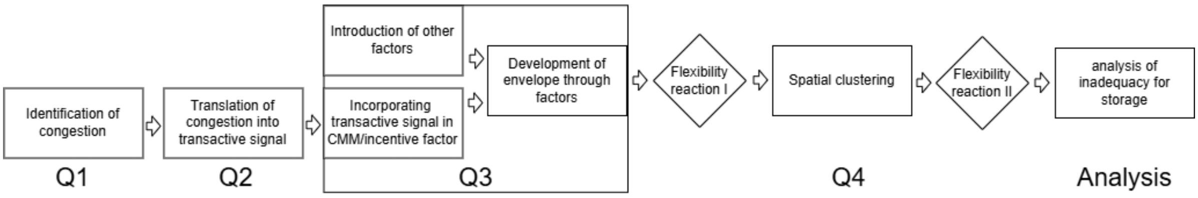
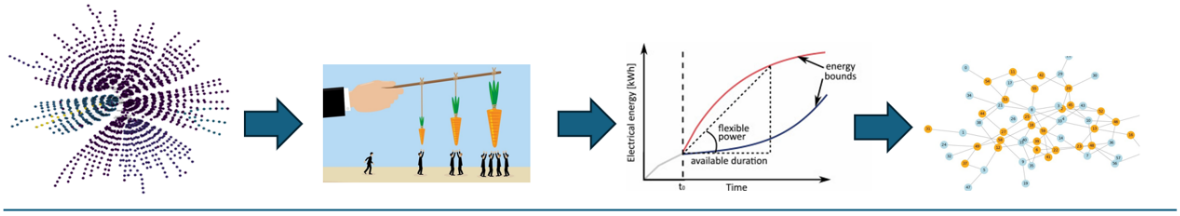


Figure 3.1: Logical process flow to model flexibility reactions with the 4 sub-questions. Step 1 focuses on the power-flow model, and 3 and 4 focus on the stochastic state evolution model. Step 2 explores how these two models should be coupled.

In the remainder of this research, each step corresponds with one of sub-questions, that are also visually represented in figure 3.2 below.



Q1
Identification of congestion per agent in network with historical profiles

Q2
Translation of congestion into incentive for distributed flexibiliity

Q3
Interplay of factors and congestion incentive, resulting in possible flexibility reactions

Q4
Adjusting reactions for spatial clustering effects and analyse congestion results

Figure 3.2: Complete process flow of sub-questions. A visual overview of the key topic per step is given.

3.1. Step 1 - Identification of congestion

The first part answers the following sub-question: *'Where does congestion occur in Dutch distribution grids under current conditions without activation of distributed flexibility?'*. In this part, congestion is identified with two main purposes. Firstly, it is used to assess where flexibility is needed to mitigate congestion. Secondly, it is used to incentivize the needed flexibility through the indirect financial CMM in the next sub-question. To these ends, a power flow model is run based on load data in an exemplary Dutch distribution grid. Historical load data is used for reference electricity profiles of the grid users. These result in varying injections and withdrawals leading to power flows. These electricity profiles are coupled in a power flow network model that includes the medium-voltage distribution structure. Upon running the power-flow model, the electricity profiles from the grid-participants might result in electro-technical congestion which differs per location as the constraints and users are spatially distributed.

Computational models for power flows and congestion

A power flow model requires the full network topology to determine flows, since electricity distributes through all available components dependent on network characteristics such as impedance. In the field of power flow modeling, DC and AC power flow models are distinguishable, each with different qualities [112]. DC models have low computational complexity and are useful for fast screening and dispatch analyses, but do not take reactive power into account. Although AC models take greater computational effort, these are suited for detailed operations in which voltage constraints and reactive power are important, which is the standard for distribution system analysis. These models can identify and distinguish between voltage constraints and current related thermal limits in different areas, which is relevant as the constraints of reactive power might also have implications for additional flexibility. The usage of a partially existing power flow model with optimization algorithms ensures quality and decreases computational effort. Therefore, the DigSilent Powerfactory software tool for modeling electrical power systems within the software environment of DSO Stedin was used.

3.2. Step 2 - Signaling congestion to assess incentivized distributed flexibility

The second part answers the following sub-question: *'How can the effect of a congestion management mechanisms that encourages the maximum potential of distributed flexibility be modeled?'*. After identification of congestion in the reference flow, the congestion at specific components and locations is connected to agent-nodes with congestion signals in this step. These congestion signals are later on used to model the effect of highly granular financial incentive CMMs.

Using congestion signals to assess relevant flexibility reactions and CMMs

Congestion signals are created per agent, to represent the maximum congestion overloading values that the agent is contributing to in the reference flow. Herewith, the hierarchical structure of the network is used to trace the underlying congestion contributors. As described in the literature review, there is limited information on how to model various types of indirect CMMs. No uniform methods to do so exist as the mechanisms each translate the historical congestion differently into an incentive. Therefore, this research does not model or implement CMMs itself. Rather it models the effect of such a CMM. To this end, the congestion signal is only used to binary appoint relevant congestion contributors at specific locations and timesteps, and reveals whether they contribute to congestion or not. Only this binary information is used in the approach, and only these congestion contributors are relevant to assess on flexibility provision. The approach does not use the magnitude of congestion to determine the level of the CMM incentive, as the magnitude of the incentive also remains largely dependent on uncertain DSO and regulatory policies. Nevertheless, the effect of varying incentive magnitudes is studied through scenarios. So, the congestion signal is used to appoint congestion contributors, and only these are assessed on their flexibility reactions. Specifically, to model flexibility reactions as described in the literature review, especially the effect of CMMs that work with financial incentives to encourage demand response are ultimately relevant in these assessments.

Assessing the effect of CMMs using highly granular financial incentives

There are various CMMs with financial incentives. However, as described in the literature review, the highly granular, financial and implicit type of CMM is ultimately relevant to explore the maximum potential of distributed flexibility. Financial incentives can be more intense in highly granular and differentiable mechanisms, as they impact social welfare to a limited extent. Heterogeneous financial incentives that differ per location and timestep can be given. Nevertheless, the DSO also has to be non-discriminatory [48]. Therefore the implicit value that the DSO has to solve congestion should be the same in each congested area. Additionally, there is a maximal limit to this value, as the DSO can realistically not implement infinite financial incentives to solve congestion through demand-response [113]. Hence, it is assumed that there is one maximal applicable financial incentive to encourage flexibility at all places and timesteps, even in highly granular CMMs. This financial limit is non-discriminatory and therefore its maximum is modeled to be the same at all locations without distinguishing between more or less severely congested areas. The magnitude of this maximal incentive is largely determined by regulatory authorities and operators. Therefore, not the magnitude of this incentive is modeled, and rather the effect of such a maximal incentive is assessed and modeled in this approach, as if applied to all congested areas. So there is a single-pass mechanism, in which there is no iteration until the 'right' level of financial incentive is found, and only the effect of one level of financial incentive is modeled. The effect of the varying magnitude of the financial incentive is analyzed through scenarios, further elaborated on in chapter 5.

Hence, the approach focuses on the maximum potential of distributed flexibility by assessing the effect that this maximal financial incentive can give at each location. It is important to note that such intense financial incentives can realistically only be given once highly granular mechanism apply, so when they are not applied at all locations uniformly. However, to assess the flexibility reactions to a high financial incentive and to assess the robustly remaining congestion, the effect should be assessed for all congestion contributors as if the maximum incentive from a highly granular mechanism applies at all places. For some congestion contributors, the flexibility provision might thus overshoot drastically, as the incentive given is maximal. For others however, the most severe congestion might still remain even under these maximal financial incentives, indicating inadequacy of flexibility.

3.3. Step 3 - Modeling factors in prosumer flexibility reactions

What remains uncertain is the potential impact of this CMM, that is dependent on grid-participants. Therefore, the third part answers the following sub-question: *'What interplay of factors influence possible reactions of distributed flexibility for congestion-mitigation?'*. To answer this question, probabilistic flexibility envelopes are created that lead to possible flexibility-reactions per distribution substation entity. The financial incentives based on the congestion signals from step 2 also impact these envelopes as a factor. To systematically model how factors play a role in the the development of an agents reaction envelope, an stochastic state evolution model with Monte Carlo sampling is developed in this step.

Stochastic state evolution model

This approach uses a data-driven stochastic flexibility state evolution model. Herein the grid-agents develop flexibility states that are derived from mathematical envelopes, as further explained and visualized in the figure below. These envelopes show possible flexibility reaction outcomes under uncertainty. The envelopes are impacted by all sorts of influences from the socio-technical environment, that can be captured by factors. In the end, such envelopes are used to derive the final flexibility state per timestep, under the influence of previous states. Ultimately, this shows how dynamic and heterogeneous grid-participants develop flexibility reactions over time. The model uses evolution and interdependencies of states to show how path-dependency from previous states influences flexibility. Such a model nicely captures the complex system-wide outputs that cannot easily be made up from the individual inputs. Additionally, the next sub-question related to spatial correlation captures another complex part of the system is captured, where flexibility states per agents influence each other.

Probabilistic flexibility envelopes and Monte Carlo sampling

Alongside CMMs that translate the congestion signals from step 1 and 2, there are all sorts of heterogeneous factors that influence flexibility states. In this approach, these heterogeneous factors are transparently captured in a stochastic manner. To this end, the model is combined with the mathematical concept of flexibility envelopes that are able to represent uncertainty in the factors, without compromising on quality needed for the precise modeling of agents. Additionally, uncertainty can be transparently represented by adding probability distributions to increase accuracy, as also recommended by Gasser et al. [109]. Such envelopes can be seen as descriptive probability distributions over multiple timesteps. They can abstractly show uncertainty, without going too much into detail about individual agents and focusing on aggregate behavior. Adding this probabilistic data introduces a third dimension to the envelope, being the probability within the slice of the envelope at a specific timestep. This is visualized in figure 3.3 below.

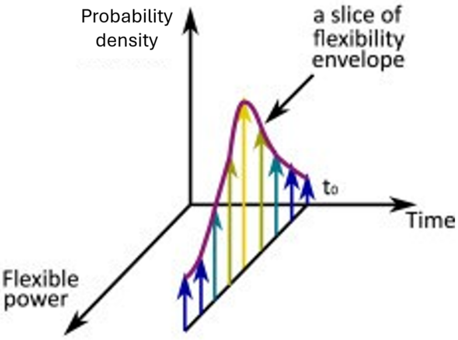


Figure 3.3: Graphical representation of three-dimensional flexibility envelope, including probabilities, and upper and lower bounds of the flexible power per timestep that is able to show how flexibility stochastically develops over time

From these envelopes the final flexibility states per timestep can be drawn. This is done through Monte Carlo sampling. Monte Carlo sampling is a probabilistic method that estimates system behavior by repeatedly sampling from input distributions and evaluating the resulting outcomes. Especially the heterogeneity of these samplees is beneficial in this modeling approach.

Conceptual framework with factors

A conceptual multiplicative reduction framework is presented to show how the agents are influenced by the factors and how the envelopes develop. Herein, uncertainty from different flexibility factors can be represented while propagating towards the final flexibility reaction state. This transparent incorporation of different factors with uncertainty was emphasized in literature review by among others Kilthau et al. [14] and Kulms et al. [79]. To incorporate how the factors impacts the final flexibility states of agents through the envelopes, factors have to be distinguished and defined. Only then can the factors be further quantified. This division is further elaborated on in chapter 4, whereas a quantification and implementation of the multiplicative reduction structure is given in chapter 6. The development of the hierarchical structure is elaborated on in section 5.3.

3.4. Step 4 - Impact of spatial correlation on congestion patterns

In the end, the final part answers the following sub-question: *'What are the implications of spatial correlation in distributed flexibility reactions on congestion patterns?'*. The flexibility states from the stochastic flexibility state model in the previous step are further adjusted and analyzed here, to evaluate how introducing spatial correlation among flexibility agents influences congestion compared to uncorrelated scenarios.

Purpose of spatial correlation

Initially, the probabilistic envelopes representing the influential factors do account for the differences between the heterogeneous flexibility providers. However, the flexibility states are individually drawn with Monte Carlo sampling from the envelopes per agent, without taking location in network topology into account. The degree to which flexibility states of one agent are related to other agents in the network is initially random, as the envelopes with factorial influences do not account for any spatial correlation.

However, as discussed in the literature review, in reality such correlation exists, that leads to spatial clustering of neighboring flexibility states. Some cities or neighborhoods have likewise factorial influences and flexibility reactions might cluster. This is caused by agents in specific areas that have unevenly similar characteristics with regard to the flexibility factors. It causes the distribution of flexibility in the whole network system to become less evenly and less randomly dispersed. Agents in close spatial proximity have similar and more distinct flexibility reactions of which the effect becomes amplified, leading to specific congestion patterns. Some places might be able to solve congestion entirely, whereas other places will not be able to solve congestion at all. Therefore, to strengthen the validity of the model, the model includes spatial correlation of agents' flexibility reaction states. The effect of spatial correlation is especially relevant to take into account under highly granular CMMs, as congestion is inherently local. At fine spatial resolutions, ignoring such correlations may lead to false estimations of independent flexibility potential.

Modeling strategy

To include spatial correlation, the likewise effect of neighbors in close spatial proximity is accounted for. Network topology and proximity is used to introduce correlation between neighbors. As further discussed in chapter 4 on the system demarcation, the electrical proximity of the network can be used as a proxy and indicator for spatial proximity. Through this proxy, electrical neighbors in the network have a high probability and tendency to be spatially connected. This spatial connectedness between neighbors enables to account for spatial correlation of all sorts of aspects, such as the factors influencing flexibility. The effects of spatial correlation between neighbor's flexibility states can then be accounted for. It is unknown what factors specifically correlate, therefore only the final flexibility state is modeled to correlate spatially. Hence, this step is implemented after the initial flexibility states have developed.

To model spatial correlation, the flexibility reaction of one agent is influenced by the flexibility reaction of its direct neighbor, based on a formula. It is unknown to what extent flexibility reactions correlate and to what extent neighbors in close proximity might have similar reactions. Therefore, this is analyzed through two scenarios. One scenario has limited spatial correlation. The other scenario has more correlation, but is still based on probabilities to incorporate heterogeneity and uncertainty. This allows for more realistic spatial dynamics and analysis how such correlation might lead to clustering of flexibility, and how this affects congestion.

4

System Description

Before modeling the flexibility reactions, this chapter provides an overview of the socio-technical system to serve as the foundation for the models. It demarcates the scope, which is essential to maintain relevance within such complex systems. Essentially two aspects are subsequently focused on in this chapter. Firstly is the electro-technical power distribution grid aspect, in which grid-participants indirectly interact and shape congestion. This part of the system is captured in the power-flow model in chapter 5. Secondly, the system also shapes demand response reactions of location-specific distributed flexibility providers through all sorts of influential factors. This part is captured in the stochastic state evolution model in chapter 5. In the section 4.2 and 4.3 of this chapter, the system is discussed with a special focus on these two aspects. First, the stakeholders are introduced in section 4.1.

4.1. Stakeholder analysis

To understand the dynamics of the system at hand, the actors that directly and indirectly impact flexibility reactions and congestion are identified, alongside their interests and influences. For flexibility provision in Dutch electrical distribution grids, the following actors play a role.

System operators and regulators

The distribution system operator (DSO) is involved in the process leading to congestion and provision of flexibility, as it manages the electrical distribution infrastructure. The DSOs hold a legal and natural monopoly on the provision of medium- and low-voltage electricity in appointed areas, as the infrastructure comes paired with economies of scale and high upfront investments. Its main task is the continuity of energy supply. DSOs are encouraged to efficiently integrate renewable electricity and use market-based services such as demand response for network operations, via EU directive 2019/944 [114]. Herewith, more interference is required from DSOs. However, the role and actions of DSOs are strictly defined in the 'Dutch Electricity Act 1998' and 'EU directive 1009/72/EC'. This arranges the unbundling of electricity markets, in which DSOs are limited to electricity distribution and activities related to infrastructure, and may not engage in electricity generation or trading. Furthermore, DSOs are publicly owned by governmental entities, should be non-discriminatory and have a neutral attitude.

Furthermore, the operators are strictly regulated by regulatory authorities, such as the Authority for Consumers and Markets (ACM). These influence congestion and flexibility by managing transparent and competitive market conditions while setting tariffs, monitoring service quality and ensuring non-discriminatory grid-access. Together, the ACM and DSOs set network tariffs that can incentivize demand-side flexibility [62]. This authority decides on the congestion management measures that the system operators can apply. The authority is heavily influenced by governmental bodies and political leadership. It operates under the Ministry of Economic Affairs, and its strategy depends on government priorities, and laws and regulations from parliament [115]. Furthermore, the ACM also influences the position of individual grid-participants and enables the existence of aggregators to provide demand response.

Grid-participants and Congestion Service Providers

These grid-participants are characterized by having autonomy in decision-making. This stakeholder group ultimately provides flexibility in their load profiles and therewith influences congestion. All sorts of participants exist, such as industrial end-users, charge point operators, battery storage operators, energy producers and residential end-users. Nowadays, these participants can increasingly engage in demand response by shifting or reducing flexible electricity usage during transportation peaks. Their energy transactions lead to system usage and, as external effect, possible congestion. To counteract this, congestion mechanisms such as GOPACS have been developed, as described in the theoretical background. However, individual grid-participants have to be represented by a congestion service provider (CSP) to act on these congestion markets [63]. These entities act as intermediaries between consumers, producers or storage operators and the grid operator. They manage trading platforms for flexibility and engage in various grid services while implementing various business models [116]. CSPs are especially relevant for residential grid users that cannot become CSP themselves, and thus require an aggregator to provide flexibility for congestion mitigation. The aggregated participants can be represented through virtual power plants, as a digital system that coordinates and controls many small, distributed energy resources to operate together [70]. Nevertheless, aggregation requires technological advancements to work properly, such as smart metering.

Technology providers

To capably provide the flexible capacity in demand response actions, both industrial en residential end-users need technology. It initiates and enables the flexibility from distributed resources [117]. Technology providers influence the capability of end-users to be provide flexibility. They develop smart infrastructure, such as smart meters, sensors and management systems, while also creating systems that enable aggregation, market access and predictive control. They also enable integration, interoperability, standards and compatibility. Exemplary technology providers are BESS, heat pump and bidirectional EV-charger manufacturers.

4.1.1. Relative power and interest of actors

To show the relative position of the actors among each other with regard to the power and interest they have for the provision of distributed flexibility, the stakeholder matrix as shown in figure 4.1 below was set up. An explanation is given underneath the figure.

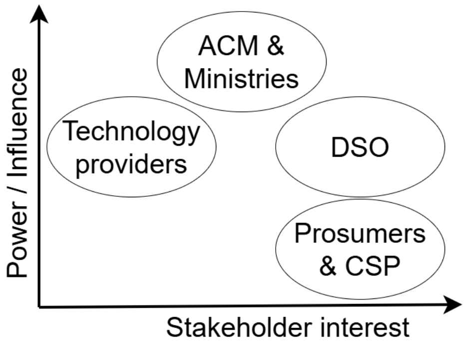


Figure 4.1: Power-interest matrix to solve congestion and provide demand response

From the figure, it becomes apparent that it is a key interest for DSOs, prosumers and aggregating CSP's to mitigate grid congestion and positively influence flexibility. For the DSO, this interest originates in the 'Dutch Electricity Act 1998' and the newer 'Energy Act' in which DSOs are obligated to mitigate grid congestion and to continuously supply energy, while also using demand-response flexibility. So, the DSO has a key interest in the deployment of distributed flexibility. Although the DSO is autonomous, its operates within the boundaries set by the ministries and ACM, therefore its power is not unlimited.

Consumers and CSP's also have a key interest in deploying of distributed flexibility, with several reasons. First of all, using flexibility might reduce energy costs by shifting electricity usage to cheaper situations. This is also a revenue opportunity for CSPs, while providing flexibility at the right time and location. Furthermore, using this flexibility is beneficial for consumers, as it improves the whole system by avoiding connection delays. Simultaneously, it supports environmental sustainability through integration of renewables and therewith increases social welfare, another interest.

Increasing social welfare is also an interest of the ACM and the ministries. However, congestion mitigation and usage of flexibility are not the only interests and not the only means to increase social welfare for these entities. Consumer protection, fair distribution of grid costs and integrity are also key interests. Furthermore, ACM and ministries are influenced by politics, where affordability and other objectives are often prioritized above congestion mitigation and usage of flexibility. Therefore deployment of flexibility is a secondary interest, while these entities have high potential to influence the system.

Technology providers have a key role in deployment of distributed flexibility, as they act as enablers. There influence is large, as they shape the feasibility, accessibility and affordability of flexibility. Furthermore, they influence technical standards and interoperability. However, their primary driver is market growth, and selling for profit. Successful demand response for congestion mitigation is no key interest, but the deployment of flexible technology is. The existence of congestion and intermittency is key to the value proposition of these technology providers, therefore actually solving congestion is no key interest.

4.2. Electro-technical Dutch distribution grid

After the stakeholders in the system have been identified, important aspects of the system can be explained. One aspect of the system is associated with electro-technical Dutch distribution grid, which is focused on in this section.

In AC distribution grids both current and voltage congestion are relevant. Herein, not only active power, but reactive power can also impact congestion. So, the electro-technical grid also incorporates reactive power aspects, in which since large-scale storage with rated power above 1 MW has the ability and requirements for both reactive power and active power management, as mentioned in chapter 3 of the Dutch grid code [48]. It is stated that these should have the ability to contribute to Volt-Var management in the future, although activation mechanisms are not implemented yet. So, both reactive and active power aspects are impacting in the system.

All of the grid-participants in this system, such as residential individuals and industrial consumers, indirectly interact in the electro-technical grid and shape congestion through their electricity profile loads. The grid-participants are located in distribution grids, which are connected to high-voltage feeders. One high-voltage station supplies around 5-10 distribution areas via sub-transmission voltage distribution transformers [29]. The distribution areas can contain up to 100 distribution substations. Distribution substations generally contains one industrial user or somewhere between 50 to 250 residential households.

In the system, several voltage or grid levels are present. Firstly the high-voltage transmission grid, e.g. 110 kV and above, which is managed by the TSO. Secondly are the distribution levels that are managed by DSOs, being the sub-transmission voltage between 110 kV and 25 kV, the medium-voltage grid from 20 kV to 3 kV, and the low-voltage grid that operates at 400 V. In these lower voltage distribution levels, distributed flexibility is typically located.

Figure 4.2 below, retrieved from Phase-to-Phase [29], gives a schematic overview of the levels. The orange and red levels are both high-voltage. The green level represents both sub-transmission and medium-voltage. The radial hierarchy in distribution networks is visible, whereas transmission grids have a meshed topology.

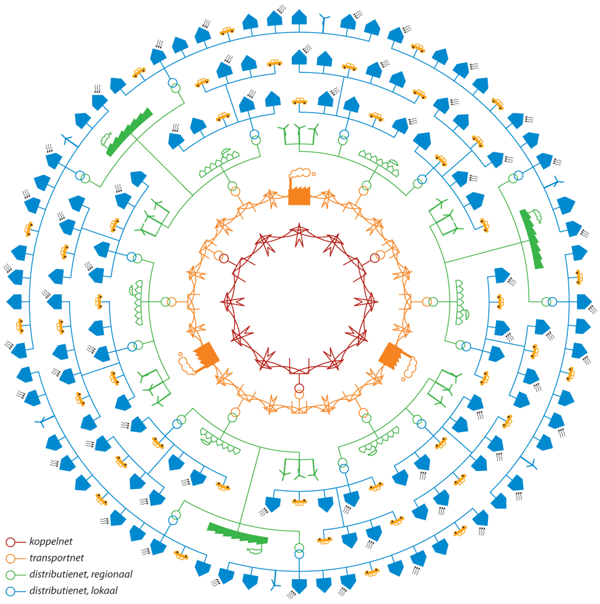


Figure 4.2: Representation of different voltage levels. The orange and red levels are both high-voltage and have meshed topology. The green level represents both sub-transmission and medium-voltage, and have radial topology.

Underneath, in figure 4.3, a publicly available figure from HoogspanningsNet [118] shows the high-voltage feeder in blue, that supplies the high-voltage substation. This substation supplies the underlying distribution areas. These distribution areas are fed by the yellow sub-transmission level feeders. Each distribution area, at the end of the yellow lines, holds multiple distribution substations. The figure also shows the different spatial areas that contain different heterogeneous actor characteristics.

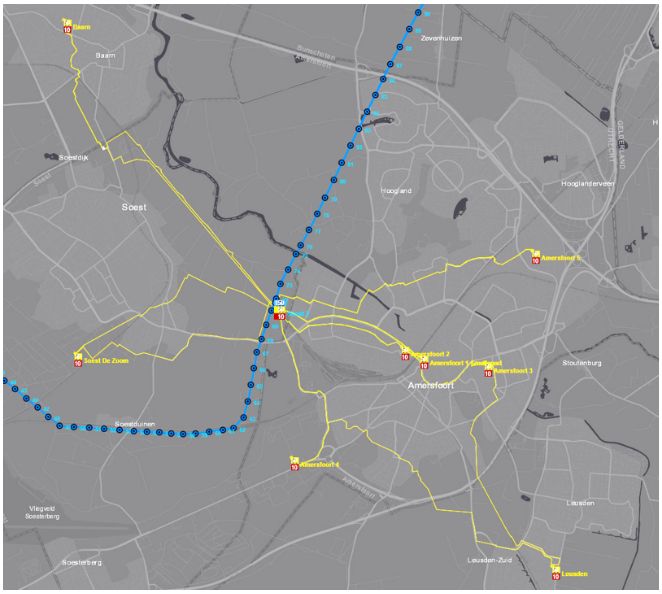


Figure 4.3: High Voltage feeder supplying the distribution feeders. The blue high high-voltage feeder supplies the high-voltage substation. This substation supplies the underlying distribution areas at the ends of the yellow sub-transmission level feeders.

In this electro-technical part, electrical proximity can serve as a proxy for geographical proximity. In most distribution networks, nodes that are geographically close tend to be in electrical proximity as well [119]. By measuring electrical distance, the operational relevance of spatial closeness can be captured without relying on maps [120]. Electrical proximity in the system can be a functional, but uncertain and inaccurate representation of geographical proximity in the networks. In this way, spatial correlation between grid participants in geographical proximity can be captured, as used in step 4 of the approach.

4.3. Socio-technical environment influencing the system

Another aspect of the system shapes the actions and characteristics of grid-participants. This socio-technical part includes influential factors that cause heterogeneity among grid-participants. These factors are the result from the complex surrounding environment, which is visualized in figure 4.4 below.

Both the electro-technical aspect and the socio-technical aspect are included in the figure. The electro-technical grid is presented in the circle with multiple grid-participants. The surrounding socio-technical environment influences the grid-participants through factors categorizations of the environment. These factors are elaborated on in the section below. The environment is represented as a fuzzy cloud surrounding the network, as most of the influences and interrelations are unclear and imprecise. The factors are represented by the arrows that emerge from the environment, and impact and shape the grid-participants heterogeneously.

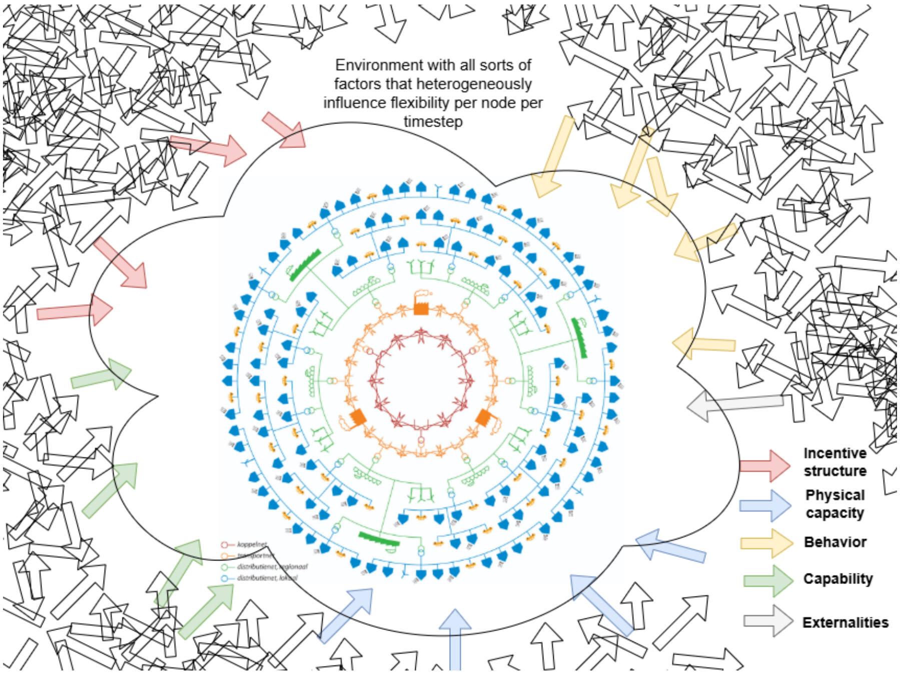


Figure 4.4: Factors emerging from the environment influencing the system. The electro-technical grid in the circle with the blue grid-participants is influenced by the surrounding socio-technical environment through factors represented as arrows.

The two aspects intersect at the grid-participant. Here, the distributed flexibility is provided from factors in the environment of the system. These factors influence the grid-participant, from which the reactions subsequently lead to power flows in the grid, and have implications for congestion.

4.3.1. Factors in the environment

A lot of influential factors that affect flexibility can be distinguished. However, in this research, the system is demarcated by a split between abstract factors categorizations. This split is provided by a concise literature review on the main factor-categories, that is provided in the remainder of this chapter.

Review on factors

A concise literature review on key factors and uncertainties that play a role in distributed flexibility reactions was performed. The Scopus database was searched with the following search string: *(”demand response” OR ”distributed flexibility” OR ”energy flexibility” OR ”demand side flexibility”) AND (factors OR drivers OR barriers OR enablers OR determinants OR components) AND (technical OR economic OR regulatory OR behavioral OR social) AND (review OR literature OR survey).*

Only a limited amount of studies actually reviews and compares different kinds of factors to create a complete oversight. The majority of literature focuses only on specific factors. Nevertheless, 6 studies were found that focused on creating complete overview in overarching factor-categories. There is general consensus on main relevant factors among these studies. However, the detailed classification of names and labels are differing per study. The main factor-categories per study are listed in table 4.1 below, after which a synthesis of the selected factors is given.

Study	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	**Factor 6**
Dawes et al. [121]	Building/asset characteristics	Occupant behaviour	Energy Systems	Others	N/A
Shepherd and Mohagheghi [122]	Building characteristics	Demand data	Appliance or technology data	Weather / climate data	N/A
Yuan and Tang [102]	Physical flexibility sources	Occupant behaviour	Control systems	Market and regulatory enablers	Climate conditions
Airò Farulla et al. [123]	Physical characteristics	User behaviour	Energy system	Control system	Others
Good, Ellis, and Mancarella [124]	Technological	Social	Market structure	Economic	Political / regulatory
Bogdanova, Viskuba, and Zemīte [125]	Technology	Customer awareness	Incentives	Pricing mechanism	Regulation

Table 4.1: Comparison and summary of key factors influencing distributed flexibility across multiple studies.

From the found factors in the literature review, the following 5 factor-categories can be synthesized:

- ***Physical capacity*** First is the category of physical characteristics. This is mentioned by all studies, although interpretation of attributes differs. This factor-category includes all sorts of characteristics that determine how well a prosumer can store and shift electrical loads, in terms of physical quantity that can be converted to energy or power. Some sources relate to data concerning building-characteristics, while others mention sources such as storage. It includes both controllable and passive flexibility. The study of Dawes et al. [121] includes specifications such as thermophysical aspects, space conditioning, insulation and thermal mass in this category. Other studies, such as Shepherd and Mohagheghi [122] include electrical storage, water heating and other household appliances, alongside renewable generation capacity. Additionally, this study also mentions industrial production data as an important factor. Additionally, the study of Yuan and Tang [102] includes thermal energy storage and other energy conversion characteristics. The study of Airò Farulla et al. [123] is concise, but still mentions physical characteristics as one of the few key factors. The studies of Bogdanova, Viskuba, and Zemīte [125] and Good, Ellis, and Mancarella [124] only mention technology in general as an important factor with subcategories such as storage and EVs, but do not focus on factors about capacity. Studies that have more detailed subcategories, capture part of this physical capacity in another key category, being energy systems. Especially, Dawes et al. [121] and Shepherd and Mohagheghi [122] mention a separate subcategory from physical capacity for factors that shape load profiles, such as generation and conversion. Nevertheless, the majority of studies mention an abstract factor related to 'Physical capacity'. Summarized, this factor represents the available shiftable energy and capacity that is effectuated through flexible resources in all sorts of structures. This factor is demarcated by technical and structural limits of equipments and systems, for example the size of a battery and the thermal inertia of a building combined with HVAC.
- ***Capability*** The overarching factor 'capability' represents technological energy system and management aspects that focus on enabling and unlocking flexibility in a technical and organizational manner. The study of Dawes et al. [121] only mentions sub-factors related to control logic, standardization, interoperability and data collection. Other sources mention this factor explicitly, while also elaborating on sub-factors. For example Yuan and Tang [102] include control systems as a sub-factor. Energy management systems such as battery- and home energy management systems (BEMS/HEMS) are captured here, alongside other factors that enable and unlock usage of the already physically available flexibility. The studies of Airò Farulla et al. [123], Good, Ellis, and Mancarella [124] and Bogdanova, Viskuba, and Zemīte [125] do not mention capability

specifically, but in their broader technology factor also include sub-factors related to this, such as metering and computing services, interoperability, potential for blockchain-technology and data security. A lot of studies mention aggregation as a key enabler for residential flexibility activation. For example, the study of Yuan and Tang [102] mentions aggregation as the enabler of market-access and integration while complying with regulatory requirements and interoperability standards. This is substantiated by Dawes et al. [121] who mentions that aggregation for residential-users is key for the scalability of flexibility solutions. Furthermore, the study highlights that capability is dependent on standardized protocols needed for data sharing and control operations. Contrasting are industrial users, as the study of Fernández García, Troncia, and Chaves Ávila [116] mentions, that do not rely on aggregation for their capability. Nevertheless, other aspects of technical organization and guidelines are still needed for these users, such as smart meters. To conclude, this organizational and technical ’capability’ factor focuses on unlocking system integration and enabling participation.

- ***Behavior*** Another recurring factor in studies is user behavior. All of the the studies mention relevance of user characteristics such as occupant behavior, customer awareness, and social factors, while others are more focused on general aspects such as willingness-to-pay. Principles related to aspects such as acceptance, awareness, user comfort and preferences also fall within this factor-category. The study of Borragán et al. [126] specifically focuses on this key factor and its the underlying components, whereas factors such as comfort, environmental benefit, education, demographics, age, income, trust, awareness, perceived economic benefits social influences and emotions associated with technology are distinguished as determinants in decisions on flexibility actions. Furthermore, the study of Dawes et al. [121] specifically mentions that consumer engagement and understanding of electricity markets is key for participation. To conclude, all of these factors are simultaneously captured in the factor ’behavior’, that is fundamental to the autonomy and ultimate decisions on flexibility reactions from users. It also captures behavior that is not driven by prices.
- ***Incentive structure*** A fourth factor that can be distinguished is market structures, incentives and drivers, possibly economic. Especially the socio-economic studies like Good, Ellis, and Mancarella [124] and Bogdanova, Viskuba, and Zemīte [125] mention these in their main factors, alongside the more broad study of Yuan and Tang [102] that mentions markets mechanisms such as dynamic pricing schemes and incentives for EV and storage technologies as important. The factors are often mentioned as important for both short-term and long-term aspects. Although not capturing it in an overarching factor, the study of Dawes et al. [121] emphasizes the need to create alignment of market pricing structures and incentives to increase participation in demand response programs. Other studies only include these incentives, policy instruments and economical drivers in external factors or factors that have no overarching category. In summary, an overarching ’incentive structure’ focuses on policy instruments and other stimuli that influence flexibility provision.
- ***Others*** The last distinguishable factor are external, exogenous factors. A lot of studies include other factors into such a separate category. such categories include factors that influence the system, but that cannot be captured in one of the other factor categories and of which the influence is not known. Especially climate and weather aspects are mentioned as relevant by a majority of studies, among which Dawes et al. [121], Shepherd and Mohagheghi [122], Yuan and Tang [102], as these shape the timing and nature of load profiles. Furthermore, political and regulatory developments are listed in this factor category, by Bogdanova, Viskuba, and Zemīte [125] and Dawes et al. [121]. Furthermore, factors that do not focus on individual flexibility providers, but are more focused on the broad landscape of factors that very indirectly impact flexibility, such as political changes, climate policy and grid operation policies are included here. Although the exact size and relative influence are often uncertain and unknown, it is certain that these factors always play a role. These factors are captured in the ’others’ factor.

By distinguishing these factors, a placeholder is given to all influences and uncertainties that influence the flexibility reaction of an agent. These factor-categories are demarcated as the aspects that influence the grid-participant flexibility as visible in figure 4.4 above.

5

Model development

In this chapter, model conceptualization is elaborated on for each of the 4 steps sequentially, alongside modeling choices and incorporation of data. In step 1 the power-flow model development is described. It determines historical congestion, and tracks this congestion to contributing distribution substations. In the second step, the congestion signal is appointed to contributors and modeled to study the effect of the financial incentive. Thirdly, the development of the stochastic flexibility state evolution model is introduced, in which the incentive develops together with other factors into flexibility states. In the fourth step, the flexibility states are extended by accounting for spatial correlation.

Coding implementation

For programming the model, the Python programming language is used. Especially, for the creation of the congestion signals and control of the power flow model in step 2, as well as data extraction from the power-flow model via the Powerfactory Python API. Additional packages are used in step 3 and 4 for computations and visualizations, for example with Networkx, as well as data wrangling with the pandas. The code that was used can be accessed at:
https://github.com/developerDuncan/Assessing-congestion-patterns-and-flexibility-reactions.git

5.1. Step 1 - Identification of congestion

To show where congestion occurs in Dutch distribution grids under business-as-usual conditions, an AC power flow model is developed within DigSILENT Powerfactory. Herein, historical loads are used to identify both voltage and current congestion in business-as-usual conditions. Later on, flexibility providers will react to these conditions, and assessment on flexibility adequacy is performed. Figure 5.1 below shows the current step in the approach.

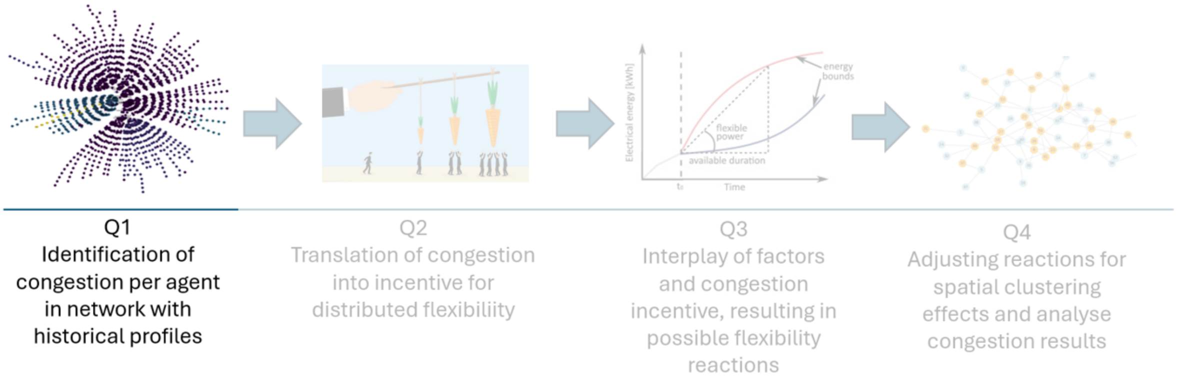


Figure 5.1: Sub-question and step 1 in process flow

Using aggregated historical load at distribution substations entities

In this research, it is assumed that flexibility is used for congestion mitigation, and only provided upon signals or incentives through CMMs from the DSO, as further defined in section 5.2. To incentivize flexibility, identifiable congestion patterns are used. Since congestion is a problem that is occurring already in society nowadays, historical load profiles are used for this without relying on additional concessions and assumptions. Such historical data in the load flow is highly available within DSOs. Especially data that is aggregated towards the distribution substations is widely available, and usable for predictive modeling while being privacy friendly for grid-participants. This load and generation data is of prosumers in the low-voltage levels is aggregated and merges at distribution substations. At these distribution substations, the voltage is typically transformed from roughly 10 kV till 400 V. The number of residential connections under such a distribution substation typically varies between 50 and 250. Alongside aggregated households and other types of small users, there are industrial users. These can have their own distribution transformer and connection at the 10 kV level, and therefore such industrial users have a separate distribution substation. The multitude of these distribution substations then aggregate towards one distribution area that is supplied by a sub-transmission voltage distribution transformer.

Underneath, in figure 5.2, an exemplary distribution area is shown, that is supplied by one sub-transmission voltage distribution transformer. There are typically 5 to 10 of such distribution areas under a typical high-voltage substation. In the figure, small blocks represent the multitude of distribution substations that step down the 3-10 kV medium-voltage into 400 V low-voltage in such a distribution area.

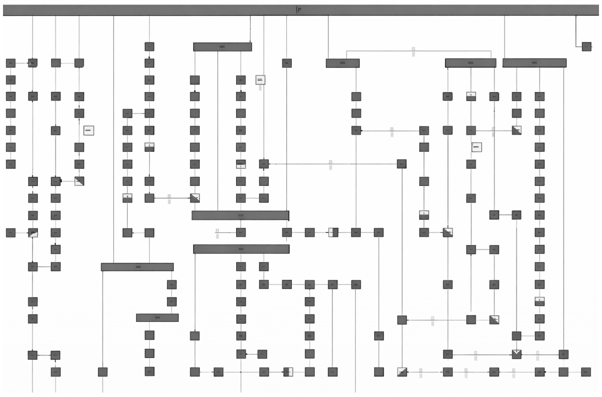


Figure 5.2: Distribution area topology under one sub-transmission voltage transformer. The distribution substations in the area are radially connected

DSO historical profile data entails both industrial users and aggregated small low-voltage users that represent one entity at the distribution substation. This aggregation from residential low-voltage users allows for abstract modeling of agent flexibility characteristics. The abstractness and availability of data are key reasons for choosing these entities at the distribution substation level to represent flexibility agents in the system. These distribution substation entities are the only agents that influence the power flows. The characteristics and actions of these agents are influenced by other actors, but these are not explicitly modeled. Rather, the influences of these other actors are modeled as the influential factors in step 3 of the model. By representing the individual residential end-users in an aggregated manner at the distribution-substations, the model representation of the system is highly practical and scalable, while avoiding the complexity and uncertainty of modeling individual user behavior in detail. Still, meaningful differences of group-behavior and spatial differences across regions can be captured [127].

The content of these historical load profiles is structured in the same way for each distribution substation, being a year of hourly values for power in MW. These loads are used to identify congestion in the current step and translate the resulting congestion into signals in step 2, but they will also be analyzed in step 3 and 4 to see whether the additional provided and externally modeled flexibility is adequate to solve congestion. The loads are in terms of active power, but the the grid in the system works with alternating current and apparent power. To perform a correct load flow, default and typical values for the power-factor are accounted for, without active decision-making and adaptations from agents. By using these default values, active power can still be modeled. This focus corresponds with the requirements stated in chapter 3 of the Dutch grid-code for entities below 1 MW, in which residential users have no incentive or obligation for reactive power management, and mainly focus on active power adaptations [48].

By aggregating the grid-participants to distribution substation entities, low-voltage levels of the grid are not included in a detailed manner. This limits the model's ability to capture finest-grained phenomena. Furthermore, the input of the high-voltage transmission feeder was assumed external and independent of the factors and agents in the model, as distributed flexibility developments primarily have implications for the distribution grid. Dynamics in the high-voltage grid are not in control of the DSOs, and therefore less relevant to include in models focused on distribution areas. Additionally, by excluding high-voltage load modeling, complicated dual-side elasticities and market clearing mechanisms were avoided, and high-voltage supply does not change through factors and sensitivities.

Creating the power flow network structure

The load profiles are used as input for the power-flow model, which also requires the full network structure. To this end, an exemplary Dutch distribution grid is modeled in the partially predefined Digsilent Powerfactory load flow network. This modeling tool is suitable for alternating current quasi-dynamic load flows with time-varying loads, which is of key importance in heavily fluctuating distribution grids. This power system analysis software application is standard within the DSO. Furthermore, the AC flow is suitable for multi-aspect congestion analyses in which both AC reactive power aspects and active power aspects can be taken into account.

In this network model, the full network from low-voltage up to high-voltage including different medium-voltage areas was manually connected. Within DSO models, medium-voltage sub-areas under the same high-voltage substation are not often coupled. However, this research focuses on spatial prosumer differences between different medium-voltage areas so that inter-regional effects can be analyzed, and were therefore coupled. Specifically, lines and transformers of different HV-MV areas were connected to the underlying distribution areas under one high-voltage substation. Figure 5.3 below shows the sub-transmission medium-voltage distribution transformers that connect the different regions.

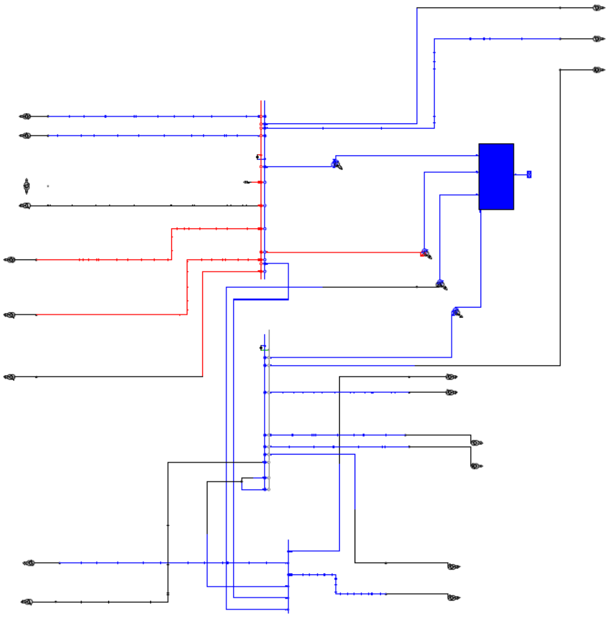


Figure 5.3: High Voltage feeder supplying the distribution feeders in Powerfactory. The high-voltage feed-in from the TSO at the blue rectangle, supplies the main busbars of the HV-substation in the middle. The sub-transmission voltage lines and their transformers originate from these busbars and depart towards the distribution areas at the ends of the lines.

Performing a load flow

After setting up the network, a load flow was performed. Therefore, the feeder and lower loads are matched and balanced in a quasi-dynamic load flow simulation. As the data used is actual historical data, the loads already roughly matched. To converge completely, small differences are captured by a slack bus in Powerfactory for feasibility. The internal Newton-Rhapson solver is used to balance the grid with power injections and demand. This is a powerful iterative solver for load flow problems, designed to capture the large set of nonlinear algebraic equations that arise from the AC injections and withdrawals [128].

Congestion output for current and voltage

Upon solving the model, load flows lead to overloading of components. These overloadings can be characterized by aspects such as voltage violations and percentual line overloading limits. These reference congestion patterns were validated by actual historical patterns from DSO congestion information. Here, it became apparent that the definition of congestion, so at what loading percentage congestion is announced, plays a big role in the identification and signaling of it. Acute congestion is only predicted for the future and only occurring to a minimal extent within recent datasets. However, formally, congestion is announced already before acute congestion happens. An early try-out of the power-flow model also showed that predefined line loading limits are only minimally exceeded, and that congestion related to current overloading is minimal. Nevertheless, to assess the effect that flexibility can have on congestion-mitigation, congestion is needed in the results. One way to handle this is by using substantiated predictions on profile growth in the loads to trigger congestion. This however, comes paired with additional assumptions, lowering validity of the research. Instead, this research focuses on assessment of peak loadings reduction with flexibility, not so much whether acute congestion actually occurs. Therefore in this model, congestion is defined as exceeding component loading above 80% of the rated apparent power capacity, instead of 100%. The potential reduction of these peaks already gives useful insights for the influence of additional flexibility in the future, with increased congestion and loads. The overloading of the components is connected to creation of the congestion signal, explained in step 2.

To identify congestion with metrics, actual loadings are compared with the nominal line ratings based on relative loading percentages. This shows where overloading occurs in the the quasi-dynamic load flow simulation results. As output, a table contained the data with the hourly loading values, as a percentage of the rated apparent power capacity in kVA from each component in the network. Once the 80% rating was exceeded, the component was defined to be in congestion. Furthermore, the voltage fluctuations were calculated for each component. Hence, a distinction between current congestion, which is more directly related to the total amount of apparent power loading in kVA, and voltage congestion was made. The voltage fluctuation magnitudes over time across buses are expressed in per-unit terms. Essentially, this shows the deviations from the normal operation voltage, which is taken as unit 1. Typical values are then between 0.95 and 1.05, as deviations are targeted to be below 5%. To this end, acute congestion occurs, when values go below 0.90 or above 1.10 magnitude per-unit. Nevertheless, also values below 0.95 or above 1.05 are undesirable and show potential for congestion, already in the historical reference load flow. Therefore, the load flow also generates these types of results, and show where the potential for congestion is highest, although actual acute congestion might not appear.

5.2. Step 2 - Signaling congestion to activate distributed flexibility

After congestion has been identified in the historical reference flow, the model incorporates this congestion to deploy distributed flexibility at specific places for congestion mitigation. This leads to new demand loads and a new congestion flow, that will be analyzed in the results. To deploy flexibility, the historical congestion is converted into a congestion signal per agent. Based on this congestion signal, a highly granular congestion management mechanisms is implemented to encourage the maximum potential of distributed flexibility, as discussed in the approach. The method to implement this in the model is described in the sections below. The congestion signal, needs network topology to be appointed to congestion contributors, which is discussed first.

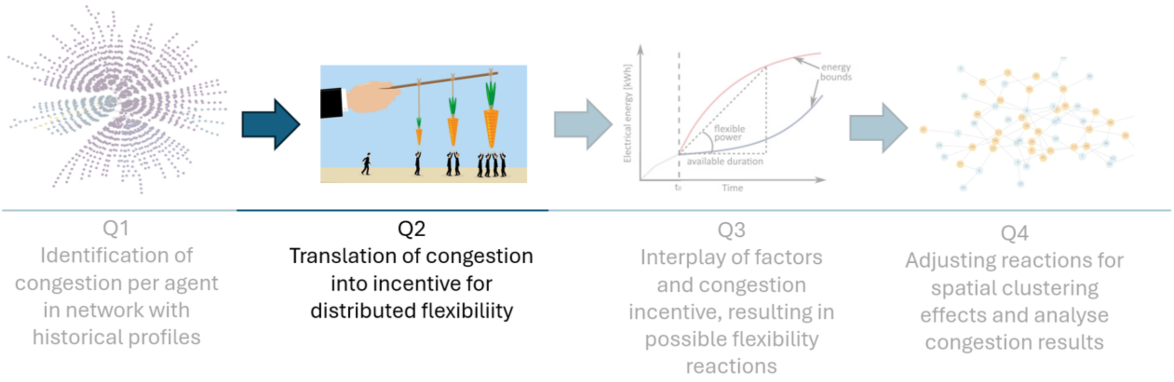


Figure 5.4: Sub-question and step 2 in the process flow

Creation of network with congestion contributors

The congestion management mechanism is not applied to all distribution substation, as assessing the effect on physical congestion is only relevant at actual congestion contributors. Therefore, only congestion contributors at components at specific nodes in the network receive the congestion signal, to assess the affect of the mechanism. The Powerfactory power flow model is not suitable to clearly appoint congestion contributors in a structured way. Therefore, a replica network model that reveals the radial hierarchy with the connected congested components and the contributing prosumers, is set up with the Networkx library. Herewith, congestion signals at grid components and edges in the model, are appointed to prosumers at nodes, while using the trivial hierarchy in such network models. Additionally, this network allows for modeling of spatial correlation between distribution substation agents in step 4.

To construct this network, all nodes and edges were extracted from the power-flow model. The nodes represent the distribution substations as congestion contributors that contain the load profile data. As discussed in theoretical background, busbars are typically not in congestion, and therefore were chosen to represent the distribution substation node 'agents' that contain the profile loads in the network. However, transformers and lines are typically in congestion, and can be represented as edge elements in the network, containing the actual overloading of congested components. Only the lines that are in usage under normal operation were taken into account, so the N-1 components that otherwise cause meshes are excluded from the model. The distribution substation nodes, and congested component edges were combined into a radial network. This revealed the hierarchical topology, in which congestion propagates. The Kamada-Kawai network layout is shown in figure 5.5 below.

Appointing congestion contributors

Congestion in a component is often the result of multiple contributors and caused by multiple sinks or sources, so understanding power transfer distribution factors (PTDFs) is of key importance. This tells what agents cause congestion in components, which influences the activation of distributed flexibility via CMMs [129]. In meshed networks, the calculation of power transfer distribution factors is a relatively complex task, as multiple parallel paths are possible and PTDFs depend on the complex network topology. However, distribution networks are typically radially connected, hence identification of the contributors is more trivial, and no PTDF calculations are needed. Overloading at places can easily

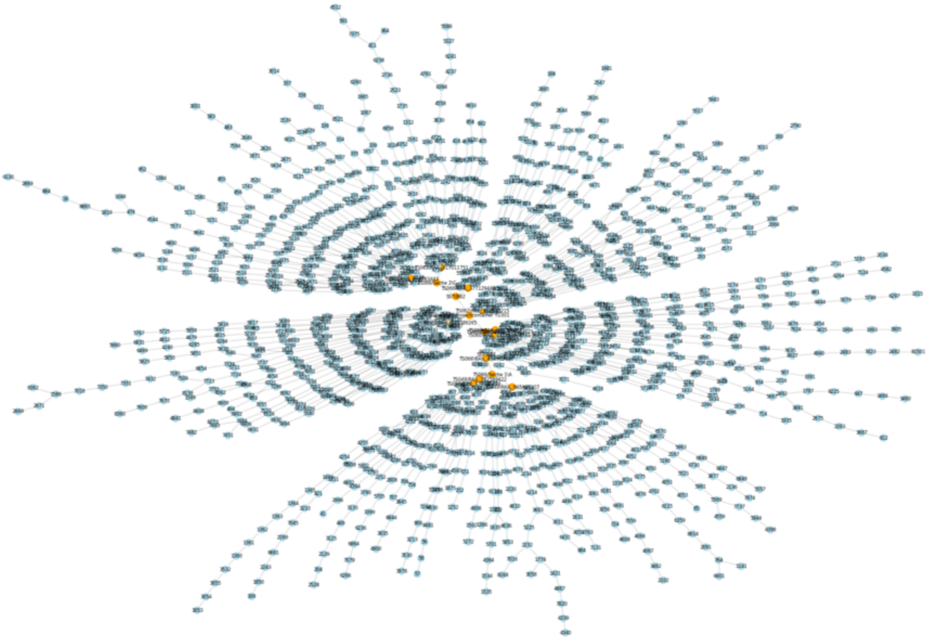


Figure 5.5: Radial network of distribution substations. The Kamada-Kawai network layout shows the network in a visually balanced way, which positions distribution substation nodes based on graph-theoretic shortest paths in a physics-inspired algorithm. The distribution substations are connected via the congested edges, representing lines and transformers

be traced back to injection and withdrawals, as all underlying nodes contribute to congestion in the overarching congested component.

Based on the network, a hierarchical chain can be made in which hierarchical dependencies are easily visible. Nodes at the beginning of these chains, directly below the high-voltage feeder, do no inherit congestion from any other nodes or only from the overarching sub-transmission distribution transformer that supplies the whole distribution area. However, nodes in the end of the feeder have a long chain of dependencies, and can inherit congestion from many other overarching distribution substation nodes.

Creation of congestion signal

After identifying the hierarchical structure of congestion contributors, actual congestion signals can be set-up. These can be seen as higly granular temporal and spatial signals that only apply for specific distribution substation agents once they contribute to congestion.

The congestion signal per timestep for each node, was calculated from the simulation results. The congestion signal was defined as the percentage overloading value from the rated apparent power for each edge component, so either a transformer or a line. Only the components and timesteps that were in congestion, so above a loading percentage of 80% were taken into account. The congestion overloading value from its overarching edge congestion components was appointed to the contributing nodes. Per node, the highest congestion value per timestep was taken, as the component with the highest congestion is the limiting factor. This resulted in each congestion causing node receiving a congestion signal at the timesteps for which there is congestion. So each distribution substation node has its own congestion signal per timestep once it contributes to overloading above 80%. This magnitude of this signal however, is not further used in this research. Only the binary information, whether the distribution contributes to congestion or not is used. Only this information is needed to be able to point out where the effects of a maximal financial incentive through highly granular financial CMM are relevant to assess flexibility reactions.

Usage of congestion signal to assess the effects of highly granular financial incentive

As discussed in the approach, only the effects of the highly granular financial mechanism are assessed. Analysis of these effects is enabled by knowledge on congestion contributor paths from the congestion signals. By focusing on the highly granular financial mechanism, the financial incentive can be more intense as it more efficient with regard to social welfare. This intensity increases the ultimate potential of the flexibility reaction and only shows inadequacy of existing flexibility and robustly remaining congestion in the most certain manner, and was therefore used for assessment.

In this highly granular mechanism, the magnitude of the financial incentive influences the effect on flexibility and congestion. In reality, once applying this granular financial mechanism, the maximum congestion signal per timestep and agent is converted into a financial incentive with a magnitude that is proportional to the congestion. This research however, assesses robust congestion that remains after the most positive flexibility reactions have occurred under the highest possible financial incentives. Therefore only the effect of one specific, but maximal value of incentive is assessed. This value is defined as the highest value possible for which the DSO is willing to solve congestion with flexibility. The value is assumed the same for each congestion area regardless of the magnitude of congestion, as the DSO is non-discriminatory and does not differentiate. The approach models the effects of these financial incentive with maximum magnitude and the model applies it for all congestion contributors uniformly, while in reality this is not applied. In such a way, the differences in reactions and adequacy can be analyzed in the highest flexibility reaction scenarios. Herewith, the most severe congestion that remains can be assessed.

Hence, each congestion contributor distribution substation agent receives the same relative financial incentive that is needed to solve the concerning congestion. It is not the magnitude of the financial itself that is modeled. Rather it is the reaction to this uniformly applied but in reality highly granular financial mechanism that shows where flexibility is adequate and where not. However, to capture the impact of different levels of the magnitude, this financial incentive is varied throughout two scenarios. One scenario with a relatively low incentive for all contributors, and one incentive with a relatively high incentive. The exact effect of the financial incentive and binary congestion signal into the flexibility reaction, is further elaborated on in section 5.3 where it is used in the 'incentive structure' factor and in chapter 6 where it is further implemented.

The contributors do not contribute the congestion equally, also with respect to the losses. It is assumed however, that lowering all individual congestion contributor loads by a uniform percentage leads to a decrease of the same percentage congestion in the overarching congested component. This implies that congestion in the component is assumed linearly proportional to the sum of contributions, and that differences in losses are ignored. Each flexibility provider is then individually assessed on adequacy for this linear flexibility provision in relative percentages, whereas all individual adequacy assessments together can be used to draw conclusions on remaining congestion.

System representation of congestion signal and incentive

Each of the distribution substation agents thus creates congestion in the historical load-flow on which its own binary congestion signal is based. This to determines whether the maximum financial incentive is applied, to later on analyze the effects. In the co-simulation, the extraction of congestion from the power-flow model is used by the DSO to make an incentive. Then, this incentive is fed back into the system for the agents, to model the effect thereof on flexibility provision in the stochastic flexibility state model. This is the only iteration between the two co-simulated models of the system. The model concerning the flexibility states of the agents in which the factors interact to shape flexible electricity loads, is elaborated on in section 5.3.

5.3. Step 3 - Modeling agent flexibility reactions with factors

All sorts of flexibility factors influence the flexibility reaction, including the financial incentive from the previous step. To quantify the potential impact of distributed flexibility, insight should be created into the interplay and effect of these influential factors. Therefore, the influential factors are systematically modeled in an insightful stochastic flexibility state evolution model, with Monte Carlo sampling per agent. The final flexibility state of each agent at a timestep is a combination of factors represented in mathematical probability distribution envelopes that is further elaborated on in this chapter. Later on, the resulting flexibility state values indirectly interact in the grid, which leads to emergent congestion. In section, the model structure is first introduced, after which the model scope is demarcated. In the end, the Monte Carlo sampling strategy is explained.

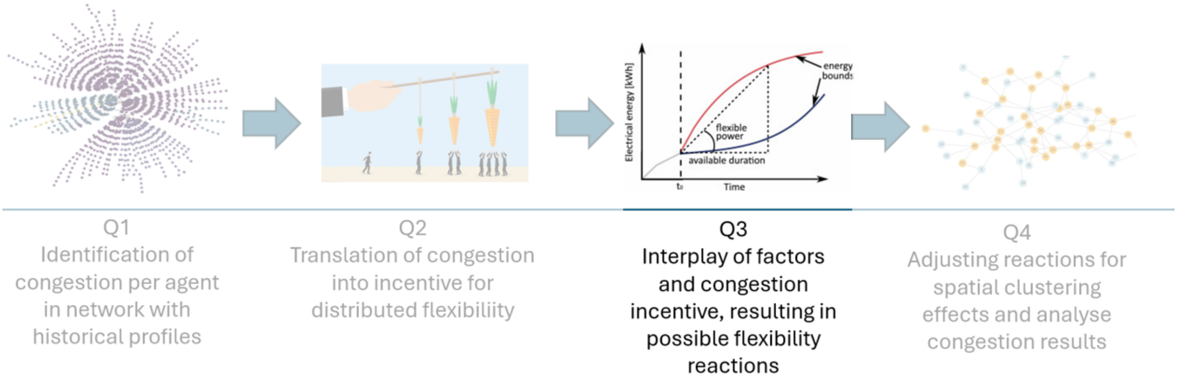


Figure 5.6: Sub-question and step 3 in process flow

5.3.1. Stochastic flexibility state evolution model

The modeling structure is introduced by first explaining the distribution substation agents and the purpose of the model in a seperate sub-section. Thereafter factors that influence their flexibility are elaborated on. Subsequently the flexibility state evolvement logic is elaborated on, alongside the initialization and temporal evolution of the states. In the end, the sequential multiplicative reduction formula.

Agents and purpose of model

The model focuses on heterogeneous agents that are independently influenced by factors in the environment, resulting in flexibility states. These states evolve over time and are influenced through certain rules. The distribution substation agents from step 1 are the only type of entity in the model. Such a distribution substation entity symbolizes either all the aggregated low-voltage prosumers in the feeder below it, or one large individual industrial end-user that has its own distribution substation. Each distribution substation agent has its own corresponding demand loads per timestep from the historical data. The model describes how much additional flexibility relatively to the maximum historical load from these profiles is provided. This relative amount of flexibility represents the final state of the agent per timestep, and is later analyzed for adequacy in solving congestion.

Influential factors and uncertainty

The flexibility states are influenced via the 4 factors from the external environment. Each of the factors influences the agent's flexibility separately in the model. However, in reality the factors also impact each other through unidentified complex factor correlations, especially on the long term where all factors are indirectly interconnected. Additionally, as explained in chapter 4 on the system demarcation, other uncertain effects also influence the factors in the short-term, represented by the 'other' factor of the review. This model however, works with envelopes, as described in section 3.3 of the approach. Such envelopes have probability distributions that can represent and incorporate such uncertainties as a quantified mathematical property in the factors. It is assumed that this mathematical uncertainty captures the influence of the 'others' factor, which is therefore not modeled as a separate factor. As a result, only four factors from remain that influence the flexibility states. These resulting categories were also compared and validated by the flexibility prediction study of [130] that DSO experts such as Hutten

[131] use, who mention roughly the same factor categories as dimensions. The following factors are distinguished:

- **Physical capacity**
- **Capability**
- **Incentive structure**
- **Behavior**

By distinguishing the 4 resulting key factors, a placeholder is given to all influences and uncertainties in the environment. Each factor has its own uncertainty, which can be represented in its own envelope, therefore referred to as factorial envelope. These 4 factorial envelopes represent the external influences from the environment and impact the agent's internal states. Together these internal states result into the final flexibility state per timestep. The agents are each influenced by the same factors, but the relative magnitudes of the factors and their envelopes differ per agent, causing heterogeneity. There is however, a specific structure in which the factorial envelopes influence the internal states, which is explained below.

Structure for evolving flexibility states

The 4 factorial envelopes that represent the influence of the factors, are not only influenced by the external environment. The external environment is the component that introduces uncertainty, which is represented in a probabilistic range that updates the state, forming new factorial envelopes. However the factorial envelope is also influenced by previous states. There are two types of states, final flexibility states, and internal states. Per timestep, there is only one final flexibility state, which is the result of the four internal states, of which there is one per factorial envelope. The states are relative percentages rather than absolute values, since local absolute values are unavailable, while relative values are.

From a factorial envelope, an internal flexibility state is drawn. There are four internal flexibility states, each state is reached after the influence of the corresponding factorial envelope has been accounted for. The factorial envelope is the sole determinant of the corresponding flexibility state. The factorial envelope however, is not only dependent on the environment. The factorial envelopes are partially shaped by past states and are path-dependent. The first factorial envelope, that of 'physical capacity', is also dependent on the previous final flexibility state, and the initialized beginning state. The other factorial envelopes, are only dependent on the external environment and on the previous internal flexibility states. This is visualized in figure 5.7 below. After the 4 internal states have been been developed sequentially, the final internal state corresponds with the final flexibility state per timestep. The factorial envelopes from which the factorial states are drawn thus evolve over time through impacts from the external environment, and also from previous states.

Initialization and temporal evolution

In the first round at the first modeled timestep, a maximum 'physical capacity' per agent is sampled from an external envelope that represents the technically possible flexibility state that an agent can have, with regard to its maximum load demand. This value stays the same throughout the whole simulation, as it assumed that the maximum physical capacity does not change over time, e.g. the technical max capacity of a residential battery does not change in size over time.

Then, in the first timestep, the first factorial state is shaped by the environment. This happens through the multiplication of the initial state with the 'physical capacity' factor in the external environment, that together lead to the first factorial envelope, as visible in figure 5.7 below. Subsequently, a state is drawn from this envelope through Monte Carlo sampling, as further explained below. Then, the second state is reached by adopting the first state and combining it with the 'capability' factors from the external environment into the second factorial envelope. Then a value is drawn from this envelope to represent the second state, and so forth for all the 4 factorial states. In the end, these 4 states lead to the final internal state, that corresponds with the final flexibility state per timestep.

The agent updates its final states based on hourly values for a whole year. There are intertemporal effects, as the final flexibility state per timestep impacts the next 'physical capacity' envelope. In the initialization however, none of the previous states matter for both the intra-temporal as intertemporal state developments and the factorial envelope and internal state is solely influenced by the environment.

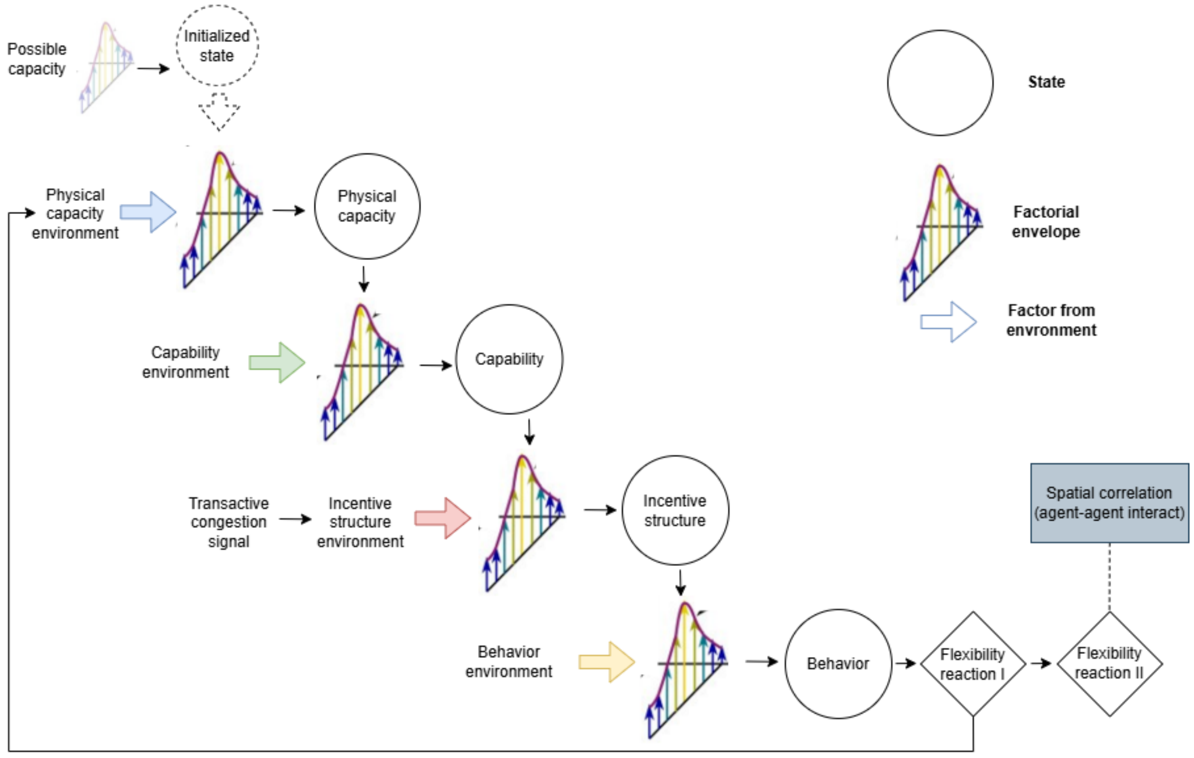


Figure 5.7: Hierarchical combination structure of factors with that influence the flexibility states. The linear hierarchy shows that all factors, that are represented by circles, are essential in developing a flexibility reaction. The first factorial flexibility state starts at the upper left at 'physical capacity'. This state then develops into an new factorial envelope for the 'capability' factor together with factorial influences from the environment. From this envelope a value is sampled, leading the the second state. So forth for the other factors. Although the factorial envelopes look the same in this figure, they reduce trough the sequential states.

Logic of chronological structure and sequential multiplicative reduction

In this combination all factors are foundational and essential, meaning that without any of these there is no flexibility state reaction. To transparently model the development of the final flexibility reaction states, an intuitive chronological logic and decision-tree is used as visible in figure 5.7 above. The development of final state can be represented as a linear chain in which the essential factors sequentially influence the state through internal states after initialization. The reaction starts at its maximum potential from the 'physical capacity' factorial state, and is then sequentially lowered by the other factors, through multiplicative reduction. In here, a funnel with 'filters' shows the propagation of the flexibility state that is sequentially lowered through envelopes with uncertainty. In this funnel, the factor states are characterized by the following functions:

• **Physical capacity**	Generates flexibility
• **Capability**	Unlocks generated flexibility
• **Incentive structure**	Encourages usage of unlocked and generated flexibility
• **Behavior**	Decides on usage of encouraged, unlocked and generated flexibility

In this logic, the previous state multiplies with the factor from the environment, to develop into the next envelope from which the next state can be drawn. However, the impact from the factor in the environment modeled so that is always has a negative impact. Hence, the state transitions always have a decreasing effect on the technically feasible flexibility reactions. The first state shows the highest potential and percentage of flexibility that is technically feasible by under the physical capacity under optimized conditions, which then decreases through the impact of the other factors.

This hierarchical chain with envelopes that reduce the flexibility, can be represented by the following mathematical formalization:

$$P_t \longrightarrow C_t \longrightarrow I_t \longrightarrow B_t \text{ and } Finalstate = P_t \cdot C_t \cdot I_t \cdot B_t$$

subject to: $0 < P_t, C_t, I_t, B_t < 1$

where:

$P_t =$ Physical capacity factor envelope at timestep t,

$C_t =$ Capability factor envelope at timestep t,

$I_t =$ Incentive structure factor envelope at timestep t,

$B_t =$ Behavior factor envelope at timestep t.

Specifying the factors and their envelopes

To further specify and take away uncertainty from the 4 factorial envelopes, sub-factors can be introduced that add information. These narrow the range or probability, so that a more precise and meaningful envelope can be created. Once all factors and sub-factors would be known and filled in precisely, the envelope and probability distribution would be extremely narrow, corresponding with a deterministic value. However, not all factors are known precisely, as external influences and complex factor-interrelations play a big role, which can be captured through the probability distributions.

In this model, only some relevant sub-factors are explicitly incorporated, as this research focuses on the modeling the factors in general. Therewith, the level of accuracy and detail for each factors' envelope differs, and envelopes will remain relatively wide and uncertain. Still, all factors need at least a minimal amount of information to feed the envelope to provide a definite range, which explained in chapter 6 on implementation.

5.3.2. Model scope

This model distinguishes 4 influential factors. However, many other categorizations and interrelations between factors might be possible. Additionally, factors might influence each other on the long-term, and the relations between influences change over time. Representing such interrelated factors would require knowledge on complex correlations and relations. However, these interrelations between factors are not explicitly modeled. Rather, they are captured through incorporation and assumptions on uncertainty in the probability distributions. Although not very detailed, the split in these 4 factors allows for more insightful analysis of flexibility reactions, by differentiating agents based on factors, instead of only assessing general energy or price-elasticities. The split exposes the underlying structure of how heterogeneous energy-elasticity is formed, especially for short-term reactions. In this split, the model is less dependent on general price-elasticities. The model especially focuses on short-term flexibility reaction envelopes, as factors are roughly independent and do not influence each other directly via complex feedback loops. Such short-term data increases the validity as it depends on fewer behavioral and structural changes with the assumption that infrastructure is fixed infrastructure and that there is lack of immediate alternatives [132].

Although complete demand loads are needed to model and identify congestion, the model does not entail development of complete demand load profiles. Rather, the flexibility states represent additional and external flexibility, which subsequently alters the historical demand profiles. This external and additional layer adds to simplicity for modeling, as it is difficult to determine the relative portions of flexible and inflexible demand from historical loads. It is assumed that that the historical reference load profiles do not incorporate any flexibility whatsoever, and are inelastic. This assumption is substantiated by the fact that the incentives for flexibility are currently nihil and have been very limited in the past [16]; [15]. As these reference profiles need to be fulfilled at all times and are inelastic, flexibility and elasticity to mitigate the already existing congestion should be provided by an additional layer of external flexibility. This flexibility is provided the final flexibility state model per agent per timestep, but might not be adequate enough to solve congestion.

5.3.3. Monte Carlo sampling to draw flexibility states from envelopes

By drawing a random sample within the customized and evolving probabilistic flexibility state envelope for each local agent at each timestep, stochastic simulation with Monte Carlo elements is performed to capture uncertainty and variability. It is no pure Monte Carlo simulation as the principles are used locally per agent and not globally. Still it relies on repeated random sampling from probabilistic envelopes to capture uncertainty and variability in outcomes. The number of samples taken is high, namely per agent per timestep per factor, and therewith it explores uncertainty and approximates system-wide outcomes, just like Monte Carlo simulation. This models stochastic influences on agent flexibility states, since deterministic rules are insufficient as no solid local data is available. The following steps are performed to analyze system wide behavior with Monte Carlo sampling:

1. Define probability envelopes for factors, that change over time.
2. For each timestep, draw flexibility state values within these 4 envelopes for each agent.
3. Compute the agent's final flexibility state based on these sampled states.
4. Repeat the agents flexibility state reaction across many timesteps and agents to observe distribution of outcomes.

In the end, this provides probabilistic insights under the uncertainty, which supports the decision-making needed to determine typical and structural congestion spots after flexibility reactions. This abstraction enables the model to produce system-wide insights rather than highly detailed predictions about congestion points or individual outcomes.

By validating that the model uses a large dataset of agents that perform individual draws from a typical envelope, statistical reliability and representativeness can be approximated, since sufficient iterations cause mean and variance to stabilize. This increases the probability that average behavior of all of the agents converges with the expected value for system-wide, typical conclusions. Such an approach was also recommended by Dawes et al. [121] to model uncertain flexibility reactions. Nevertheless, to ensure absolute validity in future research, the number of Monte Carlo iterations should be gradually increased, so that the mean and variance truly converge.

Additionally, the model up to this part does not take into account spatial correlation once drawing values via Monte Carlo sampling. However, as explained in the literature review, this spatial concentration of factors is certainly present, and thus influences the states. This has been accounted for in the next step on sub-question 4.

5.4. Step 4 - Modeling the impact of spatial correlation

In this step, after the initial flexibility reactions have been developed, the effect of spatial correlation is accounted for. This is implemented as the reactions without taking spatial correlation into account are randomly drawn from the probability envelopes for each agent. Initially they do not explicitly account for the uneven spatial dispersion of factors influencing flexibility, while agents close together in space through spatial proximity tend to be similar, because there is for example behavioral and technological homogeneity in certain regions [133]. Hence regional disparities in solving congestion are present in the the factors and therefore should be modeled. The figure below visualizes that this is the last phase of the approach before the analysis. The sections below first introduce what specifically is modeled, and thereafter elaborate on how it is modeled.

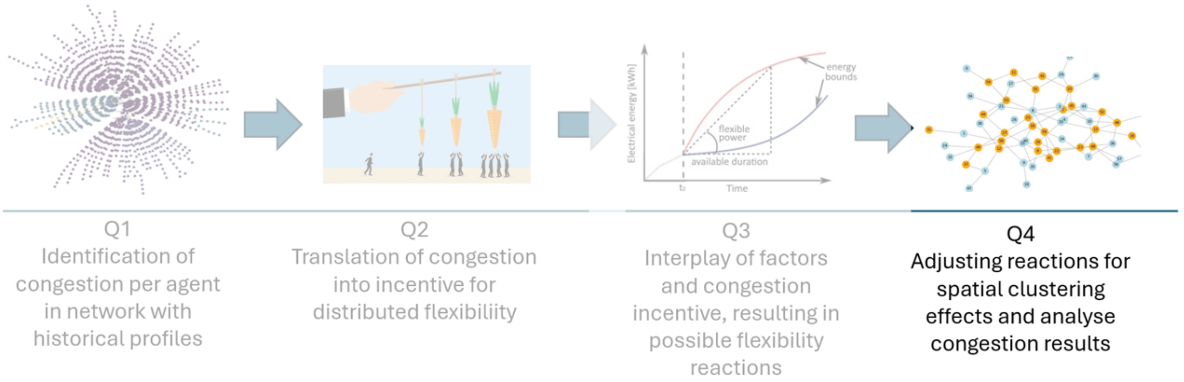


Figure 5.8: Sub-question and step 4 in process flow

Spatial correlation in flexibility states from agents in the network

In this model, spatial correlation occurs only between directly neighboring agents. Through this one simple rule, the emerging phenomenon of spatial clustering can already be captured. Agents adapt their flexibility reaction state towards the flexibility reaction of a direct neighbor in the network. The network essentially captures electrical proximity, but this information can be used as a proxy for spatial proximity. Hence, neighbors in electrical proximity are also spatially correlated. The proxy for the electrical proximity and spatial correlation will be strongest between neighbors that are the closest in the network [134]. Therefore, the spatial correlation of flexibility states is modeled to occur only between direct neighbors. That does not mean that agents further away in the network cannot be correlated. Such correlation can also occur, but only via the neighbors in-between to pass the correlation along. Flexibility reactions in close proximity are adapted and become spatially correlated, causing the flexibility reaction of agents in the same area to be more alike than flexibility reactions of agents in different areas.

However, the account to which correlation happens between neighbors, and the granularity thereof, is assumed unknown and varying. Furthermore, it is unknown what factors specifically correlate. Therefore only the final flexibility state is modeled to correlate spatially, and the extent to which is modeled to be random and varying per agent to represent heterogeneity in correlation. Nevertheless, to see the effect of various degrees of spatial correlation in the analysis of flexibility adequacy and congestion, the extent to which spatial correlation occurs is also varied in scenarios. One scenario in which correlation is zero hence without correlation, and one with random correlation, as described above. For this last scenario, the steps taken are elaborated on below.

5.4.1. Modeling spatial correlation between direct neighbors

The effect of spatial correlation on the flexibility states per timestep occur after the factorial envelope development has taken place. To model this correlation, an agents initial total flexibility state reaction that has been drawn from the probabilistic factorial envelopes, is influenced by the reaction of its direct neighbor. Still, spatial correlation between neighbors further away can propagate as the interactions happen sequentially. The correlation is modeled to happen only in one direction; the agent only inherits downwards from its overarching neighbor, and not vice versa. This prevents circular dependencies and ensures that flexibility adjustments propagate in a controlled manner, while avoiding complex feedback cycles. Hence, there is diffusion of spatially correlated flexibility reactions through the network, caused by the sequential agent-agent correlations. This diffusion leads to spatial clustering of multiple neighbors in some places as the reactions propagate through the network among neighboring agents. An exemplary overview of this sequential process is shown in figure 5.9 below.

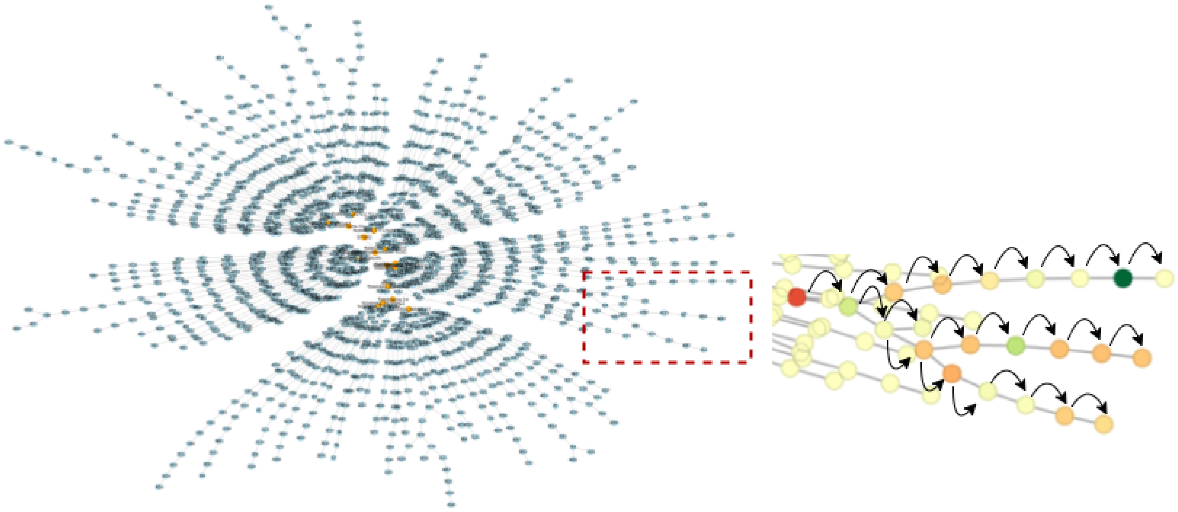


Figure 5.9: Visualization of the modeled spatial correlation, that iterates in one direction through the network, so that multiple agents can be correlated.

Characterizing correlation in a formula

There is an order in updating the agents to let the correlation propagate through the network. Therefore, direct neighbors were identified from the network. The one-directional correlation mechanism start at the ends of the radial feeders, where agents have only one neighbor. Herewith, it is assumed that the first agent of the radial distribution string is not influenced by its neighbor, it only influences its neighbor. So, the first agent that is influenced is second in the string. This second agent is influenced by the neighbor earlier in the string, which in this case is the first agent in the string. Then, the second agent in the string uses both its own flexibility reaction state, and the reaction state value from its neighbor. Then, this second agent adapts its flexibility reaction based on a normalized weighted sum between these two values. In this weighted sum, the agent decides to what extent its own reaction, and to what extent the neighbors reaction is determining the ultimate reaction of the agent itself. The weight essentially defines the influence of neighbors and spatial correlation. The formula for this correlation between an agent and its previously adjusted neighbor with the weighted sum is given below. This formula is performed for every agent that contributes to congestion, at every timestep.

$$\text{Weighted Sum: } B_e = B_i \cdot w + B_n \cdot (1 - w)$$

$$\text{where: } \begin{aligned} B_e &= \text{Final flexibility reaction of the agent} \\ B_i &= \text{Initial flexibility reaction of the agent} \\ B_n &= \text{Flexibility reaction of the already adjusted neighbor-agent} \\ w &= \text{Influence weight factor, } 0 < w < 1 \end{aligned}$$

In this formula, the spatial correlation is assumed to be constant over time for every agent, and therefore the weight and influence is only determined once upon initialization. For now, this influence is randomly determined through Monte Carlo sampling and differ per neighbor pair, as it is assumed unknown to what extent heterogeneous neighbors are spatially correlated. Hence, sometimes agents correlation between agents is high and flexibility reactions are more alike due to spatial correlation, whereas sometimes the flexibility influences do not correlate not so much, and reactions are not adjusted much. Such a one-directional interaction with influence occurs for every agent neighbor pair, so that spatial correlation can propagate and clusters can also entail multiple agents based on probabilities.

Figure 5.10 below illustrates how such direct neighbor interactions can still lead to the formation of clusters in the network. In the figure, a green and larger edge means that the agent-neighbor pair has spatial correlation, whereas a red smaller edge means that there is no correlation and no clustering. Clusters exist at the places where there are multiple green edges after each other. Especially at the ends of the feeders, such correlation is clearly visible in the figure.

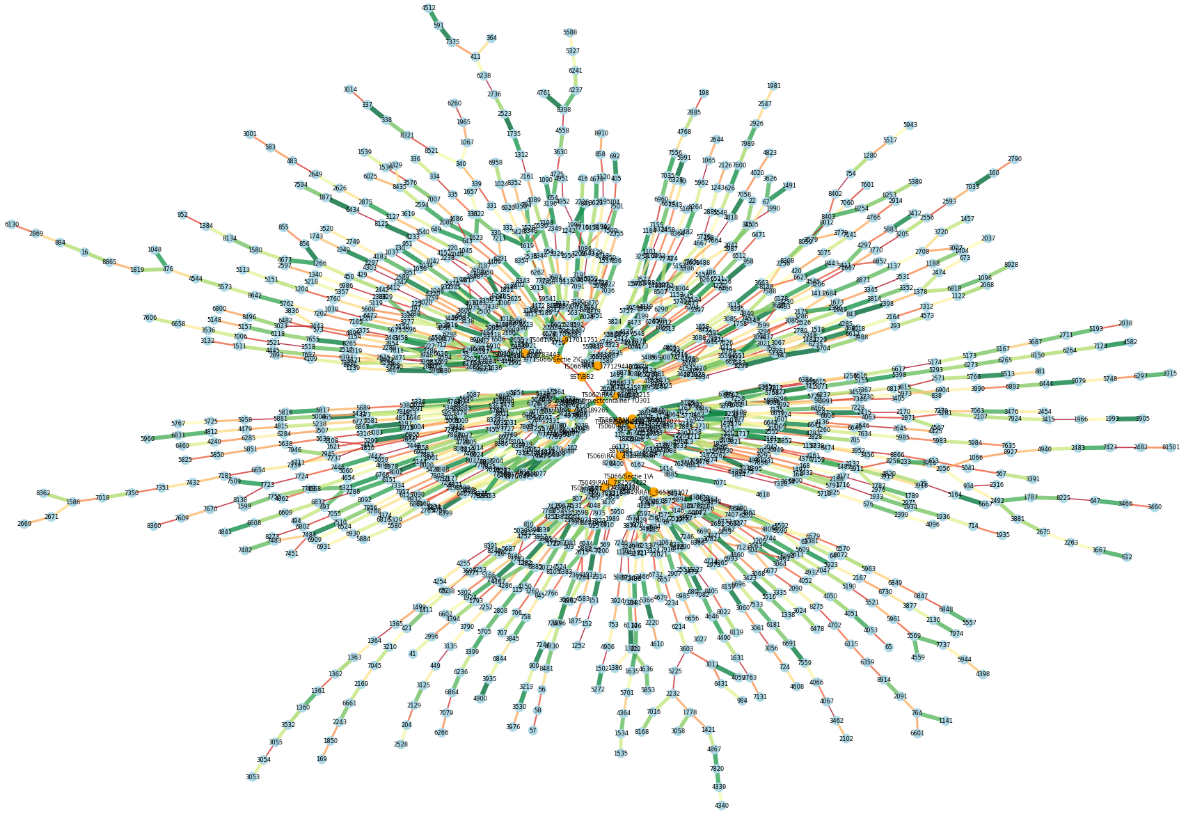


Figure 5.10: Example of spatial correlation leading to spatial clustering of flexibility. Direct neighbor connections lead to the formation of clusters in the network. A green and larger edge means that the agent-neighbor pair has spatial correlation. At these green edges, flexibility reactions between agents are similar and spatial clusters exist. Red smaller edges means that there is no correlation and no clustering. Clusters exist at the places where there are multiple green edges after each other, that are especially visible at the ends of the feeders.

6

Model implementation and experimentation

After the developing the stochastic state evolution model, the factorial envelopes are characterized and quantified in the first section of this chapter, that together lead to flexibility reactions per timestep. Each of the factors and information included in the factorial envelope is elaborated on, alongside scenarios for some of these. Additionally, in the second section of this chapter, the step on spatial correlation in which flexibility states are adjusted, is implemented.

6.1. Implementing factorial envelopes

The influence that the factors have on the internal states is dependent on definitions and conditional aspects of the factors. In the subsections below, each of the factorial envelopes in multiplicative reduction formula from, are discussed individually and a sub-formula to calculate the individual factor is provided. An elaboration on what it captures is given, alongside operationalization of the range, together with the rationale for this range by adding information through sub-factors. Extra clarification on aspects that can be substantiated by literature is added, especially with regard to their temporal variability and uncertainty. The model varies the flexibility factors per hour to show that the external environment impact changes over time, but for some factors this does not apply, as they are largely independent of time. Hence, a subsection is focused on the temporal calibration per factor.

6.1.1. Physical capacity

The first factorial state 'physical capacity', represents the physical shiftable capacity that is fundamental to flexibility. Without residential batteries, EV's and other assets and sources of capacity that enable shifting of energy usage, no flexibility can be provided.

One time initialization

Prior to developing this factorial envelope, the maximum possible amount of physical capacity that an agent has, its asset base, is initialized once in the beginning, as it is assumed that the maximum amount of flexibility that an agent can technically have does not vary over time. This initial state represents the maximum flexibility potential of technical potential at optimal conditions. The maximum percentage of flexibility that an agent has relative to its maximum demand load usually varies between 10% and 50% , dependent on uncertainties in the external environment that are not modeled. However, the bulk of the agents has around 20% flexibility with regard to their maximum demand load. Only a small amount of the agents, usually industrial users, have more flexibility [135]; [136]. Therefore a Beta(2, 5) distribution mapped to the [10%, 50%] interval was used for the initialization of maximum flexible capacity at optimal conditions. Although this is an envelope that the environment creates, it is no factorial envelope. This envelope is only used for initialization of the beginning state, which is the same at every cycle and does not vary in the time.

Continuous development into factorial state

This once initialized maximum physical capacity state, is then adjusted to turn into the 'physical capacity' factorial envelope at every timestep, under influences from its factorial environment. One such influence that is specifically modeled is the previous final flexibility state. This represents that the final flexibility used in previous timesteps impacts the current state, for example because the state of charge of the storage decreased by usage in the previous step. Such historical usage of flexibility always has a negative effect on the maximum amount of flexibility in the current timestep, but the extent to which is influenced by the external environment. Especially the final flexibility state in the previous timestep is assumed to decrease the physical capacity state. Therefore, the amount of flexibility used in previous timestep is modeled to decrease current flexibility by a value between 30% and 80% [137];[138]. The probability distribution is skewed towards 80% as most of the flexibility cannot be restored within one hour [139]. This is done with a Beta(5, 2) distribution mapped between [30%, 80%] interval. However, flexibility states of earlier timesteps also matter, and might influence state of charges in the current timestep. The flexibility usage in the step previous to the previous step is also included, to represent that not only flexibility usage in the near history matters, but also flexibility usage further in the history matters, although to a lesser extent [140]. This is not double counting but a second-order feedback in which immediate and delayed past states contribute through distinct, independently weighted channels. The flexibility state in the round before the previous round can decrease the current state between 0 and 30%, with a probability distribution skewed towards 30% in the Beta(5, 2) interval of [0%, 30%]. The decreasing effects of this factor seem large. However, often congestion is only there for one or two hours in a day, meaning that storage is still charged and not exhausted or diminished when actual flexibility is needed, as it has enough time to charge and become available again.

In addition, the maximum amount of flexible physical capacity also depends on external influences such as market developments or weather in the short-term. For example, if its cold and rainy, energy demand is high without production of solar energy, so the technical feasible amount of flexibility is lowered. Usually, such external and other factors decrease the possible flexibility by a percentage between 0% and 40 % [141]; [142]. Nevertheless, such extreme conditions rarely occur, hence the probability distribution is skewed towards zero in a Beta(2, 6) distribution.

Temporal calibration

The initial maximum physical capacity under ideal conditions was assumed constant and stable over the time. However, the other sub-factors of external and other factors, that diminish the initial maximum, such as weather and historical impacts do vary over the time.

Sub-formula synthesis

To conclude, after drawing the maximum physical capacity from the maximum capacity envelope that initialized the first initial state, the 'physical capacity' factorial envelope was created that takes into account the negative adjustment by historical flexibility usage, and also takes into account the negative adjustment of the remaining state by environmental externalities such as weather. This envelope can be represented in the following formula:

$$P_t = (R_0 - R_{11}B_{t-1} - R_{12}B_{t-2})(1 - R_1)$$

subject to: $0 < R_0, P_t, B_t, R_{11}, R_{12}, R_1 < 1$

where:

$R_0 =$ Initial maximum capacity, sampled from distribution once and constant over time
$P_t =$ Physical capacity factor state at timestep t
$B_t =$ Behavior factor state and final flexibility state at timestep t
$R_{11} =$ Influence of previous round, continuous sampling from distribution
$R_{12} =$ Influence of round before previous round, contentious sampling from distribution
$R_1 =$ Remaining influence of external aspects, continuous sampling from distribution

6.1.2. Capability

After the physical capacity state is shaped as the result of the first factorial envelope, the next state is transformed into the second factorial envelope in which the 'capability' factor is implemented. To actually use the flexibility in the 'physical capacity' one should be capable and enabled to receive incentives and to act based on these incentives. Appliances such as smart-meters and energy management systems play a role here, but also aspects such as contracts with aggregators to receive congestion signals and market accessibility.

To capture these influences, the state is lowered by a value between 0 and 80% [143]; [144]. Unfortunately for flexibility, this capability is a major factor that often decreases flexibility significantly, but there is limited information available on the extent to which this differs between agents, and to what extent most agents are influenced, therefore the the probability is assumed to be uniform.

Temporal calibration

The influence of the capability factors is modeled to be temporally stable and not varying much over time. Capability factors are often inherent design and operational characteristics that evolve only over long-time horizons. Although capability to deploy flexibility can vary a lot per agent, it does not vary much in the short-term [145];[146]. Short-term flexibiliy capability varies to a maximum of 5% in the short term [147]. Therefore, it was chosen to determine the capability only once per agent upon initialization, and letting the state vary only 5% randomly over the timesteps. Although the factor varies widely per agent, capability remains quite stable over time.

Sub-formula synthesis

To conclude, after the 'physical capacity' state has been reached, it reduced through influences of capacity, that diminished the flexibility state. This results in capable physical capacity in the factorial envelope of capability, with the following formula.

$$C_t = P_t - P_t \cdot R20 \cdot R21$$

subject to: $0 < C_t, P_t, R20, R21 < 1$

where:

$P_t =$ Physical capacity factor state at timestep t

$C_t =$ Capability factor state at timestep t

$R2 =$ External influence of capability, sampled from distribution once and constant over time

$R21 =$ External influence of capability, continuous sampling from distribution

6.1.3. Incentive structure

After the factorial state of capable physical capacity is reached, the effect of the 'incentive structure' is accounted for. The factor captures the influence of incentives for congestion-mitigation with flexibility reactions. In this research the factor is specifically tailored to the flexibility reaction and effect of the highly granular financial incentive as described in section 5.2. It uses the congestion signals per node, that represent the highest congestion that each of the distribution-substation is contributing to.

Applying uniform financial incentives for reactions

As discussed in the approach, this research does not iterate until the 'right' level of incentive to alleviate congestion is found. Rather it focuses on the heterogeneous flexibility reactions as a response to the highest possible incentive, that can be given under highly granular mechanisms. Even though the mechanism itself is highly granular and therefore can incorporate relatively high and differentiated incentives, it is assumed that the non-discriminatory DSO incorporates the same maximal price at all locations to solve congestion. Hence, the research focuses on revealing the heterogeneous reactions to this uniform applicable maximal price. This is especially relevant since it is assumed that the grid operator does not not how much flexibility there is and the corresponding elasticities. By studying reactions to the high financial but uniform incentive for congestion contributors as if the mechanism is applied in a highly granular way, locations in which robust congestion remains are assessed. This applied high financial incentive is not how GOPACS truly works, which actually works with bidding mechanisms. Still it shows how pricing based mechanisms with scarcity and opportunity cost evaluation principles lead to differences in flexibility provision. In this approach, the severity of congestion is not taken into account in determining the financial signal, as for simplicity only the binary measure for the presence of congestion is assumed to be relevant. So there either is congestion and a uniform but maximal incentive applies for only the congestion contributors in the spatial congestion area, or there is no congestion and no financial incentive is applied.

The magnitude of the incentive itself plays a big role in the flexibility reaction, but is not allocated congestion efficiently under a uniform price. Therefore the effect will imply overshoots or undershoots of flexibility. The maximum financial incentive is to be determined by the grid operator and regulating authorities, and the price setting mechanisms itself is not in the scope of this research. Specifically, the reaction to this financial-mechanism is of importance and focused on. It introduces uncertainty caused by two components. First, the various possibilities in the reaction at one price level, and secondly, how these possibilities change once the level and magnitude of incentive changes. The effect of varying incentive magnitudes is incorporated in scenarios. These topics are elaborated on below, resulting in a sub-formula synthesis that provides the ranges of the envelopes.

Reaction to price in probabilistic range

The different reactions among congestion contributing agents to the uniformly applied maximal financial incentive, can be modeled in the factorial envelope. It represents uncertainty introduced by locally differing opportunity costs, which leads to different reactions of agents. The reaction is assumed to always lower the maximum available capable physical capacity, and no additional capacity can be created in the short-term as a response [148]. There is one scenario that models the reaction to low financial incentives, and one scenario that models the reaction to higher incentives. Typically, agents supply only when the incentive exceeds their opportunity costs. Additionally, agents have a threshold that is comparable among specific agent types, which introduces a threshold effect [149]. This implies that large portions of prosumers are either below or above their threshold incentive, dependent on the opportunity costs of providers and the price set by the operator. This threshold effect is also represented in the scenarios. In the base scenario with a low financial incentive, the opportunity threshold is not always reached and the majority of the agents are not encouraged. In the additional scenario the incentive is above the typical opportunity threshold and more agents are incentivized. Reactions to the incentive vary between full willingness to provide flexibility, and no willingness at all in both scenarios. However, the distributions of the scenarios with varying incentive magnitudes are differing [150]. The reactions are is non-linearly influenced by relative changes in the magnitude of the applied uniform financial incentive, which is incorporated in the scenarios [151]. Additionally, next to increasing the quantity of flexibility supplied, extra incentivization also has another effect on the likely flexibility reactions. At low financial incentives, flexibility supply is namely more opportunistic and uncertain, which causes the spread of the flexibility reactions to be wider [152]. There exist larger differences between agents in opportunity costs and evaluation thereof at low levels. However, at higher incentive levels, opportunity costs tend to converge for agents, and the likely reactions are more certain and pronounced. This also comes back in the two scenarios.

So, the low and high incentives have different distributions. The first one at low incentive, causes small reactions with high uncertainty and wider probabilistic distribution. Therefore this scenario is chosen to impact the envelope with a Beta(3,1) to the interval of [0, 100%]. The other scenario applies a larger financial incentive, with increased activation, but also with a smaller probability envelope, as reactions are more certain. Therefore, this envelope is chosen to have a Beta(9,2.5) distribution within the same interval of [0, 100%]. So the higher incentive leads to smaller variance meaning that the values are relatively less spread out, while the mean of the flexibility reaction among agents is higher.

These different distributions properly show the relative differences, but the model calibrates for the effect of the different financial incentives. In reality, the impact of prices on flexibility provision cannot be negative as the minimum providable flexibility is not lower than zero. Therefore a scaling factor is applied based on an assumption. To compensate, the reducing part is multiplied by a factor of 0.54 for the low incentive, and 0.3 for the high incentive, so that the potential reduction is reduced, and the effect of the price is better calibrated. At higher incentive, the influence is thus larger. However, the accuracy of this calibrating assumption might not be very high, and implications hereof are further explained in the discussion.

Temporal calibration

This influence is partially controlled by the operator that either sets the incentive above or below the opportunity threshold of the agents. The incentive structure itself does not vary much over time, as it is assumed that the DSO applies one maximal incentive uniformly to contributors to solve congestion in the most encouraging way. However, the opportunity costs of flexibility vary over time, and therefore the effect of the incentive also varies over time [153]. The influence of the incentive factor was modeled to vary over time, to include the effect of differing opportunity costs over time in a likewise manner for both incentive magnitude scenarios. This was done through incorporation of a pattern of the opportunity cost of flexibility, as visible in the so called duck-curve in figure 6.1 below. The duck curve reflects time-varying scarcity in net load, which determines the opportunity cost of energy flexibility [154]. Flexibility is low-value and uncertain during periods of surplus generation, but becomes highly valuable and with high opportunity costs during steep ramping periods. In the curve, it becomes visible that the opportunity costs of flexibility rise once there is more demand, specifically at the 8 AM and 9 PM peaks. Table 6.1 below the figure shows the normalized hourly values of the duck-curve.

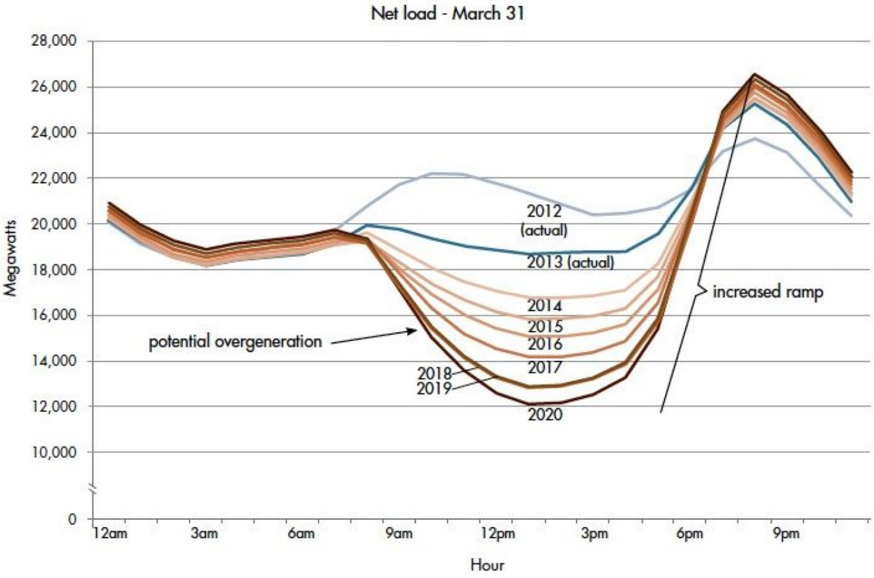


Figure 6.1: Duck-curve with varying opportunity values over time, from the study of Durán-Castillo et al. [154] It shows that there are peaks of energy demand and thus opportunity costs at different timesteps.

00:00	**01:00**	**02:00**	**03:00**	**04:00**	**05:00**	**06:00**	**07:00**	**08:00**	**09:00**	**10:00**	**11:00**
0.821	0.831	0.846	0.862	0.872	0.898	0.923	0.898	0.821	0.692	0.615	0.564
12:00	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**	**20:00**	**21:00**	**22:00**	**23:00**
0.538	0.538	0.564	0.641	0.744	0.872	0.948	1.000	0.975	0.898	0.846	0.810

Table 6.1: Normalized hourly values representing opportunity weight at different timesteps, with high opportunity weights at 8 AM and 9 PM.

Sub-formula synthesis

Alongside the financial incentive and the temporal patterns, a lot of unidentified aspects also bring uncertainty in evaluation of the opportunity costs in heterogeneous participants. Therefore, the uncertain external aspects that influence the reaction to the incentive are still modeled to be large at varying over time in the probability distribution of this factor. This state after this factorial envelope does not directly become a flexibility reaction, as execution this incentivized intention still needs to be performed, which is captured in the next factor 'behavior'.

The incentivized capable physical capacity factorial envelope after incentive structure can be captured through the following formula.

$$I_t = (C_t - C_t \cdot R3 \cdot R31) \cdot CS$$

subject to: $0 < C_t, R3 < 1; CS \in \{0, 1\}$

where:

$CS =$ Binary congestion signal, active when congestion

$C_t =$ Capability factor state at timestep t t

$I_t =$ Incentive structure factor state at timestep t

$R3 =$ External influence related to willingness at price-level, continuous sampling from distribution

$R31 =$ Prespecified opportunity cost influence $=$ values table 6.1

6.1.4. Behavior

After the incentivized capable physical flexible capacity state has been reached, the last factor is taken into account to reach the final state. The 'behavior' factor is essential as the previous factor of incentives and willingness does not necessarily mean that willingness leads to action Stampatori and Rossetto [155]. Incentives create intention, but behavior determines whether intention becomes execution. For example, people often fail to act even when it's economically rational. Behavioral and social drivers also determine the rational behavior of agents, such as political attitude, comfort preferences, habits, risk aversion, and social norms. This is embedded in the 'behavior' factor that ultimately influences this flexibility reaction. It is essential, as without the behavioral characteristics and autonomous decision-making of a user, there is no flexibility at all.

Range of behavioral reactions

The maximum bound corresponds with the maximum percentage that an agent can be committed, to execute the incentivized capable physical capacity. The the lower bound of the range corresponds to the lowest percentage that an agent is committed to do so. Literature suggests that such behavior decreases the maximum technical flexibility potential by values between 0 and 40% [156]; [157];[155]. In general however, these sources mention that once the other factors are already accounted for, behavior plays a smaller role. Especially in the reaction to the earlier 'incentive' factor, the influence of behavior is already partially implemented. This factor namely takes into account opportunity costs in the reaction to the incentive. Although the impact is smaller, behavior also impacts agents in a different way than via opportunity costs, as not all agents are assumed to always act rational and based on opportunity costs, and more intuitively [158]. Therefore the distribution is skewed to have limited influence, and a Beta(1.5, 3) distribution is applied to the interval between 0 and 20%.

Temporal calibration

The behavior factor, is typically likely to vary over the time, as attitudes and preferences also change over time [159]. Therefore, this factor remains to vary over the time has no exceptions that are further calibrated.

Sub-formula synthesis

This results in capable physical capacity in the factorial state of capability, with the following formula.

$$B_t = I_t - I_t \cdot R4$$

subject to: $0 < I_t, B_t, R4 < 1$

where:

$I_t =$ Incentive structure factor state at timestep t

$B_t =$ Behavior factor state, final flexibility state at timestep t

$R4 =$ External influence of behavior, continuous sampling from distribution

6.1.5. Consolidating the factorial envelopes and operationalization

Now that all the factorial envelopes have been set up, an overview can be made of the ranges and probabilities in these envelopes, as visualized in table 6.2 below.

Factorial envelope	Sub-factor	Letter	Range	Probability distribution	Source or argumentation
Physical capacity					
	Initialized envelope	R0	[10%, 50%]	Beta(2, 5)	[135],[136]
	Historical flexibility usage	R11, R12	[30%, 80%] and [0, 30%]	Beta(5, 2)	[138], [137], [139], [140]
	Others e.g. weather	R1	[0%, 40%]	Beta(2, 6)	[141], [142]
Capability	Capability external influences	R2, R21	[0, 80%] and [95%, 105%]	uniform(0,1)	[143],[144],[145], [146], [147]
Incentive structure					In-text motivation, [150], [149]
	Congestion signal	CS	binary	congestion pattern	
	Opportunity incentive and external influences	R3	[0, 54%]	Beta(3, 1) * 0.54 low or Beta(9,2.5) * 0.30 high	
	Temporal opportunity pattern	R31	[54%, 100%]	Customized hourly	[154]
Behavior	Behavioral external influences	R4	[0, 20%]	Beta(1.5, 3)	[156], [157], [155], [158]

Table 6.2: Framework of factors with sub-factors including ranges and probabilities

Once all the influences in the hierarchical chain are compressed in one formula, this is what it looks like:

$$\boxed{B_t = (R_0 - R_{11}B_{t-1} - R_{12}B_{t-2})(1 - R_1)(1 - R_2R_{21})(1 - R_3R_{31}) \cdot CS \cdot (1 - R_4)}$$

Essentially, by incorporating all the different envelopes and internal states, the final state can be represented as one big envelope in the mathematical formula as provided above. This is the result of the multiplications from all the internal envelopes, that each decrease the initiated technical physical capacity state and result in the last internal flexibility state of behavior, which corresponds with the final flexibility state per timestep. Additionally, figure 6.2 shows the probability distributions from each of the factorial envelopes in the multiplicative reduction logic. The reduction element of the logic becomes clearly visible. None of the factors increases the initial physical capacity envelope, shown in the blue curve. All other factors decrease possible states, such as the green and red envelopes, and turn into factorial envelopes with lower percentages. The yellow envelope shows the final flexibility state possibilities per timestep.

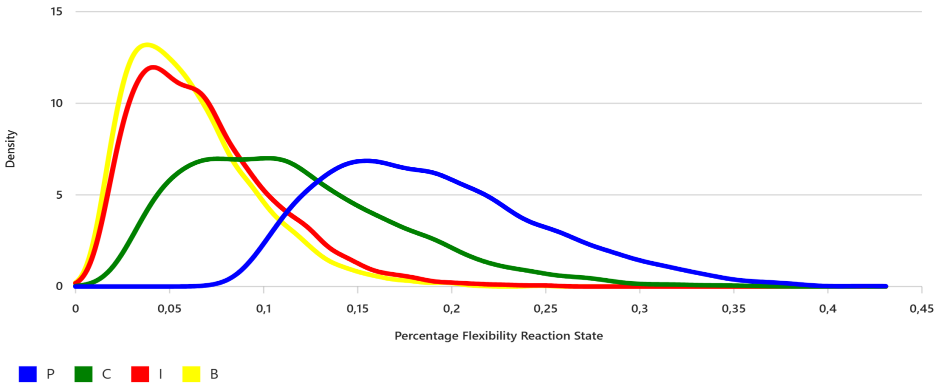


Figure 6.2: Probabilistic flexibility state representations incorporating the four factorial envelopes. The possible flexibility states start with high percentages and are reduced by multiplication into the other factorial envelopes, resulting in yellow final flexibility state

6.2. Implementing spatial correlation between agents

After the initial final states of the flexibility reactions at every timestep for the agents have been set up and sampled from the envelopes, the effects of spatial correlation can be taken into account. The agents sequentially update their reaction in the hierarchical order as discussed in section 5.4. In the formula below, the weight determines the influence of spatial correlation on the final agent reaction.

Weighted Sum: $B_e = B_o \cdot w + B_n \cdot (1 - w)$

where:

$B_e =$ Final flexibility state of the agent,
$B_o =$ Initial flexibility state of the agent,
$B_n =$ Flexibility reaction of the already adjusted neighbor-agent,
$w =$ Influence weight factor, sampled from distribution once, Beta$\big(1.5,\, 3;\, [0.2,\, 0.8]\big)$

Quantifying the influence through scenarios

To quantify the influence of spatial correlation on the final flexibility reactions, the weight for the weighted sum as above can be used. However, there are different kinds of agents, both industrial, rural and residential, that each correlate differently with their neighbors. Often, users in residential and urban neighborhoods correlate heavily, but users in industrial neighborhoods correlate weakly [160]. Correlation can is caused by spatial spillover effects, but this varies per region [161]. Especially between areas of different types neighbors of neighbors, there is low correlation. So it is known that there is spatial correlation to some extent, but the extent to which is unknown. Therefore, this phenomenon is approached through usage of two scenarios. One in which there is high correlation, and one with no correlation at all. In the scenario with spatial correlation, the extent to which there is spatial correlation differs per agent. The influence and weight of the correlation lies somewhere between 20 and 80 %, in which 100% means that the reaction of neighboring agents is exactly the same. Most of the agents are in residential neighborhoods and thus correlate heavily, therefore the distribution of the envelope is skewed towards 80%, with some outliers towards 20% to account for other correlations in rural and industrial neighborhoods. This leads to a Beta(1.5, 3) distribution in the [20%, 80% interval] for the inverse of the weight. It should be noted that the states work with relative percentages for the agent flexibility rather than absolute values, since local absolute values are unavailable.

7

Results

In this chapter, the results of the model implementation and experimentation are discussed, followed by an interpretation. First, the rationale for results analysis is introduced, building upon the approach. Secondly, in section 7.1 the application of the power-flow model to the case study is elaborated on, alongside results of the power-flow simulation as the first layer of the co-simulation. Thirdly, the stochastic flexibility state evolution model behavior and performance is described in section 7.2, alongside the base case results of the state evolution model. Fourthly, the results of the scenarios are analyzed, and the potential of distributed flexibility to mitigate congestion is assessed in section 7.3.

7.0.1. Rationale for analysis

The goal of the co-simulated models is to produce adapted load profiles per distribution substation agent, that have been adjusted as they incorporate flexibility reactions. It is already apparent from the historical reference load flow model where congestion arises and where flexibility reactions are needed. This reference load flow can be used for comparison of the needed flexibility with the actual flexibility reactions generated by the composed flexibility state model. Based on the undershoots or overshoots relative to the percentage overloading as described in section 5.2, conclusions and implications on the impact from distributed flexibility on congestion can be made. The flexibility reactions namely adapt the loads that interact in the grid, where they potentially cause emergent congestion. Generalizable conclusions and discussions on the system-wide results and scenarios can then be included, as the data is probabilistic and based on samples in the distributions from the simulation. The stochastic results do not allow do draw conclusions for individual agents. Furthermore, the model allows for analysis of the individual factorial envelopes in conceptual framework and modeled relations. These provide clear information on what causes uncertain outcomes per factor and agent.

7.1. Case study

The results are dependent on the electrical network topology and load data. Nevertheless, Dutch distribution grids are often similar in their radial network topology with roughly similar congestion patterns as elaborated on in section 5.1 [29]. Therefore, a typical case study grid was chosen to produce typical congestion results. The power-flow model grid under study entailed a typical Dutch mixed urban and suburban distribution service area, in which congestion is already minimally present and expected to increase in the future. The power-flow model results are discussed first.

7.1.1. Power-flow model results

Congestion was identified in the historical reference AC load flow. It distinguishes congestion not only in terms of thermal overload related to current in apparent power, it also distinguishes congestion caused by voltage violations. Voltage congestion results are first discussed, after which current congestion is discussed.

Voltage congestion

Potential for voltage congestion was identified by analyzing the voltage fluctuations at each component. Such fluctuations reveal where distributed flexibility might contribute to voltage congestion mitigation once having the ability to change voltage profiles. Therefore, the voltage fluctuation magnitudes that cause congestion across the buses of agents in per-unit terms were defined as values that deviate from the unit 1 value by more than 5%. This does not necessarily show acute congestion, which occurs at deviations larger than 10%. In the power flow results, such acute congestion deviations were only visible to a minimal extent. Still, the deviations larger than 5% show how voltage deviations might vary per region and therewith potential for future congestion once voltage deviations occur more often. This is especially relevant, as also loads that cause voltage deviations and congestion are expected to grow in the future [162]. The following figure 7.1 shows the summed deviations larger than 1.05 or smaller than 0.95 per unit, over a year. A 1% deviation per hour corresponds with a value of 0.01 in the scalar. As visible the maximum summed voltage deviation over a year is around 70 in the maximum bound of the scalar. This means that the most severely congested components have voltage deviations of several percentages, that occur in a multitude of hours.

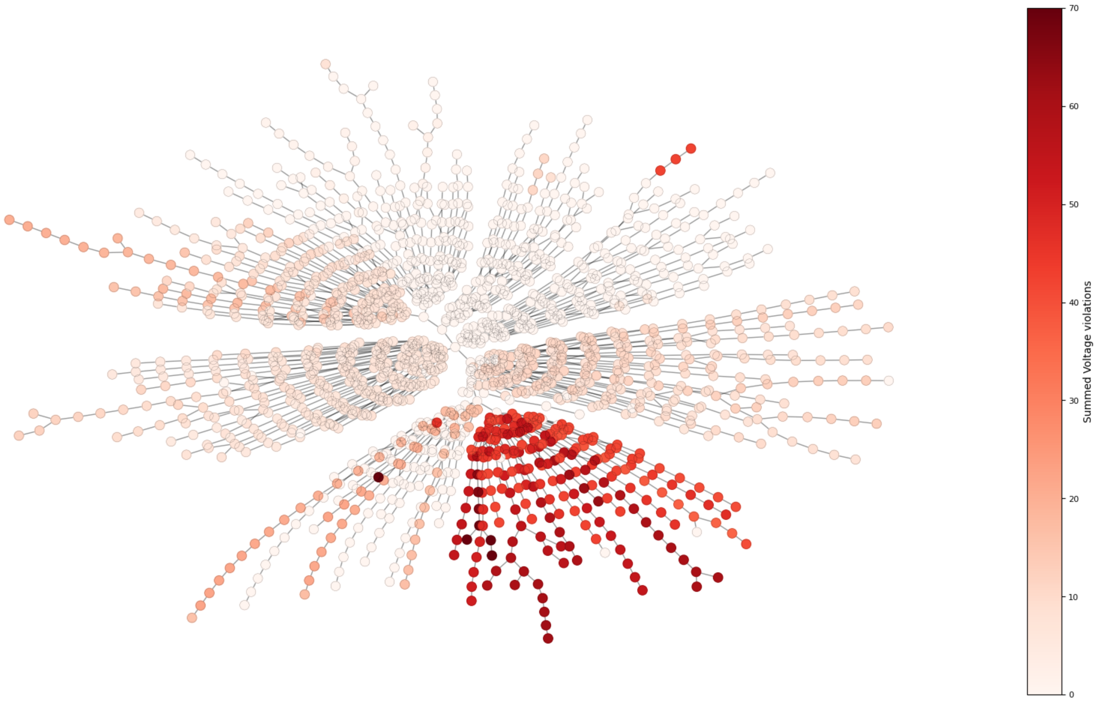


Figure 7.1: Summed voltage deviations over a year. The red nodes in various but differing local strings and especially in one distribution area, show systematic deviations of voltage exceeding the 5% target threshold, indicating potential for local voltage congestion

From figure 7.1 above, it becomes apparent that potential for voltage congestion differs per area. First of all, one larger area can be discerned by the dark red color, indicating that it has lots of voltage fluctuations over the year. This whole area is fed by and under congestion of the same sub-transmission voltage distribution transformer. Hence, the voltage problem here might be caused by irregularities in the configuration with regard to the DSO FACTS devices, OLTC or other assets that influence voltage stability in that area. Such DSO owned solutions are able to change the voltage for the whole region, but this kind of congestion might also be solved through external distributed voltage flexibility assets.

Additionally, there are voltage fluctuations throughout the whole system. Some strings of distribution substations and their feeders are also colored red Although these are less intense throughout the year, they still deviate more than the targeted 5%. These kinds of voltage deviations that are more local, might lead to congestion that cannot be easily or efficiently adjusted with centrally operated DSO-equipments, while it could be easier adjusted with more local equipments [163].

As mentioned in section 4.2, one way to deal with such local voltage deviations is by using by Volt-VAr adjustments. However, only large-scale flexibility providers are obligated and will be incentivized in the future to contribute to such grid-side flexibility for example via GOPACS [48]. Small scale flexibility providers under rated capacities of 1 MW, cannot contribute to solve such voltage fluctuations directly without diminishing active power outputs. As a result this local voltage congestion remains unadjusted by the flexibility providers that are modeled. However, the results show the potential that locally situated distributed flexibility might have to solve voltage congestion in the future, for example with Volt-Var adjustments once incentives are in place. Voltage congestion can thus be a local problem, and is not evenly dispersed throughout the network. Such overvoltage issues might be caused by increases in distributed photovoltaic generation in low-voltage distribution networks, especially once injection exceeds demand [164]. This was validated as some deviations occurred during mid-day early in the summer, when photovoltaic generation has the largest magnitudes.

Current congestion

In contrast to voltage congestion, small-scale flexibility providers below 1 MW are encouraged to explicitly contribute to reduction of current congestion, by flexibility changes in apparent power demand profiles. The needed flexibility to solve congestion was derived from the congestion patterns, under assumptions for the power factor as discussed in chapter 5. The current congestion itself was first identified.

Once assessing the general model results, it becomes apparent that only around 20% to 30% of agents in the grid are in congestion under the congestion threshold of 80% overloading, as also visible in figure 7.2. Furthermore, from the congestin outputs, it becomes apparent that current congestion in this area only occurs during winter months, somewhere between November and May. Congestion is most severe mid winter, during January and February, where congestion can last multiple hours per day. In extremes, overloading can amount up to 40% above the congestion threshold of 80%.

Therefore, actual loadings of the power-flow model are compared with the nominal line ratings through loading percentages, to see where overloading occurs in the quasi-dynamic load flow simulation results. The identified congestion was de defined as exceeding component loading above 80% of the rated apparent power capacity. As output, a table contained the hourly loading values as a percentage of the rated apparent power capacity in kVA from the congested components in the network. Figure 7.2 below shows the summed percentual congestion over the year, as a result of current thermal overloading. Again, a 1% overload per hour corresponds with a value of 0.01 in the scalar. This means that the most severely congested components have congestion overloads of several percentages, that occur in multiple hours. Overloading per hour is discussed in the next sections, but this section focuses on the summed results over a whole year. It only happens at specific sub-feeders.

From the results, it becomes apparent that specific areas under specific sub-transmission voltage distribution transformers are especially prone to congestion, whereas other regions are not at all. In figure 7.2, two of such areas that contain around 100 distribution substations are particularly red. Especially one area is severely limited by the overarching transformer, as all the underlying nodes are darker red. Within this area, there is one specific sub-string of distribution substations that is particularly congested with dark-red nodes. This indicates that this specific sub-string has a component somewhere early in the string that limits all the underlying agents, while it already receives congestion from the overarching distribution transformer. This was checked in the power flow model, where the component was indeed higher than the other elements. The element reached overloading up to 120%, so 40% higher than the defined congestion threshold in this model, causing the dark-red color. The area under the sub-transmission voltage transformer that had a lot of voltage congestion is also congested in the congestion scenario with current, indicating that the overload influenced both the voltage and current congestion. A reduction of load could mitigate both types of congestion here.

Some other, more local sub-strings that are lower in the hierarchy, are also in congestion while the overarching sub-transmission voltage distribution transformer is not. For example the most right colored string in figure 7.2. Nevertheless, in the main large area under congestion, thus the one with the most orange and red agents, congestion is only caused by current overloading instead of also voltage deviations. Additionally the figure does not only show congestion, it also shows what contributors are and where flexibility is required to mitigate congestion.

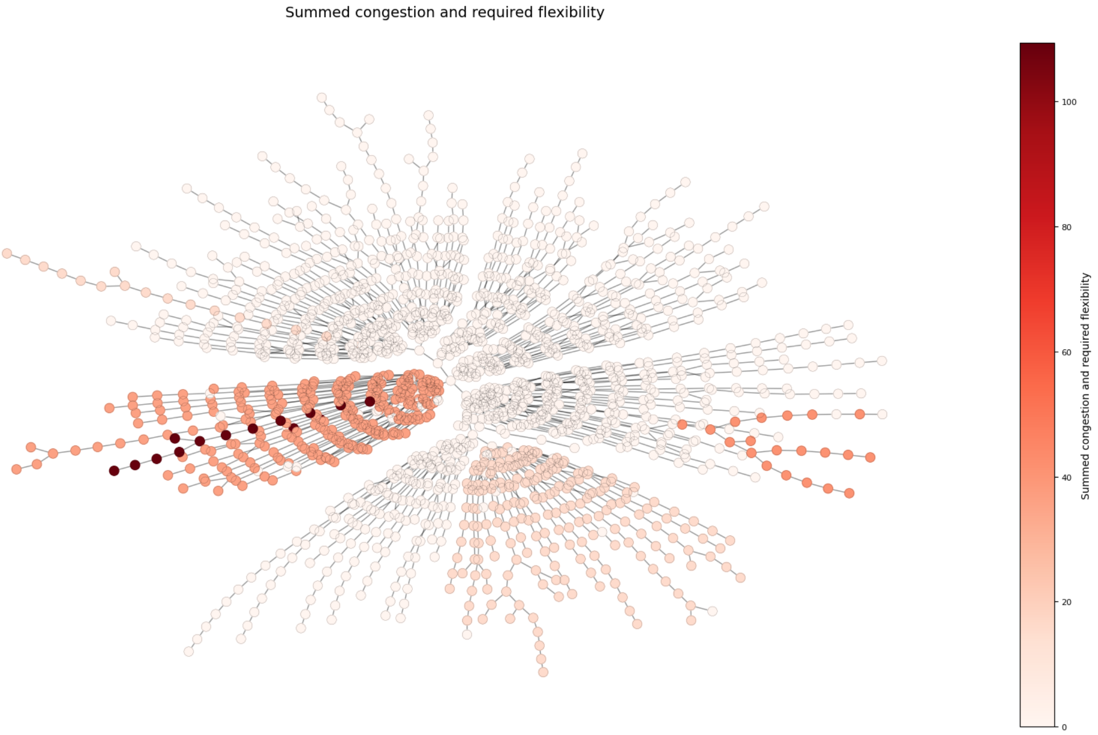


Figure 7.2: Summed current congestion over a year per node. Two specific distribution areas under a sub-transmission voltage transformer are particularly congested and colored red. Some substrings that are more local also have thermal overloading.

Using congestion to calculate required flexibility

In the remainder of the research, the apparent power profiles were analyzed using the results on current congestion. From these congestion causing profiles, the required flexibility to completely mitigate congestion in terms of active power was calculated. For the calculation of the required flexibility it is assumed that each agent that contributes to the congestion, is required to deliver the same amount of relative flexibility with regard to the overloading component, as discussed in step 2. The required flexibility is based on the congestion signals from the most limiting components, that often apply to multiple congestion contributors. This research assumes that if all contributors reduce their load by the same percentage, the total load on the congested component will also decrease by that same percentage. The required flexibility is based on this rationale, and each of the congestion contributors is individually assessed on this benchmark to provide the relative amount of flexibility from the overloading value. For example in figure 7.2 above, some nodes have the same color and congestion, and thus are required to contribute the same percentual amount of flexibility relative to their initial load.

By appointing required flexibility per agent in this way, a clear analysis can be made that distinguishes between individual agents that are able to provide the required amount of relative flexibility, and the agents that are not. Inadequacy or undershoot of this relative flexibility amount implies that congestion still remains if all of the other agents only supply precisely their individually required flexibility or less. After the assessment of the individual agents, the potential overshoots of flexibility reactions by other agents can be assessed. Once the overshoots of flexibility of some agents compensate for the undershoots of other agents, total congestion might still be resolved, on which the results provide some insight. In the conclusion and discussion, probabilistic system-wide implications will be derived from this. However, firstly actual and required flexibility provision per individual agent compared as a result from the stochastic flexibility state model.

7.2. Default scenario model behavior

In the following section, the model behavior under the default, base case scenario is explained. Here, the 'incentive structure' factor is set to have limited influence as agents have low financial incentive to be flexible. Additionally, the default scenario assumes that there is no additional spatial correlation in flexibility reactions. The format and overview of the output results of the co-simulation are first described, and thereafter the after the actual results are discussed.

Acquisition and format of results

To make the relative flexibility states comparable and meaningful, the percentage values are normalized and set to a reference point as they evolve over time and are path-dependent. This normalization uses the highest possible load from each agent as the reference point because it is the only fully quantified and consistent benchmark available. By scaling flexibility values against this maximum load, the model ensures that flexibility influences within the envelopes are measured on a uniform basis, on which the required and actually provided and activated can be compared

The stochastic flexibility state evolution model led to the final data, with the resulting categories per agent as provided below. Additionally, exemplary output of an agent's reactions at specific timesteps is provided in table 7.1, which is discussed in the corresponding subsection.

- **Timestep** The flexibility values are calculated per hour for a whole year.
- **OriginalProfile** This is the measured historical load data from the DSO at the concerning distributed substation.
- **CongestionPercentage** This is the highest congestion percentage at an element to which the node contributes. As the congestion threshold was defined at 80%, this value ranged from 80% to 120%.
- **Required flexibility** This is the required flexibility reaction needed as to solve the overloading as identified in the powerflow. It is the overloading percentage above the congestion threshold of 80%. For example, if the loading percentage is 86%, the required flexibility reaction is 6%.
- **In-between reaction** This is the flexibility reaction percentage directly after the factorial envelope.
- **Propogated** This is the flexibility reaction percentage after spatial correlation has been accounted for, and neighboring reactions have propogated through the network, as explained in section 5.4, but is not relevant in default scenario.
- **Activated flexibility** This is the ultimate provided flexibility reaction, after the relative normalization has been performed and the effect of spatial correlation is taken into account. Once it is lower than the required flexibility, flexibility provision is inadequate.

7.2.1. General results

This subsection is devoted to the general results, with sub-sections for intertemporal aspects, visualized results in the network, and anomalies.

The results of the default scenario provide information on how the model was calibrated and how it performs under basic conditions. Already in the default scenario, the final flexibility states per timestep represent a relative flexibility percentage of the actual flexibility reaction. The possible flexibility percentages directly after the calculation of the final flexibility states as output from the in-between internal reaction states, are visualized below in figure 7.3.

Once assessing the low incentive default scenario, flexibility reactions do typically not exceed flexibility reactions of 20%, as visible in figure 7.3. Already from this information, it becomes apparent that the required flexibility of individual agents is not always reached, as congestion extremes require 30% flexibility. The figure also shows that available physical capacity is technically high, but that the capability factor decreases the potential reactions largely. The financial incentive factor is modeled to not often be large enough to fully activate all the flexibility, especially in this default scenario. It becomes apparent that the low incentive causes the magnitude of reactions to become smaller The effect of behavior on the reactions is minimal, as most of the effects are already accounted for by guiding agents through their opportunity evaluation with the financial incentive. Most agents react with only 5% flexibility in the default scenario. However, outliers till 20% are possible, as some agents show opportunistic reactions

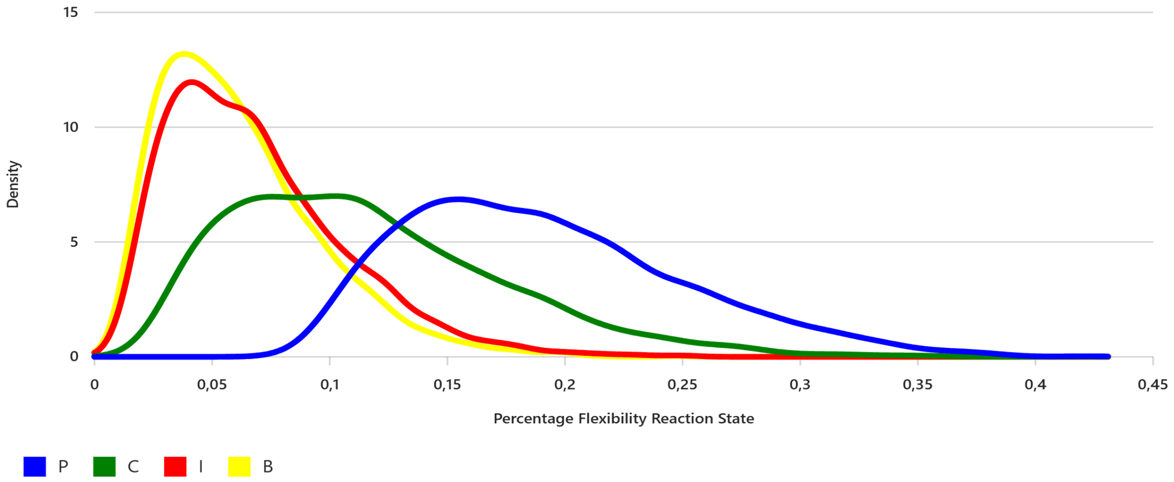


Figure 7.3: Probabilistic representations of the factorial envelopes that decrease via multiplicative reduction structure, resulting in yellow final state. The blue curve is the first factorial envelope and ultimately becomes the final yellow flexibility envelope. The final flexibility envelope shows that most reactions are only about 5% of the demand load, but outliers exist.

to the incentive factor. Spatial correlation is not accounted for in the default scenario, which is visible as the flexibility reactions are spatially random dispersed in figure 7.4, which is explained in the scenario results.

Exemplary results for one agent that happens to have higher flexibility reactions than typical are shown in table 7.1 below. The values shown are for one of the most congested agents at one of the most congested days, as visible in the congestion percentage column. In here, the last two columns provide the information needed to assess the adequacy of flexibility reactions. Actual flexibility reactions in the last column are higher than the required flexibility reaction in the second-to-last column in the first hours. There are overshoots in the first hours, as the magnitude of the congestion signal cannot be varied across hours. Implications hereof are explained in the discussion. However the results of the last column show that as time passes and more physical capacity is used to solve congestion, the reactions become smaller. Nevertheless, congestion becomes higher, which causes inadequacy in provided reactions, as also visible in the color scale of the table. This however, is an example of the dark-red congested nodes in figure 7.4 above that have exceptionally high congestion over consecutive hours. Often, congestion lasts only a minimal amount of hours, and previous flexibility reactions do only minimally impact the adequacy of flexibility reactions via physical capacity.

Intertemporal dependencies between reactions

The flexibility states also evolve over time. Especially the final flexibility reaction state of the used in previous rounds matter and influences the physical capacity state which initializes the reaction at every timestep. The final flexibility reactions often only use a part of the available physical capacity, and not all physical capacity is used within one hour. In most cases, there is enough physical capacity to provide roughly the same amount of flexibility in the hours of congestion. This is effectuated by things such as storage and thermal inertia, is not often fully unloaded and deployed. However, if previous reactions are large, and if a lot of consecutive previous flexibility reactions have occurred, physical capacity is not able to recover fast enough. The flexibility then grows smaller over time. Especially once there are multiple consecutive hours of congestion, typically more than 3, the flexibility reactions are increasingly diminished. This effect is observed in all scenarios. An example of this is shown in table 7.1 below, in which the output values for one of the most congested days for one of the most congested agents is shown. In here, it becomes visible that after a whole day of flexibility reaction and congestion, the last hours in which flexibility should be provided, the agent can provide almost zero as its physical capacity is used in previous rounds.

Timestep	OriginalProfile	In-between reaction	CongestionPercentage	reqflex	actflex
2025-03-18 09:00	0.094	0.053	87.0	0.070	0.251
2025-03-18 10:00	0.085	0.041	86.0	0.060	0.203
2025-03-18 11:00	0.080	0.039	83.0	0.030	0.203
2025-03-18 12:00	0.086	0.037	81.0	0.010	0.198
2025-03-18 13:00	0.086	0.038	82.0	0.020	0.225
2025-03-18 14:00	0.089	0.034	82.0	0.020	0.151
2025-03-18 15:00	0.124	0.035	85.0	0.050	0.142
2025-03-18 16:00	0.191	0.036	88.0	0.080	0.079
2025-03-18 17:00	0.231	0.032	108.0	0.280	0.058
2025-03-18 18:00	0.230	0.032	111.0	0.310	0.066
2025-03-18 19:00	0.209	0.037	100.0	0.200	0.081
2025-03-18 20:00	0.181	0.032	90.0	0.100	0.031

Table 7.1: Exemplary results of an agent at consecutive timesteps. The last two columns show the required and actually provided flex. The figure indicates that much of the flexibility is used in the first congested hours, leading to undershoots of flexibility to mitigate congestion later on.

Network results of default scenario simulation

Once simulating the states that are drawn from the probability distributions, the provided flexibility can be compared with the required flexibility. Figure 7.4 below shows the summed percentual congestion values over the year that remain after the incorporation of flexibility. It shows the total summed amount of percentages at times when provided flexibility is less than required flexibility per agent. In here a value of 1 means an overload of 100% at one hour. Most of the congested nodes are still overloaded at multiple timesteps per year and show dark-red, even after flexibility reactions in the default scenario. Some of the nodes are overloaded with more than 10% per hour after incorporation of flexibility, for multiple consecutive hours. However, some of the nodes in the congested area are able to fulfill the required the flexibility, and are not congested or red anymore. In specific strings however, none of the nodes is able to provide enough flexibility. Additionally, it becomes visible that in every congested string there is at least one node that is not able to solve congestion.

However, most of the agents actually overshoot in their flexibility reaction at times when congestion is only limited. Overall, the results show flexibility overshoots at most timesteps for all nodes, which indicates that if the overshoots could be used to provide flexibility at later timesteps, most of the agents would be able to resolve congestion entirely. However, such additional intertemporal flexibility other than provided in the model is irrelevant. Therefore, the most valuable information on congestion solving flexibility reactions, can be extracted at specific timesteps in which congestion is most severe while only accounting for the limited intertemporal flexibility that is modeled. Reactions in such a severely congested timestep are shown in figure 7.5 below. In this figure, the required flexibility is subtracted from the actual provided flexibility reaction by the model, to see how much flexibility remains. Some agents have a positive remaining flexibility percentage, meaning that they overshoot and provide more flexibility than required. These agents are green. Other agents however, undershoot the required flexibility and are red or orange, depending on scalar shown next to the figure. The figure shows the percentual flexibility reactions that are converted to values between -1 and 1, where the lowest undershoot is 20% corresponding with a value of 0.2

In figure 7.5 above from the snapshot at one of the most congested timesteps, it becomes visible that agents and whole strings do not provide the proportionally required flexibility to solve congestion. The congested nodes under the overarching sub-transmission voltage distribution transformers vary from green to orange and red colors. Some of the agents overshoot the required flexibility, but in the default scenario it is likely that the overshoot does not compensate for the undershoot of other agents, and that congestion remains under low financial incentives as the majority of nodes is red. Next to the congestion from the overarching sub-transmission voltage transformer, congestion also remains in substrings that receive congestion from other elements than this transformer. These congested components are lower in the hierarchy, and therefore only limited agents can contribute to congestion mitigation with flexibility provision. Especially one string is severely congested, which still colors dark-red after flexibility reactions, indicating that it is not able to solve this local congestion. At other local strings, not all required flexibility is provided, such as the largely orange string most right in figure 7.5.

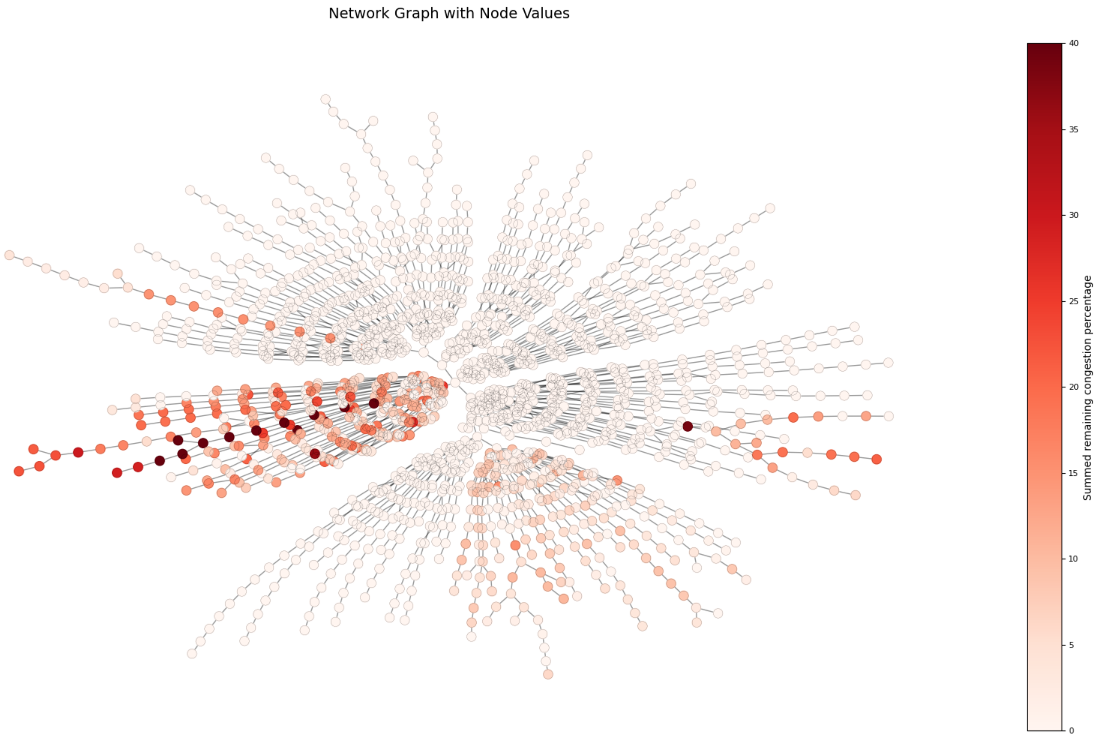


Figure 7.4: Summed inadequacies of individual flexibility providers showing where current congestion appears mostly. Some of the previously congestion contributors provide enough flexibility, while others do not and are still red. The undershoots of flexibility are randomly dispersed in the network, but more prevalent in specific areas and sub-strings

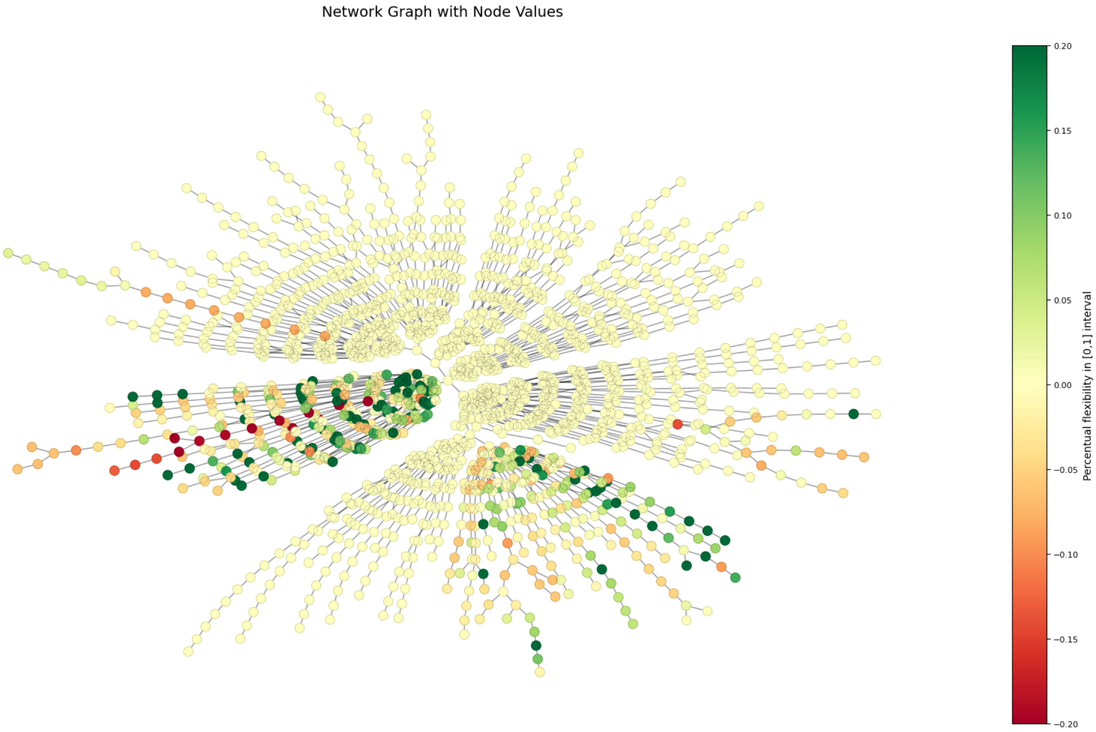


Figure 7.5: Resulting flexibility reactions at a timestep with severe congestion. Most agents provide relative overshoots of flexibility with regard to the overloading percentage and are green. Specific nodes and sub-strings however undershoot in their flexibility provision, and are not able to solve congestion. In the larger areas, more nodes are present that might compensate for under and overshoots of neighbors

Anomalies

In the results, one specific string appears to be incorrectly updated to flexibility values. As visible in figure 7.2, the congestion clearly originates at overarching nodes, and then propagates downwards to the contributors. However, the only colored string in the upper left quadrant of figure 7.5 has no updated values, and some of the nodes in this string appear to have the exact same flexibility reactions. This might be due to referencing errors in the processing of data, especially with regard to the hierarchical order in this sub-string. This could be caused by irregularities in the exceptions for manual adjustment from the power-flow model network structure into the agent-based network structure in NetworkX, or by incorrect referencing of child-parent nodes caused by the same manually updated irregularities. For the other sub-strings that appear irregular, the congestion input was checked in the source data, and it was confirmed that the actual congestion was indeed high and irregular, but no reason to assume that the values are incorrect was found as the power-flow simulation indeed show disproportional high loads and congestion there.

7.3. Scenario analysis

Additionally to the default scenario, the effects of a higher financial incentive and spatial correlation are studied in this section. Additionally the final results of the model with the assessment on required flexibility fulfillment is performed. the scenario with more spatial correlation and low financial incentive is first assessed, and thereafter the scenario with high financial incentive and no spatial correlation. In the end, the scenario on high financial incentive and low spatial correlation are presented.

7.3.1. Spatial correlation and low financial incentive

Once assessing the results after spatial correlation has been applied, it becomes apparent that the reactions of agents are indeed more similar in specific sub-strings compared with the default scenario. The colors are slightly different as both green and red nodes are altered, and there is still congestion in roughly the same quantity as before. However, in some strings it is now more prevalent, while in other strings it is mostly resolved as a majority of agents has turned green with enough flexibility. This is visible in figure 7.6 below, where the flexibility reactions at one of the most congested timesteps are shown, with implementation of spatial correlation. For example, the most right string converted from mixed color agents to mostly orange agents. In strings where the majority of agents was previously green, this color has become even more dominating. This is also visible in figure 7.6 below

This figure that has spatial correlation, is compared with the figure from the default scenario. It becomes apparent that differences between strings are more pronounced, although the minimally visible. Nevertheless, this shows that a sub-string is likely to have a similar reaction as its overarching neighbor. This is also visualized in figure 7.7 and figure 7.8 below, in which reactions that do not fulfill the required flexibility are more pronounced after spatial correlation. For the depicted sub-strings, spatial correlation caused more inadequacy. For other strings with distribution substation agents, spatial correlation might as well lead to more adequacy in solving congestion.

However, spatial correlation is now only modeled to occur between agents in electrical proximity as this is the only benchmark or proxy available to mimic geographical proximity. This corresponds only limitedly to true geographical proximity. As a result, there is no spatial correlation between agents in other strings. In reality, there might be more correlation in different areas, for example all the agents under the same sub-transmission voltage transformer. Furthermore, the spatial correlation now only propagates hierarchically through the network as visible in figure 7.7, where the first node in the hierarchy influences the other nodes drastically. Because many of the nodes at the beginning are effectively providing flexibility to solve congestion, the other underlying nodes correlate with these reactions, and the same kind of flexibility reactions become more pronounced. As a result entire strings are now mostly able to provide enough flexibility, but some other strings are not able to provide enough flexibility at all. Examples of strings that are not able to provide flexibility anymore are the orange strings in the right and lower right quadrants, that have become almost completely orange, whereas some agents were initially green.

Anomalies

The same anomalies as described under 7.2 are visible. For example in the darkest-red string, one agent turns green after implementing spatial correlation, while this cannot be caused by its neighbors.

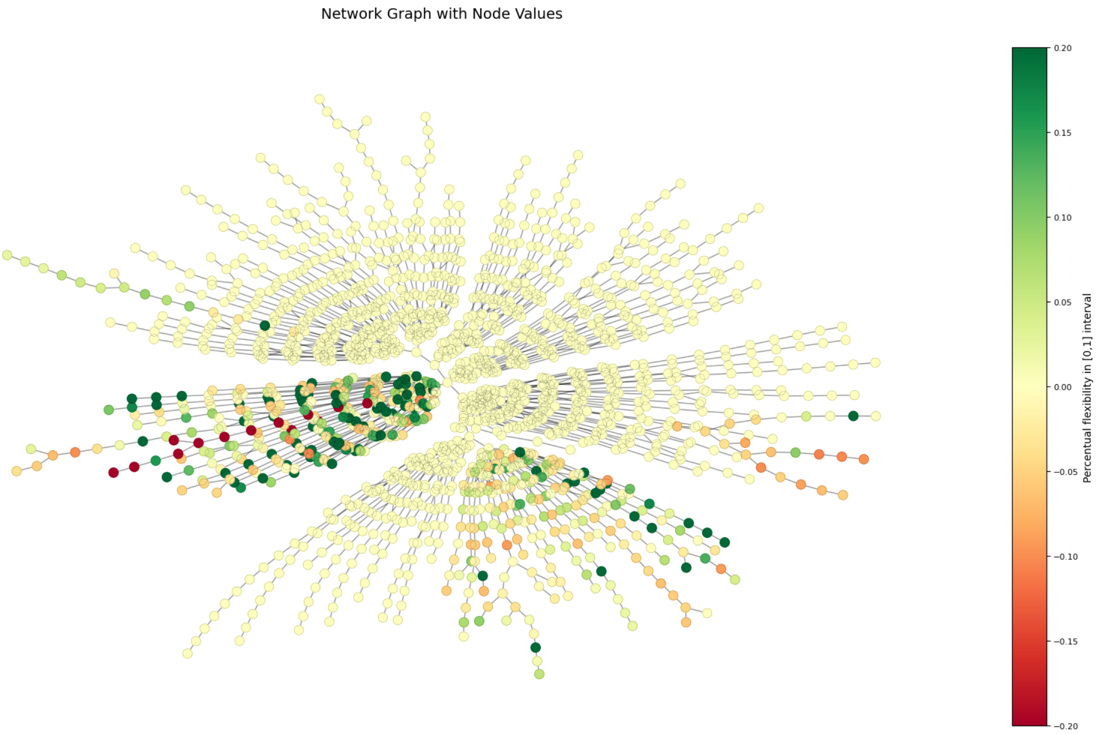
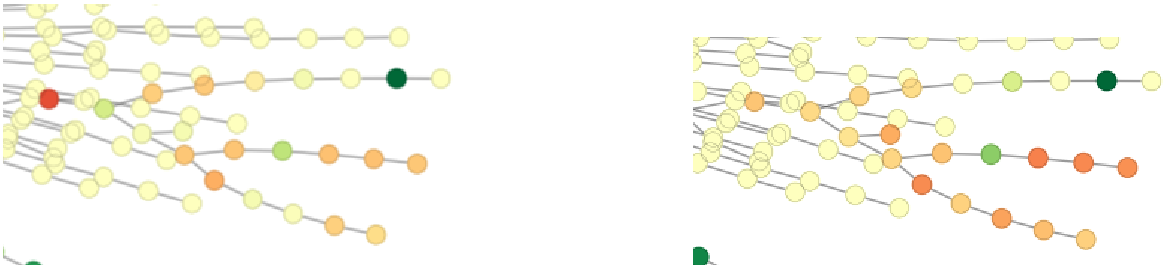


Figure 7.6: Resulting flexibility reactions at timestep with severe congestion for spatial correlation and low incentive scenario. The flexibility reactions are less evenly dispersed, but congestion still remains in the same proportions.



(a) Before spatial correlation

(b) After spatial correlation

Figure 7.7: Spatial correlation differences in a local substring. Red and orange nodes are now more prevalent, originating from the most left colored node.

(a) Before spatial correlation

(b) After spatial correlation

Figure 7.8: Spatial correlation differences in a local substring. Orange nodes are now more prevalent and undershoots of flexibility to solve congestion dominate the substring

7.3.2. High financial incentive and no spatial correlation

Once assessing the scenario with high financial incentive and low spatial correlation, it becomes visible that the flexibility reactions are modeled to be more intense, but the intensity is spatially random dispersed. As visualized in figure 7.9 below, there are much more green agents that have overshoot in their flexibility reaction state, at one of the most congested timesteps. However, there are still some individual sub-strings and agents that are mostly orange or red. These are still not able to provide the required flexibility, even under high financial incentives. Nevertheless, it is likely that in the larger congested areas, that are prone to congestion from the overarching distribution transformer, these overshoots can compensate for the undershoots of other agents, as a vast majority provides more flexibility than required.

In the smaller congested areas however, such as individually congested sub-strings, congestion can also be caused by components lower in the hierarchy, and not by the overarching distribution transformer. This very local congestion can only be resolved by the limited amount of underlying individual agents, and overshoots of agents elsewhere in the grid cannot be used to compensate. For example in the dark-red string in the mostly congested area, or the most right sub-string that is largely orange, the overshoots of the limited agents in this locally congested sub-string might not be able to compensate for other agents that cannot provide the required flexibility. At this very local sub-string level congestion might still not be resolved even though financial incentive is high, as some agents still have limited flexibility reactions. Once these agents are coincidentally in close electrical proximity, this might lead to lack of capacity to be flexible, and congestion still remains after high financial incentives.

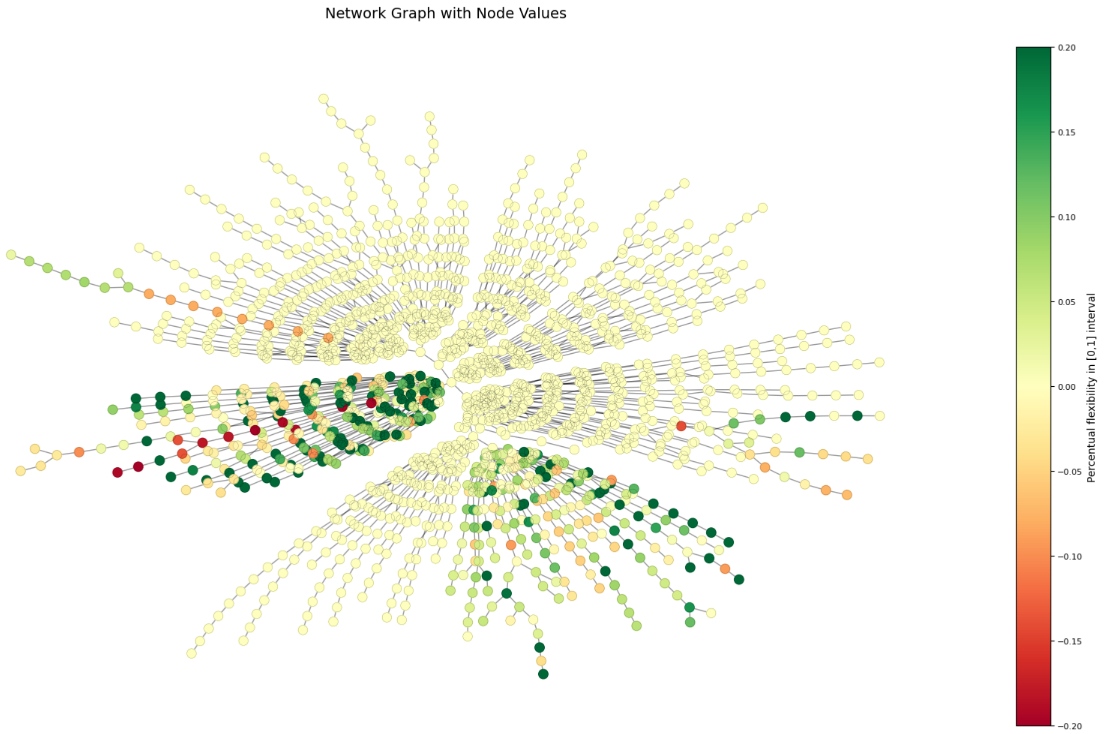


Figure 7.9: Resulting flexibility reactions at timestep with severe congestion for scenario on no spatial correlation and high incentive. Most agents are green, overshoot and solve congestion, especially in the larger congested areas. In the smaller individual sub-strings with local congestion, orange nodes are still prevalent and congestion might remain

Effects of differing financial incentives

Under higher financial incentives however, two sorts of effects might occur in the resulting reactions. First of all, higher incentives might lead to more systematic, less opportunistic and less uncertain reactions. This would cause the probability distribution of possible reactions to be tighter, but with higher percentages and thus shifted to the right. This is also visible in figure 7.10 below, which show the probability distributions of the flexibility reactions, where the red and yellow lines at the left of the figure have shifted slightly to the right in the high incentive scenario. So agent reactions would become more predictable and pronounced in certain areas, since they have higher susceptibility for higher incentives.

However, the quantity of supplied flexibility also increases. This additional flexibility introduces more uncertainty, and therefore the probability at higher incentive widens again, which is visible at the right tails of the red distribution, that show that larger reactions are more likely. So, even though some agents might be more susceptible to higher financial incentives, introducing higher incentives does not necessarily cause flexibility reactions to become more pronounced or dispersed in certain areas. This is also visible in figure 7.10 below, which compares the possible reactions of agents under the high incentive in the normal red line, and the low incentive in the dashed red line. It becomes visible that higher incentive leads to more diverse and larger flexibility reactions that are shifted to the right. In the model, the higher diversity caused by increases in reactions, dominates the tightening effect of increased predictability that higher incentives might have. The normal red line is wider than the dashed red line.

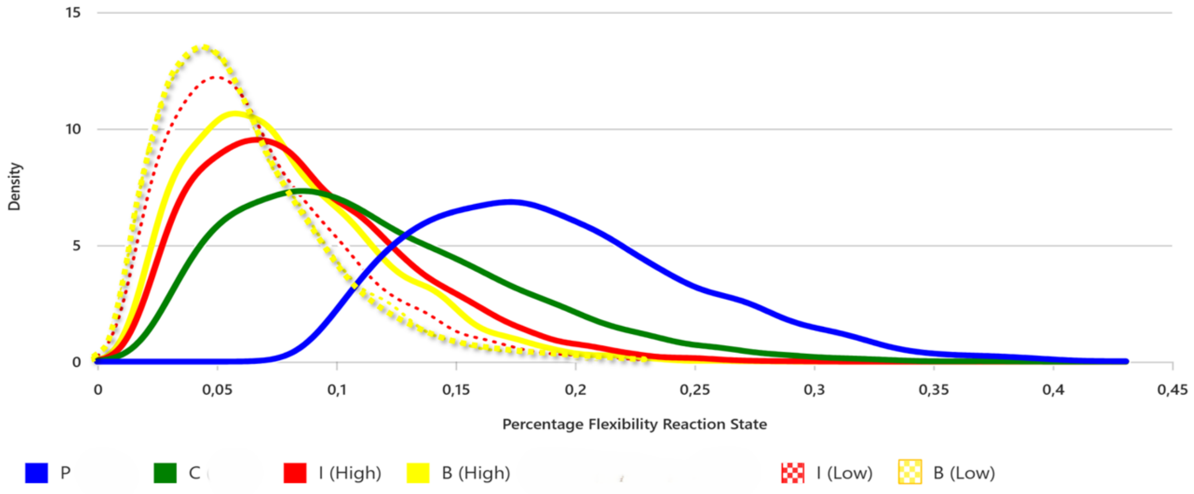


Figure 7.10: Probabilistic state representations with differences for red incentive factor influence. The probability distributions of the flexibility reactions, for the red and yellow lines and factorial envelopes at the left of the figure have shifted slightly to the right in the high incentive scenario.

7.3.3. High financial incentive and spatial correlation

Again, if we apply a high financial incentive, it becomes apparent that most areas are able to solve congestion, also once there is spatial correlation. In general, higher incentives lead to a wider and higher range of probable reactions. Therefore, the effect of spatial correlation on adequacy of flexibility provision is larger here, as previously further deviating reactions are now correlated and converging to a larger extent. Generally, higher incentives lead to more flexibility, and combined with spatial correlation such reactions pass on to neighbors more often.

However, still some highly local areas do not have enough provision of flexibility. The model does not show what factor causes this correlation, but the total effect of the flexibility reactions correlates. However, as the incentive is assumed constant and uniformly applied among congestion contributors, this does not cause the correlation. So it is either the 'physical capacity', 'capability' or 'behavior' factor that causes the correlation here. Once the effect of spatial correlation is increased in this scenario, even more areas become more flexible and green, but a minority of areas remain congested, and the quantity of red or orange agents in these areas grows as it inherits from agent to agent. If an agent early in the propagation hierarchy is not flexible enough, the other agents here will also inherit this, even if the financial incentive is high. An example of this is again the most right sub-string that is congested, where most agents are slightly orange. This is depicted in figure 7.11 below. So, the quantity of total congestion diminishes in the whole grid, but some local congestion remains, especially in such small congested areas. Compared with the scenario without spatial correlation, the undershoots in flexibility in such congested regions are less likely to be resolved by overshoots from neighbors, as neighbors have a likewise reaction. Spatial correlation causes multiple consecutive agents to become less responsive to price in these areas, and therefore congestion might become more pronounced there. This is especially problematic once spatial correlation occurs in areas where congestion is caused by a component low in the hierarchy, with few agents that can contribute to mitigation thereof.

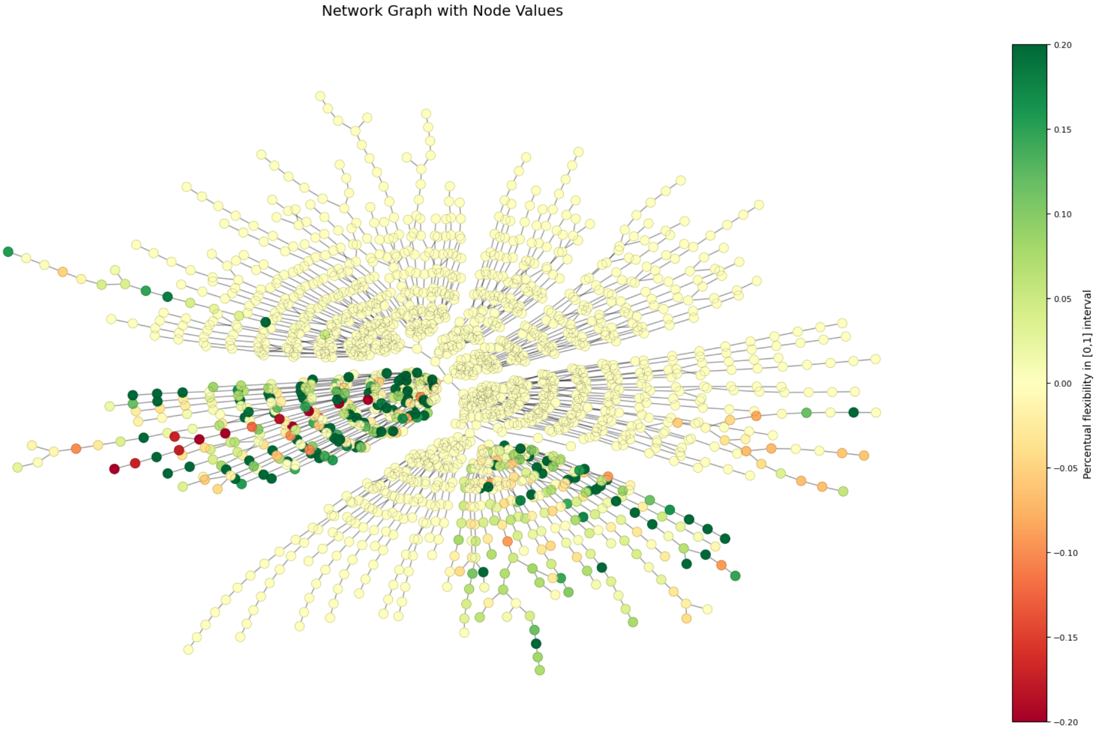


Figure 7.11: Resulting flexibility reactions at timestep with severe congestion for scenario with spatial correlation and high incentive

Resulting flexibility reactions at timestep with severe congestion for scenario with spatial correlation and high incentive. The quantity of total congestion diminishes in the whole grid as nodes are greener, but some local congestion remains, especially in such small congested areas, where orange nodes still remain, such as in the most right strings.

8

Discussion

This chapter contextualizes and assesses the findings of the model. The results and its implications will firstly be interpreted. Secondly, the strengths and weaknesses are discussed per step, after which a concise validation strategy is given to show how reliability and robustness of the model can be assessed.

8.1. Implications of results

The results imply various insights that are discussed below.

Mitigating congestion with distributed flexibility

In the first part of this research insight was created on how and by whom congestion can be mitigated, with a focus on the electro-technical grid aspects. Small flexibility providers do not impact voltage congestion directly other than via active power load adjustments, as there is no incentive to specifically contribute to voltage congestion for entities with rated capacities below 1 MW [48]. The analysis in section 7.1 has shown that potential impacts of voltage congestion are local and cannot always be efficiently solved by central, DSO-owned equipments. Therefore, potential exists for distributed flexibility providers to contribute to congestion mitigation at this local level. This potential might increasingly bu used in the future, but up till now only larger entities with generating capacities above 1MW are increasingly obliged and motivated to contribute to mitigation of voltage congestion, for example via GOPACS with reactive power compensation [48]; [15].

In contrast, small flexibility providers can impact the most prevalent type of congestion directly, which is thermal congestion as a result of current overloading. These distributed flexibility providers can adjust their active power loads with flexibility. Just like voltage congestion, current congestion can be local. Not only does it appear at the level of sub-transmission voltage transformers that supply the distribution substations. It also appears in even more local sub-strings, where only specific grid participants under distribution substation can contribute to mitigation. This emphasizes the potential and role from distributed flexibility to solve congestion in a spatial efficient manner.

Varying potential of distributed flexibility

The impact of distributed flexibility reactions by shifting active power loads is dependent on various factors, for which a categorization has been proposed. This differentiates between the following 4 factors; ’physical capacity’, ’capability’, ’incentive structure’ and ’behavior’. Each of the factors influences the flexibility reaction differently per agent as the flexibility reactions where modeled through probabilistic distributions per timestep. Although incorporating uncertainty, the probability distribution that the method uses, points out what factors contribute or obstruct flexibility on the short-term.

As it turns out, grid-participants technically often have a vast amount of physical capacity to provide flexibility, enabled by for example residential batteries and building thermal inertia. However, the capability of grid-participants to actually use this capacity is often lacking. This is caused by absence of aspects such as HEMS, flexibility aggregation and smart-meter integration. Furthermore, behavior of participants diminishes the flexibility reaction, as some participants have behavioral and social drivers that do not align with provision of flexibility. The impact of the behavior factor is only limited, as part of it is already captured by the reaction to the incentive structure. Especially the impact of the incentive structure factor on flexibility reactions is interesting, and therefore its implications are separately discussed below.

Impact of incentive structure and model recommendations

Mechanisms to incentivize and activate distributed flexibility providers are continuously developing. Temporally and spatially granular incentives targeted at specific timesteps and locations for congestion mitigation are under development or already exist. Additionally, the power-flow results show that the effect of these mechanism on congestion is only relevant to asses in certain areas and at specific timesteps, where congestion actually occurs.

Therefore, this research puts forward that to robustly model severely remaining congestion, the reaction of flexibility participants should be tested under high incentives for flexibility provision. It is suggested that the highest incentives for congestion contributors can practically only be given once highly granular incentives apply, as these have minimal effects on on social welfare compared to low granular incentives. To model the impacts on congestion, applying spatially uniform incentives makes less sense, as these also target the redundant grid-participants that do not impact congestion, while lowering social welfare. Also for temporally varying mechanisms, the highest incentives can be given once the mechanisms are highly granular. In the analysis of congestion, it was put forward that congestion only occurs at a minimal amount of consecutive timesteps, often around 17:00 till 20:00. However the exact peak varies per congestion contributing agent. Once targeting these peaks with low temporal granularity, there is not one efficient time-interval to design incentives for flexibility and solve congestion everywhere for all agents. Hence, although already more efficient and targeted mechanisms are applied than in the past, also time-off-use tariffs do not provide the highest granularity and therewith may not provide the highest possible incentive to assess flexibility reactions and robustly remaining congestion.

However, once focusing on these highly spatially and temporally granular mechanisms, there is a maximum financial magnitude as the DSO does not have unlimited resources. DSOs in the Netherlands should be non-discriminatory and allocate costs in a fair way. Therefore, it was assumed that the DSO attaches and assigns the same maximum value to each congested area to solve congestion, regardless of its severity and size. The maximum of this internal value that the DSO has to solve congestion, is uniformly applied to the congestion contributors to assess adequacy in the flexibility reactions. In such a way, the maximum effect of highly granular mechanisms such as GOPACS is assessed in a uniform way, so show heterogeneous reactions and adequacy in the ability to solve congestion.

In this approach, no incentive per agent has to be calculated. Only the heterogeneous reactions to the uniform incentive is used to assess the final flexibility reactions. It should however also be acknowledged that his is a shortcoming, as the model does not iterate until the 'right' level of incentive is found to alleviate congestion. To evaluate the impact of differing incentives, scenarios were used. By applying such a uniform price that is varied in scenarios, the complex price setting mechanisms that determine the magnitude of the financial incentive does not have to be modeled. Modeling this is uncertain and dependent on DSO and regulatory authority decisions.

The research is now focused on highly granular mechanisms. However, because the effect of this in only studied through one, maximal incentive that is uniformly applied to all congestion contributors, the approach can also be used for analysis of the impact on physical from other, less granular and also uniform mechanisms in a likewise manner. For example the uniform method to can also be used to study the coming time-of-use tariffs.

Impact of various levels of financial incentives and spatial correlation on congestion

To assess flexibility reactions at different incentives, scenarios were used. The results show that the modeled higher financial incentives are needed to make sure that the majority of agents provides enough or even more flexibility than required. If some agents provide more flexibility than required to contribute proportionally to congestion mitigation, the undershoots of other agents to provide the flexibility relative to the overloading, might be compensated for. Especially once many agents in an area contribute and are prone to the same congestion, such as under one overarching distribution transformer, a large pool of possible flexibility providers can compensate for the undershoots. However, if limited amount of agents are prone to congestion when it occurs in a small local areas, only a limited amount of agents can provide overshoots of flexibility to solve congestion and compensate for the undershoots. This might diminish the local mitigation of congestion. This is also visible in the results, where even under high financial incentive, highly local congestion might not be resolved.

Whereas the exact flexibility reaction of agents are uncertain, their reactions are nevertheless stochastically captured by the factorial envelops shown in figure 7.3. However, higher financial incentives make individual reactions more systematic and predictable. This would normally tighten the distribution of outcomes of the factorial influences, as on average agents are disproportionally more susceptible to high incentives. However, the large increase in agents that provide flexibility at higher incentives, introduces more variability in the probability distribution of flexibility reactions than this tightening removes. Thus, higher incentives leads to overall more and wider applied flexibility and congestion is lower, although some areas react harder to this than others. These reactions can be compounded by spatial correlation. The positive effect of spatial correlation is larger under high incentives as relatively more overshoots of flexibility propagate. The negative effects of spatial correlation are more pronounced and critical under low financial incentives. Here, it also causes the more often occurring insufficient flexibility reactions to propagate increasingly often, and undershoots can less often be compensated by overshoots.

The scenario of low financial incentive with spatial correlation among agent flexibility reactions causes the most congestion. In this scenario, only a limited amount of agents are able to provide the required flexibility. Without spatial correlation, such undershoots are more likely to be compensated for by neighboring agents that have overshoots. However once spatial correlation applies, neighboring agents are likely to also have undershoots, and such compensation cannot happen. Especially when congestion is very local, for example when it is caused by a component that is lower in the hierarchy than the typically congested sub-transmission voltage distribution transformer, agents elsewhere cannot compensate with their overshoots. Congestion might remain in these local areas. Spatial correlation causes inadequacy of only specific regions. Hence, clusters of low flexibility can exist under low financial incentives with high spatial correlation, which are then more likely to result in remaining congestion.

8.2. Strengths and weaknesses

During modeling of the system, several concessions had to be made. These and their implications are sequentially elaborated following the research approach and its four steps and sub-questions as also visualised below in figure 8.1..

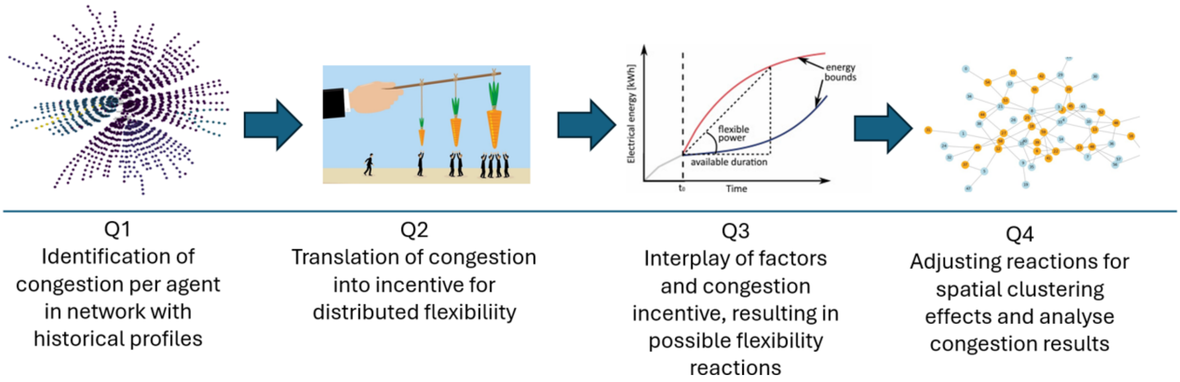


Figure 8.1: Process flow of sub-questions

8.2.1. Step 1

In step 1, the power flow model was used to identify congestion. By using a detailed AC power flow model, both voltage and current congestion were identified, which is a strength of this research. Additionally, the model added to detailed understanding of congestion components and grid topology. It enables analysis of components that need AC modeling, such as transformers that can only work via AC power flows. However, it needs assumptions on power-factors that are not always known. The power flow model also enables the integration and connection of multiple voltage levels, ranging from low-voltage to high-voltage, which is not often done in existing models. Additionally, it forms a basis for more advanced studies in the future, where for example reactive power flexibility aspects can be implemented. However, the program and simulation software is already quite detailed, as it creates data for thousands of components that cannot always be integrated with other applications. This made the data processing challenging, while not necessarily needed for some of the general results in this model reflecting afterwards.

The power flow model environment allows for many adaptations of network configuration, that each impact the behavior of the model. This could add to understanding of the system behavior under all sorts of electro-technical conditions. However, these features of the model are not used as they require knowledge on local configuration settings and only the default settings were used. The system can be significantly impacted by operational changes in the configuration that are now unaccounted for. This however, can be used a strength in future research, especially once targeting both reactive and active power flexibility reactions.

The power-flow model allows for aggregation of grid participants at the distribution substation level. This allows the deployment of real grid data, whereas working with sensitive individual low-voltage profiles from consumers is not allowed. However, by aggregating grid participants into one distribution substation in this model, the level of detail and accuracy diminishes. Additionally, there is only little information on how individual grid participants within different distribution substation areas differ. Therefore, it was assumed that distribution substations that aggregate the underlying grid participants have a wide range of possibilities, similarly to the possibilities of the individual grid participants. However, in reality aggregated distribution substation totals in different areas might have less variance and have more similar reactions because variations among the underlying grid-participants compensate for each other, so that the variance of the individuals is compensated and decreased upon aggregation to the medium-voltage level. This is not captured in the model as the same probability distributions for both individual grid-participants and aggregated grid-participants are taken, and therefore the aggregate reactions might have larger variance than in reality. To counteract, this effect was partially accounted for by implementing the scenarios on spatial correlation. This decreases the variance of aggregated distribution substations again, although in a spatially directed manner. Nevertheless, more insight on the level of spatial granularity to which spatial correlation is applied and at which level variance occurs, can benefit the stochastic assessment of flexibility reactions and their accuracy.

In the results, it became apparent that there is indeed potential to solve congestion by altering voltages instead of active power, for example through reactive power management. It was suggested that this type of congestion could mainly be solved by flexibility providers with capacities above 1 MW, as only these are nowadays obliged and encouraged to do so [48]. However, in the future smaller distributed flexibility providers might also supply such services, since advanced inverters are increasingly adopted nowadays. Furthermore, these entities might, once aggregated, also surpass the 1 MW threshold. Therefore, it might also be beneficial for future research to incorporate this in flexibility provision models.

8.2.2. Step 2

As discussed in the literature review, CMMs to encourage flexibility reactions nowadays are under development and changing continuously. In this step of the approach, a uniform way to signal congestion was proposed, via congestion signals, which then can be translated into a way into a highly granular CMM. The strengths and weaknesses hereof are discussed below.

The congestion signal holds information on congestion contributors, and the amount to which their load should be more flexible to decrease congestion linearly over the contributors. Therewith, it has very high temporal and spatial granularity, and therefore a lot of CMMs can be based on this congestion signal. This allows for comparison of different CMMs. For example, the signal could also have been converted into a mandatory capacity limit at specific timesteps. Such an approach would be more effective, and the effect would be easier to analyze, as the the predefined limits allow for more deterministic mathematical models, in which consumer characteristics play no role, especially in the short-term. This research however, focuses on differences in the ability from prosumers to engage in flexibility reactions from voluntary demand response mechanisms, as these are more likely to be implemented. Hence, no such comparison and deployment of multiple CMMs is made. Furthermore, the deployed CMM of implicit financial incentives in this model, is assumed to be uniform in magnitude for all contributors at the congested timesteps and congested locations, and therefore does not incorporate the magnitude of the incentive in this spatially and temporally detailed information. Nevertheless, this congestion signal information could be used to increase the incentive even more proportionally to congestion, and more accurately model the most robust reaction. Such interesting comparison of multiple CMMs however, is unfortunately not focused on in this research, while it could provide insights for DSO and regulatory authority policies.

A benefit of using and studying a highly granular mechanism to stochastically model the effect of individual local participants, is that it is dependent on local characteristics, whereas non-granular mechanisms cannot differentiate between local heterogeneous grid-participants.

Furthermore, since the model does not work with defined financial incentives, but only with the reaction to high and low incentive in relative scenarios, the sensitivities to gradual price changes are now unaccounted for. Therewith, the model does not capture non-linear elasticities, and it does also not specify at what exact magnitudes the reactions and congestion occur. The mechanism used is a single-pass mechanism. It does not iterate until the right level of incentive is found to alleviate congestion. This is a shortcoming and should be acknowledged. The relative and system-wide results can be used to explain relations, but do not quantify thresholds or information on optimal levels of incentives and reactions.

8.2.3. Step 3

In step 3, the framework to evaluate and develop potential flexibility reactions per agent in different areas with insight in the influential factors was proposed, as the literature review indicated that such frameworks were lacking. The strengths and weaknesses hereof are discussed below.

In the model, it was assumed that there were no previous flexibility reactions, because CMMs are only applied to a very limited extent nowadays. Therefore, the historical load could be assumed inelastic for congestion mechanisms and without incorporation of any flexibility whatsoever. This strenght of the data was used for external modeling of the flexibility as if additional to the load. The effect of the factors could therefore be analyzed separately from the historical load. However, in the future, historical loads will already incorporate partially flexibility, and flexibility cannot be modeled externally anymore. Nowadays however, research might still take advantage of these historical loads that are still pure and with nihil incorporation of flexibility for congestion mitigation.

The multiplicative reduction hierarchy that determines the flexibility reaction states per agent and timestep, properly captures the uncertainty and the wide possibilities of impactful factors, while incorporating a high level of detail in the grid topology. However, the probability distributions that impact the flexibility states are still wide and uncertain, as no local information is incorporated per agent. Unfortunately, the model now uses the same distributions for all types of grid-participants for each factor separately. However, it is known that some grid-participant types have typical factor fulfillment, and specific factors and spatial correlation are linked to this. For example typical industrial users are not often spatially correlated, very dependent on the financial compensation, often have higher capability, and are not so dependent on behavior. So by assessing each of the factors randomly without correlation or interdependent things between them for an agent, there is no way in which typical types of agents, with specific factor values, can be distinguished. As a result agents might have more random reactions than in reality. Not with respect to spatial correlation, which is manually accounted for. In reality, some groups of agents have more typical fulfillment of factors. Factor correlation is general is not taken into account, only spatial correlation between agents is taken into account. Since factor correlation not taken into account, the outputs are more randomly dispersed than in reality. This leads to reduced accuracy, and in reality some types of reactions might be more typical than others.

Additionally, the model now assumes stochasticity and probability envelopes for each of the factors. The model nicely captures that some of the factors are initialized in the short-term model, and others vary over time. However, still, the model assumes probability distribution for all factors, and states are often somewhere between the maximum and the minimum within the distribution. In reality however, some of the factor states are more deterministic, and the factor is either fulfilled or not, in a more binary sense. For example the influence of aggregation policy at the capability factor, in which aspects can significantly influence the final response. These are poorly captured by envelopes, as they are essentially binary: either present and thus affecting all agents and values, or absent and preventing any response. Such influences are not well represented by stochastic models as these are essentially deterministic aspects. In this case, the entire envelope would shift, but the model does not allow this.

To model the flexibility state per agent and timestep, 4 factors are combined. Each of these factors has its own probability distribution which for the largest part is determined per timestep. The model now has probability distributions in factorial envelopes, and these are independent of each other. This is done under the assumption that in the short-term, the factors are not interdependently correlated. However, once exploiting the model towards the long-term, such interrelations and feedback loops between factors should be taken into account. For example, a rise in the magnitude of the incentive does not lead to more capability or physical capacity in the short-term. However in the long-term, a rise in the incentive might cause agents to adopt more physical capacity and install HEMS for capability, and therefore the incentive structure factor might impact the capability or physical capacity factor. This however, is not modeled in the short-term model which limits its applicability.

The short-term focus of this model was initially chosen as it was expected that the short-term variability would be large. However, as it turns out, some of the factors, such as physical capacity and capability are not so variable in the short term. The same accounts for the incentive structure, that is largely dependent on policy developments in the long term, and, depending on the implementation of the type of CMM, only to a limited amount dependent on the intertemporal congestion pattern. Hence most of the variability is not short-term. Therefore, the long-term, and in this research initialized values are of high relevance in the flexibility reactions. For future research it might be more relevant to focus on long-term changes in flexibility reactions.

The multiplicative reduction hierarchy assumes that factors are independent. However, once determining the actual probability distributions of the factors via literature, the factors are not so easy distinguishable and demarcated. Hence, some of the factors are not really independent. As the hierarchy reduces, all the factors differently and negatively impact the state. However, as the factors in their operationalization are not fully independent, some influences might be integrated doubly in the envelopes, which lowers the final flexibility reactions state percentage more than necessary.

Beneficial is the split in the influential flexibility factors, that adds to understanding of the elasticity of energy flexibility. Rather than only investigating the price-elasticity of flexibility, this research also captures influential factors. Still, the factors cannot be crystallized completely, and sensitivities with regard to the separate factors are still needed. To evaluate all aspects is highly complicated as there will always be uncertainty. By distinguishing between multiple types of elasticities, instead of only price elasticity, flexibility reactions, congestion patterns, and their impact on system decisions can be aligned with broader objectives beyond economic efficiency only.

8.2.4. Step 4

The flexibility reactions before step 4 did not account for spatial correlation. However, as a strength of this research, such spatial correlation was implemented to account for the differences in variance between flexibility reactions. This has impact on congestion, as certain types of flexibility reactions then become more pronounced in specific areas, as the results have also shown. There is only limited information on the extent to which spatial correlation leads to clustering. Therefore, this model used scenarios to approach this in which there is still a lot of uncertainty in the extent to which spatial correlation happens. Unfortunately, the approach only correlates the final reaction state per timestep, as it is assumed unknown what factors specifically correlate. However, it is known that certain factors correlate more often than others, depending on the geographical area. Therefore, it is recommended that future research incorporates correlation per factor instead of per agent, so that the resulting reactions become more accurate.

The spatial correlation is now only accounted for by taking into account agents that are in close proximity via the electrical distribution grid. Spatial correlation now only occurs via the hierarchical sub-strings between agents in electrical proximity, that does not allow for spatial correlation by specifying based on geographical areas. In reality the geospatial topology might differfrom the electro-technical topology. This makes the measure somewhat inaccurate. Nevertheless, as no other local information was available, this electrical proximity was the closest measure towards geospatial proximity. To more accurately present spatial correlation in the model it is recommended to incorporate actual geospatial proximity data rather than electrotechnical proximity.

8.2.5. General reflection on model methodology

In this research, essentially two models were coupled in a co-simulation. The power flow model captured the congestion effects and historical loads to which flexibility was applied. Additionally, it also revealed the network topology, which was also used in the second model. However, as it turns out the power flow model was hard to integrate with the agent-based model as data extraction was intensive with a lot of exceptions.

The congestion from the power flow model was used to incentivize the grid-participant agents in the stochastic state model, through which flexibility states where developed, via factors in the environment and through spatial correlation. However, there was only one type of action modeled that, being spatial correlation. Nevertheless states do develop over time. Although not performed in this research, the model allows for a whole array of other specifications and interactions so that the influences of the factors can be further specified. For example energy trading or energy transport via EVs could have been modeled to adapt the physical capacity factor. Still, the model shows how these separate parts lead to complex overall results in congestion and (in)adequacy of provided flexibility, as a result of heterogeneous dynamic probabilistic flexibility envelopes and states with interdependencies between agents.

The model properly shows differences in possible flexibility reactions among different grid-participants at different locations, through probabilistic ranges that are only able to capture the more deterministic variables to a limited extent, especially for the content of the incentive structure factor. This is largely dependent on regulatory policy and would shift distributions and flexibility outcomes significantly. Nevertheless, results are based on scenarios with relative differences and do not rely on exact quantification to show the relations and outcomes.

This is however, also weakness of this research. The model is not able to show at what level or at what level from the factors effects occur. The model only stochastically shows outcomes, within probability distributions that are still wide, uncertain and inaccurate. The focus of this model was not so much on the exact quantification of the probability distributions. Therefore, the outcomes are rather approximate to show the logic of the model, without focusing too much on the development on the accuracy of the envelopes. Nevertheless, the model is able to show causality through the multiplicative reduction hierarchy of the flexibility reactions.

8.3. Validation of model

The conceptual validity is based on literature and theoretical and logical reasoning. The realism depends on how well the envelopes were calibrated, in which a lot of uncertainty is still incorporated to remain valid. This however decreases accuracy. Nevertheless, the model gives system-wide insights and not granular predictions, which is consistent with the design. By running the simulation with a lot of agents, timesteps and iterations for factors, actual system behavior should converge and stabilize. However, empirical validation is lacking as future states in full scale nor pilots are yet not realized.

Strategy for future validity assessment

A potential approach to further analyze congestion patterns is to perform multiple simulation runs of the model using the same set of input envelopes. By repeating the model execution, for example 1000 times, it becomes possible to identify whether congestion consistently occurs in the same neighborhoods. This stochastic or repeated-run analysis can provide insights into systemic vulnerabilities and highlight areas that are most prone to congestion under varying prosumer responses, thereby supporting more robust planning and targeted flexibility measures.

To further increase the validity, more empirical data on flexibility reactions can be collected, especially on the factors that vary the most. Especially these factors that can vary much per agent or timestep are relevant to analyze and increase model accuracy. Such factors are especially relevant as they either have a large effect on heterogeneous locations of flexibility or might vary much under future developments over time. Additionally, factors related to policy are relevant, as both the capability and incentive structure factor largely depend on choices made there, that are now not properly captured in the model. These indirectly also influence the other factors on the long-term. Such a selection is good as it focuses less on the technological factors, that are actually not often a limiting factor, but more on the policy and operation factors. The input distributions can then be further calibrated. Then, after calibration, especially in future scenarios where flexibility is already implemented, one could compare the flexibility generated by the model with the flexibility deployed in reality. This might become apparent via bids on the GOPACS platform, where aggregators also show their willingness. Hence, the historical bidding data on such platforms might be used to further calibrate and validate existing models.

9

Conclusion

This final chapter presents the conclusions, and answers the main research question after the sub-questions, in the first section. Subsequently, the scientific and societal relevance is elaborated on in the next section. Thereafter, the recommendations for stakeholders are put forward in the third section, after which the recommendations for future work are presented in the last section.

9.1. Overall conclusions

9.1.1. Sub-questions

Sub-question and step 1

The first step focused on the following sub-question: *'Where does congestion occur in Dutch distribution grids under current conditions without activation of distributed flexibility?'*

The power flow model has proven that acute congestion happens only to a limited extent in the case-study grid. However, acute congestion does not show formal congestion, that already occurs once new connections cannot be contracted anymore. Therefore, extrapolated acute congestion gives insight in where congestion occurs, and a congestion threshold was defined at 80% of of the apparent power ratings. The results show that both voltage and current congestion occur locally under sub-transmission voltage distribution transformers. Furthermore, both types of congestion also occur lower and more locally in the radial distribution hierarchy.

Sub-question and step 2

The second step answered to following sub-question: *'How can the effect of a congestion management mechanism that encourages the maximum potential of distributed flexibility be modeled?'*

Small distributed flexibility providers are not encouraged to explicitly mitigate voltage congestion, other than via direct active power load adjustments. For current congestion however, caused by thermal overloads, distributed flexibility providers can be encouraged by all sorts of indirect congestion mechanisms, of which the implicit financial mechanism that is able to differentiate in terms of temporal and spatial detail was focused on in this research. This highly granular mechanism is able to provide the highest incentives. Therewith it is able to robustly model the most severe congestion that remains after incentivization. Since the DSO is non-discriminatory, the maximum internal value that the DSO has to solve congestion through this mechanism is the same throughout all congested regions. Therefore, the model proposed to uniformly apply this maximum highly granular incentive mechanism, to see where robust congestion remains and where flexibility reactions are inadequate.

Sub-question and step 3

The third step answered to following sub-question: *'What interplay of factors influences possible reactions of distributed flexibility to mitigate congestion?'*

A lot of factors influence the possible reactions. This research revealed and categorizes four key factors: physical capacity, capability, incentive structure and behavior. In the proposed interplay, the factors are combined into a sequential multiplicative reduction framework where they develop independently and are quantified by a separate formula. Initially, there is enough physical capacity to provide flexibility. However, grid-participants are not often enabled and capable enough to use this flexibility, which lowers reactions. The financial incentive also plays a role, and as it is not infinite and not always surpasses opportunity costs of participants, it also lowers the possible flexibility reaction. However, the magnitude and structure of the incentive structure might differ, and therewith also impacts the potential flexibility provision. Lastly, behavioral issues also cause participants to provide less flexibility than technically possible. The heterogeneity among agents caused by these factors causes inadequacy of flexibility reactions and congestion to arise only in specific regions.

Sub-question and step 4

The fourth step answered the following sub-questions: *'What are the implications of spatial correlation between distributed flexibility reactions on congestion patterns?'*

Spatial correlation between the flexibility providers and their influential factors in certain regions causes spatial clustering of flexibility reactions. Once located in larger congested areas, such as under an overarching sub-transmission voltage distribution transformer, the model shows that spatial clustering between distribution substation areas has limited impact on remaining congestion after flexibility reactions, as the undershoots that are prevalent in one underlying locally clustered area, might be compensated for by overshoots in other underlying areas that do not belong to the cluster but are in the same overarching congested area. Also, once financial incentives are smaller, reactions are typically lower. Additionally, once the congested areas are smaller and caused by a component lower in the radial distribution hierarchy, spatial correlation might lead to more prevalent undershoots in the overall flexibility provision and congestion is more likely remain. In these smaller areas spatial correlation might lead to overall undershoots that cannot be compensated for by overshoots, as the area is not that large.

9.1.2. Main research question

The following main research question was posed: *"How can the impact of location-specific distributed flexibility on congestion locations in Dutch distribution grids be evaluated?"*.

To answer this question and assess robustly remaining congestion and inadequacy of flexibility under the optimal flexibility reactions, a high financial incentive should be considered. The highest incentives can be given under incentives that are accurately targeted with high spatial and temporal detail, as such mechanisms minimally impact social welfare. Nevertheless, the DSO and regulatory authorities are deemed to be non-discriminatory. Therefore, this research proposes to apply the maximum financial incentive that DSO internally has and is allowed to solve congestion, which is an incentive uniform in magnitude for all flexibility providers. To this end, flexibility reactions are assessed as if the maximum from these temporally and spatially targeted financial incentives, is applied uniformly.

Taken together, a combination of the factors physical capacity, capability, incentives structures and participant behavior leads to different flexibility reactions per location. This causes heterogeneous differences in the ability of grid participants, possibly aggregated, to solve congestion, which leads to various resulting congestion patterns.

Although being a local problem and requiring fulfillment of all flexibility factors, small distributed flexibility providers have no incentive to contribute explicitly to voltage congestion mitigation, other than via active load adjustments. Contrasting, small distributed flexibility providers are engaged to contribute to mitigation of current congestion from thermal overloads. Nevertheless, based on a combination of probability distributions that describe the states of the combined flexibility factors, congestion might still remain after the activation of such distributed flexibility providers.

In congested areas that are caused by overloaded sub-transmission voltage transformer that supply the area, there are typically many flexibility providers. Once financial incentives are high enough, congestion in these areas can be solved as the undershoots of flexibility of some users can be compensated by overshoots of other flexibility providers. Even once spatial correlation is high, meaning that reactions of flexibility providers in specific areas are increasingly similar, congestion can be resolved once the geographical congestion area is large enough. Here, spatially clustered areas that undershoot to provide flexibility can be compensated for by other clusters in the large area.

However, the analysis reveals that once congestion is more local and caused by a component lower in the radial distribution hierarchy than a sub-transmission voltage distribution transformer, there might not be enough flexibility to locally solve congestion. Once low financial incentives apply, the undershoots of some flexibility providers might not be compensated for by overshoots of others. Especially once there is a lot of spatial correlation between flexibility providers in such a small and highly local congested area, flexibility reactions that undershoot might be more common, causing inability of the participants in the area to solve congestion together.

9.2. Scientific and societal contribution

By answering the research questions through the model, a contribution to science was given as the research gaps described in the review were addressed. These gaps and their contributions are respectively summarized below.

1. There is lack of insight in adequacy of flexibility at congested locations as the impact of incentivesis unknown. This is partially caused by the limited available information in how to assess the locally differing impact of congestion management mechanisms, as discussed by among others Hennig, Vries, and Tindemans [17] and Attar et al. [34] in section 2.2.2.
2. Flexibility reactions depend on heterogeneous flexibility factors that vary per participant and are complex to create insight into. There is no consensus on uniform frameworks to transparently evaluate potential of distributed flexibility with local differences on congestion. Existing literature does not focus on decentralized decision-making while elaborating on the complete overview of uncertain heterogeneous background factors that might influence distributed flexibility reactions, partially because this is computationally extensive, as argued by among others Holst et al. [21], Fattaheian-Dehkordi, Aghaei, and Amjady [81] and Edmunds et al. [83] in section 2.2.3.
3. Flexibility reactions differ per location. This can have large impacts once flexibility is spatially correlated between concentrated flexibility providers in close proximity. However, limited deterministic local information is available to model these differences. Additionally, existing models do not incorporate systematic ways to model such spatial dependencies and regional disparities in the grid. Such gaps were found in section 2.2.4 by among others Michaelis, Schneider, and Weibelzahl [100] and Wüllner et al. [43].

This research contributes to these knowledge gaps respectively in the following ways:

1. It puts forward a strategy to assess robustly remaining congestion , by using the maximum financial incentive of a voluntary congestion management mechanism. The mechanism itself can be applied in a highly temporal and spatial targeted manner and therewith has high incentive. This maximum financial incentive is however, uniformly applied in the model to reveal inadequacy of flexibility of grid-participants,
2. It provides a framework to transparently evaluate potential of distributed flexibility to provide congestion mitigation, differing per location. It elaborates on the heterogeneity of various factors and assesses the impacts on congestion, without relying on computationally extensive and deterministic mathematical optimization methods.
3. It provides a way to visualize and compare congestion caused by heterogeneous flexibility reactions in which the effect of spatial concentrated and correlated flexibility is also visible. Additionally, it transparently shows required flexibility and actually provided flexibility in a systematic and clear manner.

Not only does the research add to scientific research. By providing these insights, it also has societal relevance. By providing insight into flexibility reactions, the research contributes to more effective strategies for congestion mitigation. It provides insights for capacity assessments that can be used for more efficient grid and expansion plannings, which improves grid reliability, cuts costs for DSOs and society. Furthermore, it provides guidelines for regulatory policy to effectively activate flexibility at the right places and enhances market efficiency. By mitigating congestion, grid connections can be enabled again for economic growth. Additionally, it enables the integration of renewable energy and supports the energy transition to decrease emissions and global warming. Furthermore, it keeps the provision of electricity affordable.

9.3. Recommendations for stakeholders

The conclusions also have implications for the key stakeholders from in chapter 4. These are elaborated on below.

Grid operators

For TSOs and especially DSOs, it is important to take into account that flexibility responses vary under different congestion management mechanisms. Decision-making with regard to additional storage locations and acquisition of new flexible contracts should take such future developments into account for congestion-efficiency and complementarity.

The analysis has shown that congestion might not be solved once caused by components low in the radial distribution hierarchy, in which the area of potential flexibility providers is small. Especially once there is a lot of spatial correlation, congestion might not be solved. Therefore it is recommended to DSOs to create insight in flexibility provision per location, and whether such flexibility is highly concentrated and correlated in specific regions. Additionally, it is recommended to create insight in specific regions that might be prone to very local congestion, thus in components lower the than sub-transmission voltage transformer. Once both this very local congestion occurs, and once the flexibility provision is highly unevenly dispersed, it is recommended to strategically incentivize additional flexibility at these locations, via all sorts of congestion management mechanisms.

As the analysis reveals that congestion can sometimes be very local, it is recommended to further develop and implement highly granular mechanisms that can be spatially targeted. Distributed flexibility can be increasingly incentivized at these locations, which is a congestion-efficient way of solving congestion, while minimally impacting social welfare. Nowadays, such mechanisms are only used to a limited extent. This lowers the attractiveness of such mechanisms for storage operators. In GOPACS for example, load adaptations, capacity restrainment contracts and redispatch requests are only used to a limited extent. This lowers the potential revenue of storage operators that can engage in these services, which makes business cases less attractive. To increase distributed flexibility and engagement of storage operators, it is therefor recommended to DSOs to make a more reliable and active platform for such highly granular congestion management services, in which more congestion problems are requested. In such a way, it becomes attractive for flexibility providers to engage in such services.

However, such highly granular mechanisms can only be implemented once there is actual congestion. Recent developments have shown that other congestion management mechanisms with lower granularity, such as the time-off-use-tariff, will also be implemented in the future. This might lower the extent to which the highly granular incentive is applied, as there is less remaining congestion to be solved. However, the extent to which this less granular mechanism impacts congestion is unknown and dependent on the magnitude of the incentive. Therefore, it is recommended to DSOs to investigate the impact from these combined congestion management mechanisms with different granularities is, so that they can be aligned complementarity. It might for example also be the case that the less granular mechanisms mitigates congestion almost entirely, also at specific locations and specific timesteps. In that case, the impact of highly granular mechanisms to solve congestion diminishes, and the attractiveness and efficiency of such mechanisms diminishes significantly.

Storage operators and flexibility providers

For storage operators, congestion service providers and all sorts of other flexibility providers, it is recommended to exploit the differentiated and local congestion problems in an efficient manner. The provided framework creates insight in where congestion remains after deployment of already sited distributed flexibility. This information can be used to exploit flexibility at exactly the right places and times, so that additional revenue can be generated under the highly granular mechanisms that differentiate incentives through time and space. To use this information to further mitigate the remaining congestion, it is recommended to optimize the spatial deployment of possible storage applications and flexibility assets to optimize business cases. For example, mobile storage applications might be able to efficiently predict remaining congestion locations, and generate additional revenue by optimizing mobile storage dispatch algorithms, that are able to shift in space and time. Such mobile storage systems might especially be useful in the small congested areas with small feeders, where stationary large scale-storage makes no sense as congestion appears only on occasion. Stationary storage might be more beneficial near the places where congestion appears more systematically, such at the sub-transmission voltage transformer.

Regulatory authorities and ministries

However, the DSO and flexibility providers are prone to the instititions from the regulatory authority and ministries. These create the playing field that impact congestion mitigation, and therefore are served with specific recommendations. This model and the results might also have implications for energy justice. It becomes visible that under uniform mechanisms, flexibility reactions at some areas are more adequate than at other areas. There are different ways to solve such inadequacies, each with different implications for energy justice.

However, all of the above recommendations on congestion-efficient placement of flexibility and storage, can only be incentivized once congestion management mechanisms apply that are able to differentiate in a spatial and temporal manner. For congestion-efficiency, it is therefore recommended to further develop such highly granular mechanisms such as GOPACS, while limiting social welfare to a minimal extent. Inadequacies can then be resolved by increasing and differentiating incentives based on local evaluation of scarcity and opportunity costs to mitigate congestion, for example through bidding. However, some participants are endowed with more flexibility, while others are in contrast endowed with less flexibility and frequent congestion through more local constraints. This leads to regional disparities in congestion solving flexibility adequacy, which is important to take into account for regulatory policy and incentive structure development, as it impacts fairness.

Although this tension might lead to a collective action problem, it is important to note that improving the energy system as a whole through measures like local flexibility incentives, boosts efficiency and social welfare, even if allocation isn’t perfectly fair. Wealthier and more endowed participants might benefit more of such differentiating mechanism, as they can afford flexibility assets and pay less and less endowed participants might face higher costs. This might raise short-term equity concerns, but overall system costs decline which indirectly benefits everyone. Such considerations should also be taken into account when modeling and assessing the effects of congestion management mechanisms.

Not only the type of incentive used is of relevance. The split in factors that were used to model flexibility reactions has shown that both a capability and incentive are severely negatively impacting the technical feasible provision of flexibility. Once congestion becomes even more severe and limiting in the future, it is therefore recommended to specifically target the increase of these factors. For example by enabling energy management systems and increased aggregation of residential users, flexibility reactions can become larger. Furthermore, increasing the maximum financial incentive of all sorts of mechanisms always increases the size of flexibility reactions. Therefore, it is recommended to assess to what extent increases in financial incentives for flexibility might lead to decreases in loss of social welfare, for example through cost-benefit analyses.

9.4. Recommendations for future work

Essentially, this research provides a framework to assess flexibility reactions under expected future developments, where flexibility providers are increasingly motivated to contribute to congestion mitigation. Since it is likely that more extensive implicit congestion mechanisms are implemented, the relevance of this research as fundament for future research directions increases. However, some aspects might be especially relevant to focus on in future research, that are described below.

Congestion management mechanism modeling

First of all, the model now only specifies that the maximum value from a highly granular financial incentive is uniformly applied among congestion contributors, to see where inadequacy of flexibility reactions remains under the most robust scenario. However, the magnitude itself is not focused on, while changing this leads to non-linear behavior which significantly impacts the reaction. The price-setting mechanism of the financial incentive is also not explicitly modeled, while this differs based on the temporal and spatial granularity of the incentive. It is recommended to gain more insight in creation of the financial incentive magnitudes, as it impacts flexibility reactions and unevenly distributed congestion.

Furthermore, It should be noted that the congestion pattern is currently scaled to 80%. Nevertheless, the results remain relevant, as the load profiles are expected to grow in the future. The conclusions drawn from this analysis are therefore considered robust. For future work, it is recommended to gain deeper insight into the autonomous growth of individual load components and their impact on congestion. Load growth is unlikely to be linear across all components simultaneously; instead, certain load components are expected to grow faster than others, which may significantly influence future congestion patterns.

Agent-based modeling

In the stochastic flexibility state evolution model, agents are modeled that have certain flexibility reactions. The agents are now only impacted by the factors, for which envelopes with probability distributions are specified. However, additional modeling techniques exist, such as agent-based models. Such model can be used to enrich the accuracy of the influences. Such models can show feedback loops, relations, interaction and connectivity, influencing the envelopes and probabilities. Agent-based modeling is especially useful for modeling complex behavior arising from social interactions that allow for differences and interactions between agents [165];[166]. Hence, the various correlations between the agents might also nicely be represented through such agent-interactions, that can properly represent heterogeneity, adaptive behavior, network effects and the resulting emergent phenomena such as congestion. Furthermore the impacts of various mechanisms with multiple types of agents such as energy sharing, electric vehicles and mobile battery charging and transportation behavior can be captured through such models. For example the exchange of power transport by electric vehicles in can be incorporated via the replica network with agents. Adding more of such detailed interactions is recommended for future research to increase accuracy, and for integration and testing of more experimental and innovative ideas. The model up till now assesses the congestion on which actions from such agents in future models can be based.

Nevertheless, the model up till now only includes one type of agent. This type represents all sorts of underlying grid participants. To gain a more detailed insight in flexibility reactions, it is recommended to differentiate more between users as some of these can have typical factor fulfillment that increases accuracy. Additionally, by zooming in more on the different types, insight can be created in differences between agents under one underlying distribution substation, which is now considered to be one aggregated agent, without elaborating on the where the differences and variance of these differences are built upon.

Modeling influential factors and spatial correlation

The model now focuses in the short-term, in which the agent's factors that determine flexibility are independent on each other. However, it might be interesting to look at long-term developments, where more significant changes happen. Factors might then become interdependent, as fulfillment of one factor affects the other factor. For example, increased incentives might on the long term cause more investments in physical capacity, hence a feedback cycle between the factor develops. Such interdependent factorial developments increase complexity and thus might be interesting to focus on in further research. Such developments might also be systemically modeled, by modeling the factorial states as separate entities that can interact with each other via rules for interdependency.

Furthermore, spatial correlation is now barely elaborated on with supported by quantified data. The existence of the effect however, is certain. Therefore, it is recommended to further crystallize information to what extent clustering happens. It might be especially relevant in what influential factors it specifically happens, whether it varies over time and in what granularity the effect of correlation occurs. Additionally, it is recommended to find a way to correlate this via real geographic proximity instead of via proximity in the electrical distribution grid, to more accurately represent spatial correlation.

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