Congestion Management and Tariffs for Electric Distribution Networks

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Congestion Management and Tariffs for Electric Distribution Networks

Enablers of Flexibility in the Energy Transition

Congestion Management and Tariffs for Electric Distribution Networks

Enablers of Flexibility in the Energy Transition

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TU Delft Delft University of Technology

NWO Nederlandse Organisatie voor Wetenschappelijk Onderzoek

Contents

Summary

Background

Two concurrent developments lead to challenges for electric distribution networks: On the demand side, there is an increase in the electrification of heating, transportation, and industrial processes, and on the supply side, there is significant growth in the capacity of intermittent electric generation based on wind and solar. Both of these developments lead to a strong growth in the peaks of electricity flows through networks. These networks were often not designed for such large peak flows, and they may be unable to accommodate the desired peak flows with the current infrastructure. As network upgrades have extended lead times and high resource demands, upgrading the network fast enough everywhere is impossible. This leads to the question of what can be done to manage high electricity peak flows, which may overload the network. The peaks can often be flattened on the demand side using the flexibility inherent to the new electrical end-uses. This process is also called congestion management. In this thesis, we investigate different methods for congestion management, with a particular focus on the role of network tariffs and a class of congestion management mechanisms based on limiting network capacity. We analyze how network tariffs and electricity-generation-related end-user prices influence household investments and energy dispatch decisions.

Congestion management mechanisms

We developed a framework to categorize congestion management methods based on their design choices. At a high level, they can be distinguished based on who controls the flexible loads to flatten network peaks: the network operator or the user/a representative of the user like an energy supplier. In the former case, we call the mechanisms direct load control (DLC) approaches. Another important distinction is whether the network operator pays users for a reduction in the network access rights as part of congestion management or whether the access conditions for the network already include congestion management. If the network operator pays users for reduction, and

the reduction payment is determined through auctions, we call the mechanism a local flexibility market (LFM).

If the access conditions already include congestion management, we call the mechanism network-access-price-based or smart network tariffs. In general, the primary function of tariffs is to allocate the costs of building and maintaining the network to its users. As a secondary function, these tariffs can incentivize more intelligent network use, which flattens peak flows through the network. In this case, they are also called “smart” tariffs. Thus, in smart network tariffs, congestion management is included in the tariff, while in LFMs and DLC-based methods, congestion management is typically added on top of the tariff. Smart tariffs can be based on static price signals, such as a higher price during certain fixed hours or a price on network capacity, or they can be based on dynamic price signals. In dynamic tariffs, the price for accessing the network varies, e.g., by hour, and is announced on the day ahead or only shortly before real-time, based on the expected flows in the network.

Each method has different strengths and weaknesses and is associated with a particular risk. Static tariffs give rough signals that can resolve regular and predictable congestion. They are pretty simple and non-discriminating. On the other hand, they are not adaptable to unforeseen events and may have a residual risk of network overload. Dynamic tariffs are more adaptable. However, they create a price risk for the network users who cannot adjust their network load based on prices.

LFMs can theoretically remove congestion efficiently, meaning at low prices to the network operator and society at large, since an ideal market would induce the loads with the lowest required adjustment price to remove the congestion. However, in practice, ideal markets rarely occur, and many of the current proposals may have an exceptionally high price risk for the network operator due to the potential problems of gaming such markets. They may be more suitable to congestion at larger spatial scales due to the higher liquidity of the market in larger areas. We found that market methods based on market participants’ submitted baselines should be avoided due to potential problems with misrepresenting such baselines.

DLC-based approaches apply to both predictable and unforeseen congestion events and reduce the risk of overload and the price risk of the network operator. On the other hand, they create a risk of curtailment for the end-user, who may experience limited quality of service and possibly incur portfolio imbalances for energy suppliers.

Network tariff assessment

We found that network tariffs are a promising instrument to manage network congestion. These tariffs are expected to fulfill several regulatory objectives and recover costs for the network operator. The main goals for tariffs are to be cost-reflective, induce efficient network usage, and be transparent and non-discriminating. However, how a given tariff performs concerning these objectives is often unclear.

To overcome this problem, we developed a framework for performance assessment of network tariffs based on quantifiable indicators for the regulatory objectives. We developed a network cost model in which the cost contributions of individual users can be approximated and related to their tariff charges. We used this cost model and the framework to assess a few options for network tariffs that are currently discussed. In this case study, we limited the investigation to static network tariffs, for which we found that capacity-based tariffs are particularly suitable to flatten peaks of flexible loads and have generally good cost-reflectiveness and low complexity.

Capacity limitation based congestion management methods

In addition to capacity-based network tariffs, which implement a capacity limitation in a long-term timeframe, more dynamic methods of capacity-limitation-based congestion management have also been proposed: capacity limitations activated day-ahead based on expected congestion and interruptible connections, where the capacity limitation is implemented in near real-time based on observed network load. We investigated versions of these proposals proposed by the Dutch and German regulators and compared them with a capacity-based network tariff.

All three methods can efficiently manage congestion, and the resulting cost differences for users were not found to be significant. However, they pose a trade-off between the risk of unforeseen curtailment for the energy user and the restriction of users during non-congested times. The capacity-based network tariff gives long-term certainty on the available capacity. However, this capacity is always limited to the contracted value, even when more network capacity is available. In the day-ahead capacity limitation, users can use available capacity when no congestion is expected. When capacity limitations are announced, energy suppliers can consider this in their day-ahead purchases. However, if congestion is not anticipated correctly, there is a residual risk of overload for the network operator, who has to procure additional peak-flattening measures in this case. This may incentivize the network operator to be conservative in its congestion estimates and activate the limitations frequently, even at low likelihoods of congestion. Lastly, network capacity can be used to the maximum extent possible in the near real-time capacity limitation, as this measure is based on the most up-to-date information. However, the near real-time reduction of network capacity may create portfolio imbalances for energy suppliers, which may incur additional costs.

As a synthesis of our analysis of these mechanisms, we proposed introducing a 2-part capacity tariff: one part of the tariff is for firm network capacity, which is guaranteed to be available[1]. This is meant to cover all base-load and inflexible loads of network users. The second part of the tariff is for non-firm capacity, which is offered at lower prices but can be curtailed in near real-time by the network operator during congestion. This could be complemented by day-ahead publications of congestion expectations of the network operator, which would give energy suppliers better information for day-ahead purchases but not create an overload risk for the network operator. Moreover, this mechanism exhibits strong cost-reflectiveness by distinguishing between firm and variable capacity.

Investments and energy dispatch in households with different network tariffs and electricity generation-related prices

In the last chapter of this thesis, we expanded our analysis to combine network tariffs with the generation-related price component of electricity retail rates. We modeled different network tariffs and energy-related rate components in a residential neighborhood of 25 homes implemented in the energy system model Calliope. We used four pricing scenarios to combine network and energy-related components: 1. A flat per-kWh including both components, 2. A Time-of-Use per-kWh including both components, 3. A fixed fee for the network component and real-time prices for energy, and 4. A capacity-based fee for the network component and real-time prices for energy. The prices for the energy-related component were based on the marginal prices of generation that we produced with a national model of the Netherlands with the stated renewable capacity targets for 2030 of the Dutch government. We assumed that households optimize their investments and dispatch based on the given prices for the energy and network components.

Our analysis showed that there are significant financial gains for households when the energy-related component of the retail rate is passed to consumers in the form of a real-time price, and the distribution-network-related component is not added on to the energy-related component as a volumetric rate, but rather as a fixed price or capacity-based price. However, fixed network tariffs do not incentivize reducing load peaks, which may overload existing infrastructure. The capacity-based network tariff

[1] "Guaranteed" means during normal operation conditions here. There may still be exceptional situations, e.g., when a power line has accidentally been cut, so a 100% certainty can never be guaranteed, but we do not include such cases in our analysis.

strongly reduced load peaks in our analysis and, thus, may help to prevent required grid upgrades. The rate designs with volumetric network tariffs may also induce households to install solar panels, even when this is inefficient at the system level. Similarly, these rate designs and the capacity-based network tariff may induce the installation of batteries, even when it might be more cost-efficient at the system level to install grid upgrades or communal batteries. Lastly, the usage of the gas network strongly decreases in all studied rate designs, which raises the question of whether these networks should be built back completely.

SAMENVATTING

Achtergrond

Twee gelijktijdige ontwikkelingen leiden tot uitdagingen voor elektriciteitsdistributienetwerken: aan de vraagzijde is er een toename in de elektrificatie van verwarming, transport en industriële processen, en aan de aanbodzijde is er een aanzienlijke groei in de capaciteit van intermitterende elektriciteitsopwekking. op wind- en zonne-energie. Beide ontwikkelingen leiden tot een sterke groei van de pieken in de elektriciteitsstromen via netwerken. Omdat deze netwerken vaak niet zijn ontworpen voor zulke grote piekstromen, kunnen ze met de huidige infrastructuur mogelijk niet de gewenste piekstromen opvangen. Omdat netwerkupgrades lange doorlooptijden en een hoge vraag naar middelen met zich meebrengen, is het onmogelijk om het netwerk overal snel genoeg te upgraden. Dit roept de vraag op wat er in de tussentijd gedaan kan worden om elektriciteitspieken, die het netwerk kunnen overbelasten, te beheersen. Aan de vraagzijde kunnen deze pieken vaak worden afgevlakt met behulp van de flexibiliteit die inherent is aan het nieuwe elektrische eindgebruik. Dit proces wordt ook wel congestiemanagement genoemd. In dit proefschrift onderzoeken we verschillende methoden voor congestiebeheer, met een bijzondere focus op de rol van netwerktarieven en een klasse van mechanismen voor congestiebeheer gebaseerd op het beperken van de netwerkcapaciteit. We analyseren verder hoe verschillende netwerktarieven en aan elektriciteitsopwekking gerelateerde eindgebruikersprijzen de investeringen van huishoudens en beslissingen over energiedistributie beïnvloeden.

Netwerk congestiemanagement aanpak

We hebben een raamwerk ontwikkeld om methoden voor congestiebeheer te categoriseren op basis van hun ontwerpkeuzes. Op een hoog niveau kunnen ze worden onderscheiden op basis van wie de leiding neemt over het regelen van de flexibele belastingen om netwerkpieken af te vlakken: de netwerkbeheerder, of de gebruiker/een vertegenwoordiger van de gebruiker, zoals een energieleverancier. In het eerste geval noemen we de mechanismen Direct Load Control (DLC)-benaderingen. Een ander belangrijk onderscheid is gebaseerd op de vraag of de netbeheerder gebruikers betaalt voor een verlaging van de netwerktoegangsrechten als onderdeel van congestiemanagement, dan wel of de toegangsvoorwaarden voor het netwerk het congestiemanagement al omvatten. Als de netbeheerder gebruikers betaalt voor de reductie, en de vergoeding voor de reductie wordt bepaald via veilingen, noemen we het mechanisme een lokale flexibiliteitsmarkt (LFM).

Als de toegangsvoorwaarden al congestiebeheer omvatten, noemen we het mechanisme kortweg netwerktoegangsprijsgebaseerde of slimme netwerktarieven. Over het algemeen is de primaire functie van tarieven het toewijzen van de kosten voor het aanleggen en onderhouden van het netwerk aan de gebruikers ervan. Als secundaire functie kunnen deze tarieven een intelligenter netwerkgebruik stimuleren, waardoor de piekstromen door het netwerk worden afgevlakt. In dit geval worden ze ook wel 'slimme' tarieven genoemd. Bij slimme netwerktarieven is congestiebeheer dus inbegrepen in het tarief, terwijl bij LFM's en op DLC gebaseerde methoden congestiebeheer doorgaans bovenop het tarief wordt toegevoegd. Slimme tarieven kunnen gebaseerd zijn op statische prijssignalen, zoals een hogere prijs tijdens bepaalde vaste uren of een prijs op netwerkcapaciteit, of ze kunnen gebaseerd zijn op dynamische prijssignalen. Bij dynamische tarieven varieert de prijs voor toegang tot het netwerk bijvoorbeeld per uur en wordt deze de dag ervoor of pas kort voor realtime aangekondigd, op basis van de verwachte stromen in het netwerk.

Elke methode heeft verschillende sterke en zwakke punten en gaat gepaard met een bepaald soort risico. Statische tarieven geven ruwe signalen af die reguliere en voorspelbare congestie kunnen oplossen. Ze zijn vrij eenvoudig en niet-discriminerend. Aan de andere kant zijn ze niet aanpasbaar aan onvoorziene gebeurtenissen en kunnen ze daarom een restrisico op netwerkoverbelasting met zich meebrengen. Dynamische tarieven zijn beter aanpasbaar, maar creëren een prijsrisico voor de netgebruikers die hun netwerkbelasting niet kunnen aanpassen op basis van prijzen.

LFM's kunnen in theorie congestie efficiënt verwijderen, omdat ze marktgebaseerd zijn. Ze kunnen echter een uitzonderlijk hoog prijsrisico met zich meebrengen voor de netwerkexploitant vanwege potentiële problemen van market manipulatie. Ze kunnen geschikter zijn voor congestie die zich op grotere ruimtelijke schaal voordoet vanwege de hogere liquiditeit van de markt in grotere gebieden. Hoe het ook zij, we zijn tot de conclusie gekomen dat marktmethoden die gebaseerd zijn op ingediende profielen van marktdeelnemers moeten worden vermeden vanwege de gevoeligheid voor manipulate van profielen.

Op DLC gebaseerde benaderingen zijn toepasbaar op zowel voorspelbare als onvoorziene congestiegebeurtenissen en verminderen het risico op overbelasting en het prijsrisico van de netwerkbeheerder. Aan de andere kant creëren ze een risico op inperking voor de eindgebruiker, die mogelijk te maken krijgt met een beperkte kwaliteit van de dienstverlening, en mogelijk onbalans in de portefeuille van de energieleveranciers.

Beoordeling van netwerktarieven

We concludieren dat netwerktarieven een veelbelovend instrument zijn om netwerkcongestie te beheersen. Het is seen vereiste dat deze tarieven naast het terugverdienen van de kosten voor de netbeheerder ook aan een aantal reguleringsdoelstellingen zullen voldoen. De belangrijkste doelstellingen zijn kostenreflectief te zijn, efficiënt netwerkgebruik te bewerkstelligen, transparant en niet-discriminerend te zijn. Het is echter vaak onduidelijk hoe een bepaald tarief presteert met betrekking tot deze doelstellingen.

Om dit probleem te ondervangen hebben we een raamwerk ontwikkeld voor de prestatiebeoordeling van netwerktarieven, gebaseerd op kwantificeerbare indicatoren voor de regelgevingsdoelstellingen. We hebben een netwerkkostenmodel ontwikkeld waarin de kostenbijdragen van individuele gebruikers kunnen worden benaderd en gerelateerd aan hun tarieftarieven. We hebben dit kostenmodel en het raamwerk voor prestatiebeoordeling gebruikt om enkele opties voor netwerktarieven te beoordelen die momenteel worden besproken. Hiervoor hebben we ons beperkt tot statische netwerktarieven, omdat dynamische netwerktarieven politiek controversiëler en moeilijker te modelleren zijn. Voor statische netwerktarieven hebben we vastgesteld dat op capaciteit gebaseerde tarieven bijzonder geschikt zijn om pieken van flexibele belastingen af te vlakken en over het algemeen een goede kostenreflectie en lage complexiteit hebben.

Op capaciteitsbeperking gebaseerde methoden voor congestiebeheer

Naast op capaciteit gebaseerde netwerktarieven, die een capaciteitsbeperking op lange termijn implementeren, zijn er ook meer dynamische methoden voor op capaciteitsbeperking gebaseerd congestiebeheer voorgesteld: capaciteitsbeperkingen die day-ahead worden geactiveerd op basis van verwachte congestie en onderbreekbare verbindingen, waarbij de capaciteitsbeperking vrijwel direct wordt geïmplementeerd op basis van de waargenomen netwerkbelasting. We hebben versies van deze voorstellen van de Nederlandse en Duitse toezichthouders onderzocht en vergeleken met een op capaciteit gebaseerd netwerktarief.

Alle drie de methoden kunnen congestie efficiënt beheren, en de daaruit voortvloeiende kostenverschillen voor gebruikers bleken niet significant te zijn. Ze vormen echter een afweging tussen risico en beperking van gebruikers tijdens niet-overbelaste tijden. Het capaciteitsgebaseerde netwerktarief geeft op lange termijn zekerheid over de beschikbare capaciteit. Deze capaciteit is echter altijd beperkt tot de gecontracteerde waarde, ook als er meer netwerkcapaciteit beschikbaar is. Bij de day-ahead capaciteitsbeperking kunnen gebruikers de beschikbare capaciteit gebruiken wanneer er geen congestie wordt verwacht. Wanneer capaciteitsbeperkingen worden aangekondigd, kunnen energieleveranciers hiermee rekening houden bij hun day-ahead-aankopen. Als er echter niet goed op congestie wordt geanticipeerd, blijft er een restrisico op overbelasting bestaan voor de netbeheerder, die in dit geval extra piekafvlakkingsmaatregelen moet treffen. Dit kan de netwerkexploitant ertoe aanzetten conservatief te zijn in zijn schattingen van de congestie en de beperkingen regelmatig te activeren, zelfs als de kans op congestie klein is. Tenslotte kan bij de near real-time capaciteitsbeperking de netwerkcapaciteit maximaal benut worden, omdat deze maatregel gebaseerd is op de meest actuele informatie. De vrijwel realtime vermindering van de netwerkcapaciteit kan echter leiden tot onevenwichtigheden in de portefeuille van energieleveranciers, wat tot extra kosten kan leiden.

Als synthese van onze analyse van deze mechanismen hebben we voorgesteld een tweedelig capaciteitstarief in te voeren: een deel van het tarief is voor vaste netwerkcapaciteit, die gegarandeerd beschikbaar is, ondanks netwerkstoringen. Dit is bedoeld om alle basislasten en inflexibele lasten van netwerkgebruikers te dekken. Het tweede deel van het tarief geldt voor niet-vaste capaciteit, die tegen lagere prijzen wordt aangeboden, maar tijdens congestie vrijwel realtime door de netbeheerder kan worden ingeperkt. Dit zou kunnen worden aangevuld met day-ahead publicaties van de congestieverwachtingen van de netbeheerder, waardoor energieleveranciers betere informatie krijgen over day-ahead aankopen, maar er geen overbelastingsrisico ontstaat voor de netbeheerder. Bovendien vertoont dit mechanisme een sterke kostenreflectie door onderscheid te maken tussen vaste en variabele capaciteit.

Investeringen en energiegebruik in huishoudens met verschillende netwerktarieven en aan elektriciteitsopwekking gerelateerde prijzen

In het laatste hoofdstuk van dit proefschrift hebben we onze analyse uitgebreid om netwerktarieven te combineren met de opwekkingsgerelateerde prijscomponent van elektriciteitsretailtarieven. We hebben verschillende netwerktarieven en energiegerelateerde tariefcomponenten gemodelleerd in een woonwijk van 25 woningen, geïmplementeerd in het energiesysteemmodel Calliope. We hebben vier prijsscenario's gebruikt om netwerk- en energiegerelateerde componenten te combineren: 1. Een vast bedrag per kWh inclusief beide componenten, 2. Een gebruikstijd per-kWh inclusief beide componenten, 3. Een vaste vergoeding voor de netwerkcomponent en real-time prijzen voor energie, en 4. Een capaciteitsgebaseerde vergoeding voor de netwerkcomponent en real-time prijzen voor energie. De prijzen voor de energiegerelateerde component zijn gebaseerd op de marginale prijzen van de opwekking die wij produceerden met een nationaal model van Nederland met de gestelde duurzame capaciteitsdoelstellingen voor 2030 van de Nederlandse overheid. We gingen ervan uit dat huishoudens hun investeringen en gebruik optimaliseren op basis van de gegeven prijzen voor de energie- en netwerkcomponenten.

Uit onze analyse blijkt dat er aanzienlijke financiële voordelen voor huishoudens zijn als de energiegerelateerde component van het retailtarief aan de consument wordt doorgegeven in de vorm van een realtime prijs, en de distributienetwerkgerelateerde component niet wordt toegevoegd aan de energiekosten-gerelateerde component als een volumetrisch tarief, maar eerder als een vaste prijs of een op capaciteit gebaseerde prijs. Vaste netwerktarieven stimuleren echter niet het verminderen van belastingspieken, die de bestaande infrastructuur kunnen overbelasten. Het op capaciteit gebaseerde netwerktarief heeft in onze analyse de belastingspieken sterk verminderd en kan zo de vereiste netwerkupgrades helpen voorkomen. Ook de tariefontwerpen met volumetrische netwerktarieven kunnen huishoudens ertoe aanzetten zonnepanelen te plaatsen, ook al is dat op systeemniveau inefficiënt. Op soortgelijke wijze kunnen deze tariefontwerpen en het op capaciteit gebaseerde netwerktarief aanleiding geven tot de installatie van batterijen, ook al zou het op systeemniveau kostenefficiënter kunnen zijn om netupgrades of gemeenschappelijke batterijen te installeren. Ten slotte neemt het gebruik van het gasnetwerk in alle bestudeerde tariefontwerpen sterk af, wat de vraag doet rijzen of deze netten volledig moeten worden herbouwd.

Acronyms

ACER European Union Agency for the Cooperation of Energy Regulators.

ACM Autoriteit Consument & Markt (Dutch regulator).

ASHP Air-Source Heat Pump.

BNA Bundesnetzagentur (German network regulator).

BRP Balance Responsible Party.

CEER Council of European Energy Regulators.

CLS Capacity Limitation Services.

CM Congestion Management.

CPP Critical Peak Pricing.

DER Distributed Energy Resources.

DG Distributed Generation.

DLC Direct Load Control.

DLMP Distribution Locational Marginal Prices.

DSO Distribution System Operator.

ENTSO-E European Network of Transmission System Operators for Electricity.

EV Electric Vehicle.

GSHP Ground-Source Heat Pump.

ICEV Internal Combustion Engine Vehicle.

LFM Local Flexibility Market.

LV/MV/HV Low/Medium/High Voltage.

NCPC Network Coincident Peak Charges.

PV Photo Voltaic.

QoS Quality of Service.

RTP Real Time Prices.

ToU Time of Use.

TSO Transmission System Operator.

1

INTRODUCTION

1

1.1. BACKGROUND

To reduce anthropogenic greenhouse gas emissions, we need a global transition to renewable and emission-free energy sources [1]. One of the main pillars of this transition is the electrification of energy end-uses, such as transportation, heating, and industrial processes. Simultaneously, the electricity to satisfy the energy demand of these end-uses is increasingly produced by intermittent renewable energy sources, especially wind and solar. This means that the size of the electricity demand and generation peaks is increasing.

This increase in electricity flow peaks can lead to overloading of the electric network, which was not designed for this situation. When most of the current network infrastructure was built, electricity was generated in large power plants based on coal or gas, which could be scheduled as needed. Moreover, aggregate demand was more stable and predictable, with shallower peaks. This is no longer true with the transition to new electric end-uses and intermittent generation. In this situation, the network limitations may become a bottleneck for the further development of the energy transition.

In this thesis, "congestion" in electric networks is defined as a situation where load flows, without further interventions, are expected to exceed the required safety margins of network equipment. Currently, in the Netherlands, large parts of the grids are already considered to be congested (Figure 1.2)[1]. To resolve this problem, different solutions can be applied at different time scales (see Figure 1.1). In the long run, network planning can prioritize upgrading the network capacity in congested areas such that higher electric currents can be transmitted and distributed to these. Moreover, large demand centers like electrolyzers and data centers can be built close to supply centers of renewable energy like wind and solar farms with dedicated, short connections between them. Moving closer to the near term, these solutions are not applicable as they have long lead times and high capital requirements. It is not possible to upgrade the grid at the required pace and in all potentially congested areas at once [2]. Thus, further solutions are required which can be applied to the existing network infrastructure.

Luckily, many new electric end-uses also have a high degree of flexibility: EVs often only need to be charged to a certain minimum state-of-charge overnight and do not need to charge right after connecting to the charger. Heat pumps can pre-heat houses during the day rather than in the evening when there is a more significant

[1] https://capaciteitskaart.netbeheernederland.nl/

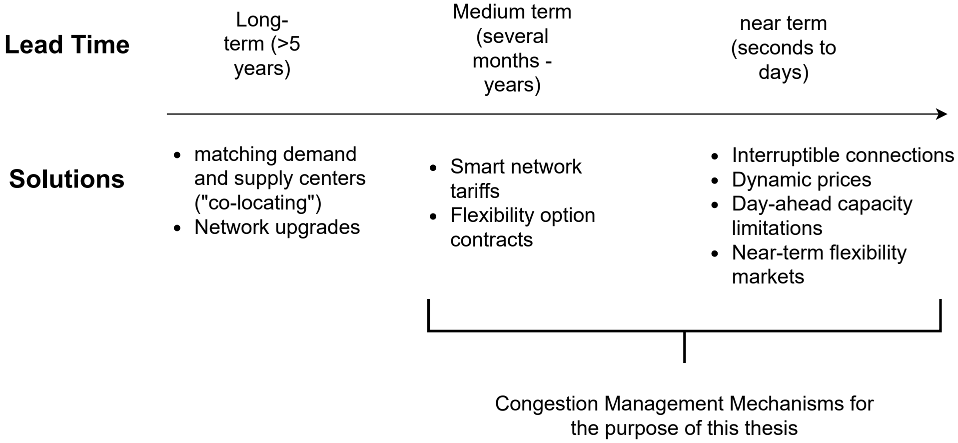

Figure 1.1: Solutions to network congestion at different time scales.

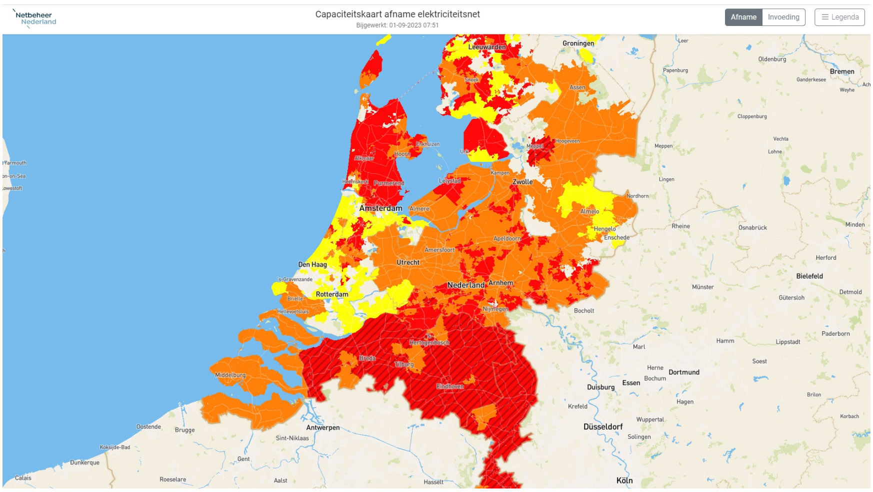

Figure 1.2: Map of congested areas for consumption in the Netherlands. Source: Netbeheer Nederland, 2023. No color: "transport capacity available", yellow: "limited transport capacity available", orange: "No transport capacity available for the time being pending the outcome of the congestion management study", red: "No transport capacity available: congestion management cannot be applied", red shaded: "no capacity available, congestion management fully used".

peak in demand. Industrial processes may be flexible in ancillary processes like steam and heat generation [3]. To use this flexibility, the end-use devices have to be controlled or incentivized by a mechanism such that their power consumption is scheduled to avoid network overload but can still make use of the availability of fossil-free power sources. These enabling mechanisms are called "Congestion management mechanisms." in this thesis.

1.2. CONGESTION MANAGEMENT MECHANISMS, NETWORK TARIFFS, AND RETAIL RATES

As mentioned above, in this thesis, "congestion management mechanisms" are understood to be a set of contractual, financial, and technical mechanisms to prevent congestion in electric distribution networks. This definition includes both *preventive* long-term contractual measures aimed at lowering the incidence of congestion in general and *reactive* measures that respond to a concrete expectation of a specific congestion situation in space and time. This differs from other interpretations of the term, which may consider congestion management to only refer to reactive measures taken when congestion is already expected to be imminent.[2] However, both preventive and reactive mechanisms deal with the same problem and can complement each other.

Under this definition, network tariffs that give longer-term (on the scale of months or years) price signals are also considered to perform congestion management. These tariffs are regular payments charged by the network operator for network usage. Their primary purpose is to recover the costs of building and maintaining the network. In addition, they can also be set in ways that stimulate more efficient usage of the network. If they do so, they are called "smart network tariffs" throughout this thesis. This relation is depicted in Figure 1.4 (taken from Chapter 2).

This thesis mainly concerns distribution networks operating at low and medium voltage. The tariffs for these distribution networks are only part of the electricity bill of an end-user. In addition, customers also pay for other components, as shown in Figure 1.3: the energy procurement cost at the market, (high-voltage) transmission fees, taxes, and other surcharges, and renewable energy subsidies. Retail companies

[2]For example, in the Netherlands, the regulator seems to imply that congestion management ("congestiemanagement" in Dutch) only refers to mechanisms that deal with imminent congestion rather than preventive mechanisms. This observation can be inferred from the network code and was pointed out to us by employees of network operators.

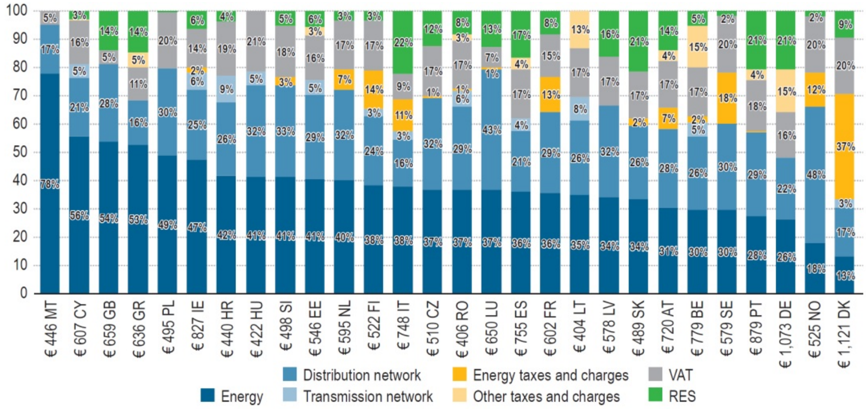

Figure 1.3: Electricity price components in European countries. Numbers below the x-axis refer to the total yearly cost of electricity for household consumers. Source: JRC Distribution System Operators Observatory 2018 [4].

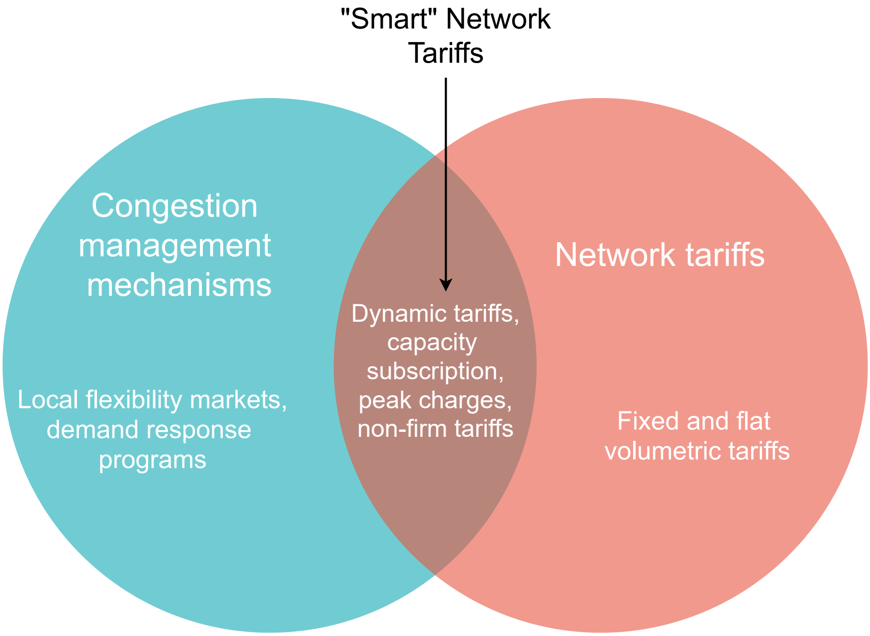

Figure 1.4: Congestion management mechanisms and network tariffs

usually bundle these components into one final electricity retail rate, which can be designed differently. For example, it can be a flat price per kWh consumed, a Time-of-Use rate with a fixed price schedule, or a dynamic real-time price (RTP) based on wholesale market prices for generation with additional charges for the other components. We investigate different rate structures in Chapter 6.

1.3. STAKEHOLDERS AND RESPONSIBILITIES

To clarify the roles and responsibilities of the different relevant stakeholders for this thesis, Figure 1.5 shows a map of them. Starting from the bottom: End-users in the distribution grid can have flexible and inflexible loads. They must pay network tariffs to the network operator and retail rates to their electricity retailer for their electricity consumption.[3] On top of that, the network operator may have other contractual mechanisms to resolve congestion. These can be as contracts with individual end-users, in particular, to shift their flexible loads to flatten peaks. Or, they can be with an aggregator or retail company, which has mechanisms to control flexible end-user loads and deliver the peak reductions the network operator desires.

The retailer purchases and sells electricity on markets. These can be the day-ahead and intraday markets or long-term bilateral agreements. The relevance of these markets enters this thesis in the form of wholesale prices. We assume that the retailer or aggregator can pass through the wholesale price signal directly to the consumer, either for flexible loads only (Chapter 4) or as a dynamic retail rate for the complete household connection (Chapter 6).

Lastly, the national regulator is responsible for regulating the network operators, among other responsibilities.[4] As part of this responsibility, it has to assess whether the investments and revenues of the network operator from tariffs are adequate [5, 6]. Furthermore, network tariffs must fulfill certain regulatory principles, which we investigate in Chapter 4. The regulator has to ascertain whether the tariffs do this satisfactorily.

[3] In practice, these are mostly integrated into one bill with other charges that the customer pays to the retailer, as described in the previous section.

[4] It is also responsible for oversight of electricity markets, but we do not focus on that aspect in this thesis.

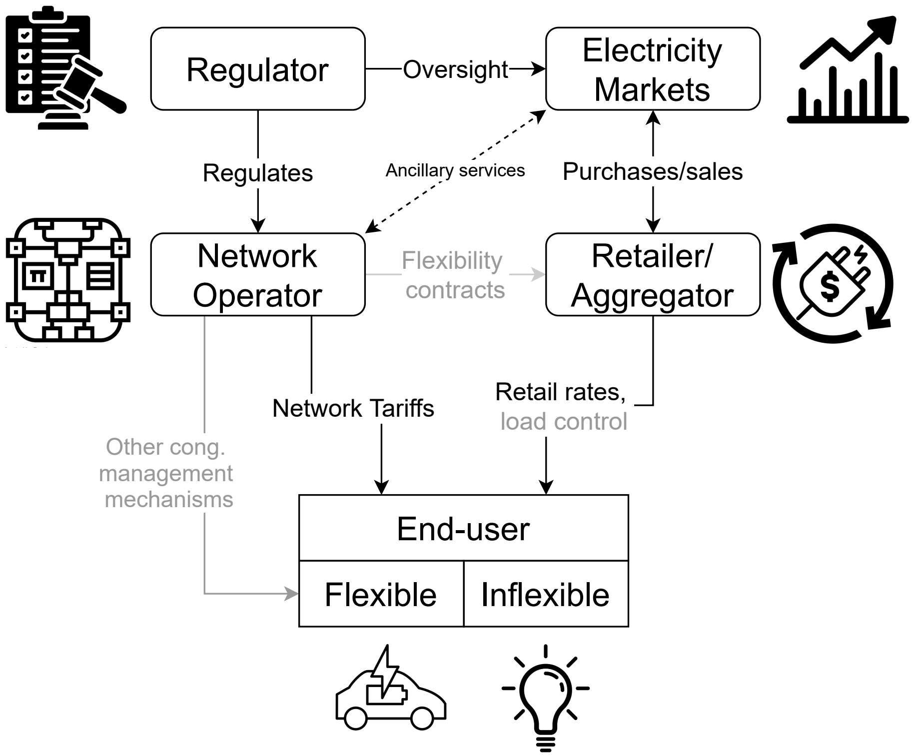

Figure 1.5: Map of stakeholders and responsibilities. In black: stakeholders and relations always in place in unbundled and regulated electricity systems. In gray: additional optional contractual mechanisms for flexibility procurement. Icons from https://thenounproject.com/

1.4. OUTLINE: RESEARCH QUESTIONS AND METHODOLOGIES

The motivating question for this thesis was: *How can a cost-efficient transition to renewable and carbon-free energy sources be enabled in the residential sector?* The focus on the residential sector was chosen as it is one of Europe's largest sources of GHG emissions. According to Eurostat, "In 2021, households represented 27% of final energy consumption".

An initial investigation of the literature showed that one main pathway for decarbonizing the residential sector is the electrification of residential energy end-uses (such as heating and transportation) and an accompanying switch of electricity generation to renewable sources.[5] This means that deploying high-power flexible devices such as EV chargers and heat pumps needs to accelerate significantly in the coming years [10–12]. However, the newly created load peaks of these devices may overload the current electric network infrastructure, and networks may become a bottleneck to further progress in the energy transition. This led us to the main research question for this thesis:

How can congestion in electric distribution grids be avoided by controlling flexibility of new end-use devices?

To answer this question, we followed a chain of sub-questions. The first of these were:
Which options for managing congestion of electrical loads have been proposed, how do they relate to each other, and which risks are present in each?

We answered these questions using a literature review and a design framework analysis of congestion management methods in Chapter 2. We identified risks and qualitatively reflected on the influence of different design choices in congestion management on the performance of the proposed mechanisms. We found that Local Flexibility Markets are often proposed as a solution, but we consider them vulnerable to strategic behavior when applied at neighborhood-level scales. Thus, in Chapter 3, we demonstrated potential market failures in these proposals in a simplified toy model.

Based on the preceding analysis, network tariffs emerged as a promising tool for preventive congestion management. However, using this tool would require a comprehensive change to the network tariff structures in most European networks. This is complicated because such a change will lead to differences in how much users must pay to use the network. Some will have to pay more and others less under a new tariff. Thus, the discussions surrounding these changes are often contentious. We also found that these discussions are often not based on objective reasoning but on individual preferences and subjective impressions. Thus, the next major sub-question for this thesis was:
How can the performance of new network tariff proposals be analyzed objectively?

To answer this question, we developed an analytical framework to formalize the

[5] Heating transitions to heat networks and changes to other energy carriers, such as hydrogen, will likely also play a major role in the energy transition (see, e.g., [7–9]) but were considered out of scope for this thesis.

feedback between network costs and tariffs in Chapter 4 and proposed indicators for tariff objectives that can be computed within this framework. We demonstrated the use of this framework with a simulation model of a residential neighborhood with flexible loads in which different tariffs are applied. Based on this analysis, capacity-based tariffs are particularly promising candidates for high-performing tariffs based on their cost-reflectiveness and ability t0 perform preventive congestion management.

During this PhD project, new tariffs and congestion management were also becoming more urgent in national regulatory discussions in Germany and the Netherlands. In Germany, the national regulator Bundesnetzagentur (BNA) proposed a new mechanism that allows the network operator to curtail new flexible loads down to a capacity of 4.2 kW during congestion. In the Netherlands, the regulator proposed a similar method, only that the curtailment has to be announced on the day ahead, before closing of the day-ahead market. Interestingly, these methods and the capacity subscription tariff investigated in Chapter 4 are all based on limiting the available capacity for flexible loads. The main difference between them is the timing of the announcement of the capacity limitation. As all of these methods are focused on managing congestion through a limitation of network capacity, this led us to focus on the following questions next:
How do the costs of different capacity-based congestion management approaches compare, and how can their performance be improved?

We investigated this question using a simulation model that optimized the scheduling of flexible loads under the different capacity-based approaches in Chapter 5.

After we tackled the issue of how to avoid network congestion with the help of network tariffs and congestion management mechanisms, we wanted to expand our analysis to include household investment decisions and another part of the final electricity rate: the generation-related component. This was done to gain insights into how different designs of final electricity rates may influence household decisions, costs, and network peaks. Thus, the research question for the last chapter of this thesis was: "*How do electricity retail rates and network tariffs influence investments and dispatch in residential energy usage?*"

To analyze this, in Chapter 6, we employed the open energy system optimization model Calliope to model energy usage in residential neighborhoods. In the model, we implemented different forms of retail rates and network tariffs as inputs for electricity and capacity prices. Additionally, we applied a constraint on the total carbon emissions of the complete neighborhood, which was varied to simulate different decarbonization levels.

In Chapter 7, we list our findings regarding the research questions posed above and additional insights gained, as well as summarize recent regulatory developments. Chapter 8 concludes this work with a summary and reflections on policy advice and future research directions.

1.5. CONTRIBUTIONS

In addition to the practical insights into congestion management and network tariffication, this thesis also contributes to scientific theory and methodology in the field in several ways: firstly, in Chapter 2, we add a conceptual contribution in the form of an overarching design framework of congestion management methods. Network tariffs, flexibility markets, and direct control methods had mostly been considered in isolation before, disregarding how they might be interchangeable and how fundamental design choices may influence the outcomes.

In Chapter 3, we develop conceptual pathways that can lead to market failures in local flexibility market proposals from the literature. We also contribute a toy model to illustrate these pathways.

In Chapter 4, we contribute a proposal for an assessment framework of network tariffs. Previously, regulatory objectives of tariffs have often been mentioned and investigated in idiosyncratic ways. Still, they had not been placed in a theoretical framework to assess performance holistically and objectively. The framework given in this thesis can serve as a starting point for such a holistic framework. We also developed a simulation model for assessing network tariffs, which is available publicly on GitLab[6].

In Chapter 5, we provide a comparative assessment of capacity-limitation-based congestion management mechanisms and a publicly available model for this assessment[7]. Furthermore, we develop the main recommendation for an efficient and cost-reflective network tariff of this thesis: a combination of subscriptions for both firm and non-firm network capacity.

Lastly, in Chapter 6, we contributed to an existing modeling framework using the energy system model Calliope to optimize the decarbonization of a single

[6] ANTS (Assessment of Network Tariff Systems)
[7] ANTS-Capacity Subscription

neighborhood with different network tariffs and retail rates. Calliope had not been used for this purpose previously, and we made changes to the input assumptions of the model to implement different retail rate forms (flat, ToU, dynamic) and network tariffs (capacity, volumetric, fixed).

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2

Congestion Management in Electric Distribution Networks: Smart Tariffs, Local Markets and Direct Control

This chapter reviews different congestion management methods, their benefits, and risks. This review provides the starting point for our analysis of how flexibility in distribution grids can be used to avoid congestion from new high-power loads.

The chapter was originally published as R. J. Hennig, L. J. de Vries, and S. H. Tindemans: "Congestion management in electricity distribution networks: Smart tariffs, local markets, and direct control" [1] in Utilities Policy 85 (2023), p. 101660. ISSN: 0957-1787. DOI: 10.1016/J.JUP.2023.101660. Spellings and formatting have been standardized throughout this thesis.

Abstract

Increasing peaks from high-power loads such as EVs and heat pumps lead to congestion of electric distribution grids. The inherent flexibility of these loads could be used to resolve congestion events. Possible options for this are smart network tariffs, market-based approaches, and direct control of flexible loads by the network operator. In most instances, these approaches are looked at in isolation, without considering potential connections and trade-offs between them. In this contribution, we aim to bridge this gap by presenting an overarching design framework for congestion management mechanisms. We classify proposals based on design choices and qualitatively discuss their benefits and risks based on an extensive literature analysis. As there is no one-size-fits-all solution, we map possible risks and discuss the pros and cons of different mechanisms for various problem types. We caution against using market-based mechanisms for local congestion, as they can be susceptible to undesired strategic behavior of market actors.

2.1. INTRODUCTION

Background

More Distributed Energy Resources (DERs) like PV cells, EVs, batteries, and heat pumps are connected to the electric grid daily. These resources help to decarbonize the energy system. Still, they also bring new challenges for electric distribution networks: high power usage or feed-in from these sources can lead to overloading or voltage problems, also called network congestion.

Upgrading the network to the point where it could accommodate all these new loads and generators is not an option: it would be very costly and likely not be possible at the required pace. However, it is also unnecessary: In many cases, these new DERs are highly flexible: EVs, batteries, and heat pumps do not need to run at a specific time, but instead, they need to fulfill an energy requirement over a time interval. PV feed-in can be curtailed or absorbed by batteries and other uses. Therefore, it is possible to flatten the peaks created by these energy resources and ensure that the total load stays within safe network limits. Thus, a much more efficient solution is to resolve grid congestion more smartly by using this flexibility to flatten network peaks [2].

The main options for doing this are: making network tariffs smarter, using local markets for redispatch, or directly controlling loads that sign up for demand response programs. In the latter two cases, the congestion management method is added to the existing network tariff, which can create confusion around the relationship between congestion management and network tariffs. In general, the primary function of tariffs is to allocate the costs of building and maintaining the network to its users [3, 4]. As a secondary function, these tariffs can incentivize more intelligent network use. In this case, they are also called "smart" tariffs. For congestion management, the problem is how to make the best use of flexible loads to remove congestion. This relation is shown in Figure 2.1.

These methods are mainly discussed in isolation, and how they relate is often unclear. The lack of clarity may lead to uncertainty and delays in preparing appropriate congestion management strategies. These delays can be costly: failing to anticipate what is needed to manage congestion may lead to forceful curtailment of loads, overload of grid equipment, or inefficient solutions. Network operators, regulators, and other stakeholders need to understand the possible solutions to decide on their strategies to be prepared for a future where congestion is becoming much more common.

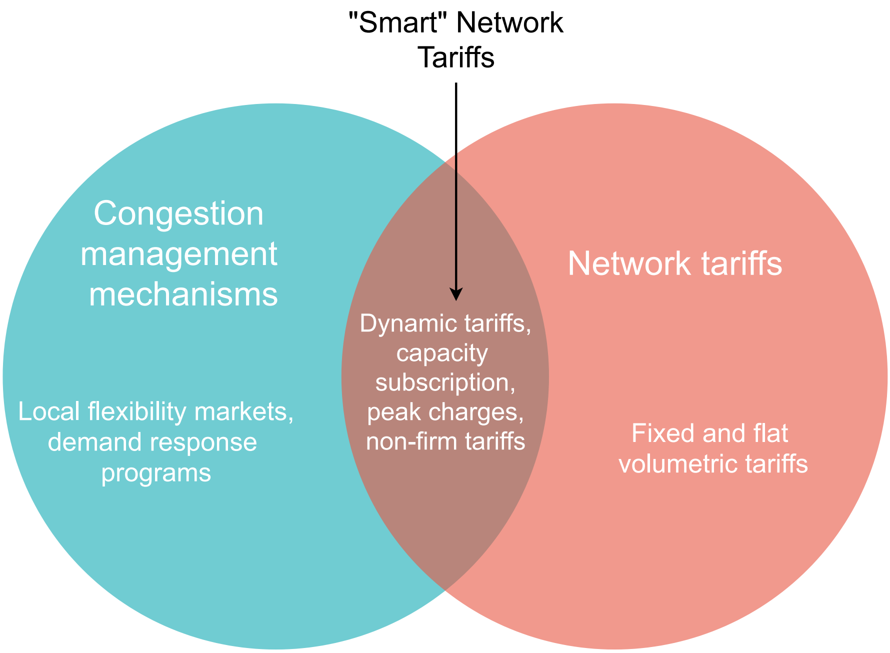

Figure 2.1: The relation of congestion management and network tariffs

Contribution of this chapter

In light of these challenges, the contributions of this chapter are:

1. To structure the literature by investigating the design choices of congestion management (CM) approaches. Based on the design choices, we divide CM methods into four families: static and dynamic access prices, Local Flexibility Markets (LFMs), and direct control methods.[1]

2. To qualitatively discuss the benefits and drawbacks of these types of methods.

3. To consider the influence of design choices on performance and risk.

The leading search terms to identify relevant literature were "congestion

[1] Standard network tariffs belong to the static access price category, while smart tariffs can integrate aspects of dynamic aspect prices and direct control.

management," "network tariffs," "dynamic tariffs," "flexibility markets," "demand response," and "load curtailment". We also used snowballing from these articles and web searches to identify further relevant literature and industry reports of related stakeholders. These articles were synthesized to identify the possible design choices at a higher level and reflect on the impact of these design choices on performance and risks.

The questions addressed in each section are as follows. Section 2.2: What types of congestion problems occur in electric distribution networks? Section 2.3: What are the required objectives of a successful congestion management (CM) mechanism? Section 2.4: What are the crucial design choices for CM mechanisms? Section 2.5: Which are the main proposals for CM mechanisms, and how can they be classified based on their design choices? Section 2.6: What are the benefits and drawbacks of each method concerning the objectives, what risks exist, and how do design choices influence performance and risks? Section 2.7 concludes the chapter.

2.2. CONGESTION PROBLEM SPECIFICATION

There is a wide variety of congestion problems regarding their spatial localization, timing and predictability, type of network limitation, and external circumstances. These parameters strongly influence the types of solutions that apply to the problem. We give a brief overview of the different options.

In terms of the spatial location of network problems, the options range from highly localized to spread out over larger areas:

- LV feeders or transformer stations for up to about a hundred households,
- MV feeders or transformer stations for hundreds to thousands of households,
- HV transmission cables or transformer stations for 10,000 or more households,

For timing and predictability of the problem, the main question is: Does the congestion problem occur at a relatively regular and, on average, predictable time or at random times? In the former case, it is likely related to a corresponding increase in firm loads during peak hours in the network, e.g., the evening hours when many people come home from work. In the latter case, it is likely related to external factors such as outages and maintenance events, low wholesale energy prices, or extreme weather events. The Council of Europen Energy Regulators [5] distinguishes these two types as: "structural" congestion which is regular and predictable long in advance, and “sporadic” congestion which is irregular and predictable only in the near term or near real-time.

In general, the predictability of the problem may be better for larger spatial areas, as random fluctuations tend to average out over larger samples. Thus, larger MV substations may be associated with a higher degree of structural congestion and a lower degree of sporadic congestion relative to smaller LV-network feeders, where overload can occur due to relatively few EVs charging at full power. Nevertheless, this general tendency does not rule out predictable congestion of highly loaded LV feeders, e.g., in the case of industrial sites with well-known schedules or residential areas with excessive solar PV generation.

Regarding the type of network limitation, we focus here on mechanisms that deal with the thermal load limits of network equipment. This limitation is often the most pressing one, and the one for which most proposals have been made, according to Anaya et al. [6]. Other types include voltage and reactive power limits [6, 7].[2] A further distinction for thermal load limits can be made by the “direction” of congestion: Is it caused by too much load on the feeder or too much feed-in?

Dronne et al. [8] review several external circumstances and how they may impact the design of new CM solutions. In addition to the type and depth of congestion, they consider the existence of and need for new flexibility resources, the organizational structure of network operation (e.g., number of customers per DSO and interactions between DSOs with each other and the TSO), the regulatory landscape and pre-existing approaches for CM. All of these may influence the choice of the solution.

Unfortunately, data on the specifics of congestion problems is hard to find. At the European level, the JRC ([9]) and the European Commission [10] have undertaken and published data-gathering exercises from DSOs across Europe. These reports include aggregate service quality measures like SAIDI and SAIFI. Unfortunately, they do not include detailed information on existing and anticipated congestion problems: their type and depth, localization, and timing. This information would benefit academic and regulatory purposes to develop fit-for-purpose solutions.

2.3. Objectives for congestion management

The main objective of CM is to flatten network peaks such that all network constraints are respected. However, there are also several related objectives. These

[2]Voltage constraints may be more relevant in rural feeders, especially with PV penetration [**JRC104718??**].

include reliability, social cost minimization, non-discrimination, management of complexity, and allowing the use of flexibility for other purposes.

Reliability. Thermal load limits and voltage constraints of all network nodes should not be exceeded. Ideally, this should always hold, though, in practice, minor violations of thermal load limits and power quality can be acceptable [11].

For this objective, it is necessary to take a holistic perspective of congestion in space and time. A mechanism that merely moves congestion from one point in space and time to another (also called *displacement* or *spillover*) or does not fully resolve it would not be reliable.

Social Costs. This objective concerns the costs of complete congestion removal. In some mechanisms, the network operator has to bear these costs, while in others, it obtains "congestion rents" (e.g., in dynamic network pricing). A societally cost-efficient mechanism will remove congestion by shifting or curtailing those loads with the lowest willingness to pay at a given moment. These are typically EVs or heat pumps with much slack in their constraints. Furthermore, the mechanism should only lead to network costs around the marginal cost of shifting these loads to another time. This marginal cost can often be related to the wholesale price difference between the congested times and the next-lower price time steps.

If prices are significantly higher than that, the network operator overpays flexibility providers or charges excessive congestion rents (depending on the mechanism, see Section 2.4). The first case is problematic because these expenses must be recovered from the general user base. In contrast, the second case is problematic as it means that network capacity would not be used to the extent possible when it is highly desired. Ideally, congestion should be removed by shifting only those necessary loads with the lowest cost of moving and setting prices close to their marginal cost of shifting.[3]

Non-discrimination. On average, the congestion management mechanism should not treat network users differently. However, since different network areas are congested to different degrees, some form of discrimination is inherent to the problem. Discrimination can be mainly due to price differences, where consumers in congested areas pay higher prices on average, or quality-of-service (QoS) differences. This situation occurs because some CM approaches are based on limited curtailments of flexible loads signed up for contracts with interruptible connections.

[3] We refer to shifting loads here as this may be the most common form of congestion removal, but avoidance of load or generation (i.e. curtailment) is also possible.

Users with such agreements in congested areas will be curtailed more often than in non-congested areas.

One possibility to resolve the dilemma could be to tie the price discrimination to the QoS discrimination: users of flexible loads that are curtailed more often could receive compensation through the CM mechanism accordingly.

Complexity. A common practical problem is that elaborate solutions are often difficult to implement and understand for users, which can hamper their effectiveness in real-world conditions, even when they are theoretically highly efficient. Therefore, CM mechanisms should be easy to implement and understand for all participants. The rules and parameters of the mechanism should be transparent and be communicated to users. It should also build on existing network codes and ensure that new functions are thoroughly tested and verified to work under real-world conditions at the required scale.

Flexibility for other purposes. If possible, the congestion management mechanism should not prevent flexibility providers from making it available for other purposes as well, such as services for the Transmission System Operator (TSO) and Balance Responsible Parties (BRPs) portfolio management [12, 13][4].

Significant in this regard is the further enhancement of TSO-DSO coordination. As analyzed in [14], TSOs and DSOs often have overlapping needs for flexibility products. Some of these may be satisfied by common market mechanisms, while others may have to be satisfied by non-market-based mechanisms, e.g., due to low liquidity. Either way, it is essential to ensure that mechanisms activated by the TSO or DSOs do not adversely affect the operation of the other party (DSOs or TSOs, respectively). Many projects are currently studying this issue in the European context.[5]. For further literature on the topic, we refer to [14].

[4] One option to fulfill this objective, is to leave some headroom between the scheduled flexible loads and the binding network constraint. For EVs, charging can be scheduled to up to 80-90% of the rated transformer capacity. This practice allows flexibility in up and down directions for additional purposes at the TSO level or real-time portfolio balancing. It also has the added benefit of reducing operational uncertainty and costs of losses and transformer aging [11] for the DSO, as these are higher when the transformer is loaded near 100%.

[5] See CoordiNet, SmartNet, INTERRFACE and OneNet, among others

2.4. DESIGN CHOICES OF CONGESTION MANAGEMENT MECHANISMS

There is a large variety of different proposals for CM mechanisms. However, many studies or reports only present one proposal without discussing how choices in its design would influence the outcomes. Thus, in the following, we want to answer the question: What are the fundamental decisions for CM mechanisms?

Note that our primary focus is on the situation in Europe. In the EU and the UK, electricity systems have been subject to “unbundling” since the late 1990s. The formerly integrated utility companies for electricity delivery have been split up during this process. Transmission and distribution system management is now handled by independent system operators (TSOs and DSOs), while power generation has been liberalized and opened up to market competition [15]. For reference, we also include considerations for the vertically integrated utilities, operating in North America and other parts of the world. Not all design choices discussed here apply in all contexts, depending on the market design and the regulatory environment. [6]

2.4.1. LOAD/FEED-IN CONTROLLING PARTY

Ultimately, the DSO ensures stable electricity delivery through the network which avoids dangerous network overload that could cause equipment failure. However, there is a question of how this control is achieved. The DSO has three options. The first is to directly control loads or curtail generator/battery feed-in of end-users. The second is to let end-users control their loads and generators. In this case, the DSO needs to give contractual specifications and financial incentives for users to maintain control to stay within network bounds. This practice particularly applies to large, industrial, or commercial consumers [17]. The third is to have contracts with aggregators to control end-user loads or generators. The contractual specifications and financial incentives are then agreed upon with an aggregator that handles many individual end-user loads rather than directly with the end-users.

2.4.2. DSO POSITION: OFFER OR BUY-BACK OF NETWORK ACCESS

This design choice concerns whether the required control is included directly in the network access conditions or whether network access is offered without tight

[6] Furthermore, we consider only contractual forms of CM, not technical network reconfiguration, as discussed by [16]

limitations (i.e., in a way that may lead to network overload) and then effectively "bought back" by the DSO. We call this the "DSO position" and distinguish between:

- Offer: In unbundled electricity systems, the DSO already has contractual agreements that specify network access conditions and tariffs [4][7]. Thus, incentives to reduce network stress can be included in the access conditions offered by the network operator. These incentives can be part of the standard network tariff or separate agreements for flexible loads [18] and generators [19]. These incentives may not always be sufficient to remove congestion, especially in static tariffs. A remedy like buy-back approaches or curtailment may be necessary in these cases.

- Buy-back: The DSO asks end-users for a "buy-back" of network access rights. There is a two-stage process to determine the final network access conditions. The DSO offers network access under its general access rules in the first stage. In the second stage, it estimates what is needed to resolve network congestion and pays users or aggregators to deliver load (or feed-in) shedding services to resolve the congestion.

The Universal Smart Energy Framework (USEF), proposed by the USEF foundation [20], distinguishes similar perspectives from the point of view of the flexibility provider: flexibility that is steered through the access conditions of the DSO (in conjunction with other charges) is called "implicit flexibility", whereas a buy-back of network access is an example of "explicit flexibility" trading. The latter can also be traded for purposes such as TSO network management or portfolio optimization [12, 20].

2.4.3. END-USER POSITION: APPLIED LOADS, RELATION TO TARIFF AND CONSENT

Similar to the DSO position, we can also look at contractual options from the end-user's perspective. CM mechanisms may be distinguished by the devices to which they apply. Options are:

- Applies equally to all loads and distributed generation.

- Targets flexible loads like EVs and heat pumps specifically. In practice, this

[7]Note: Similar contractual agreements exist for vertically integrated utilities. However, in this case, they are not just for distribution network access, but for all parts of the power provision chain: generation, transmission, and distribution.

requires the installation of a separate meter for these loads to be able to make a distinction in the tariff.[8]

- Distinguishes between feed-in and take-off (i.e., "up" and "down" regulation in analogy to balancing at the transmission level).

Secondly, they can be distinguished by the relation between the CM mechanism and the default network tariff.[9] The CM mechanism can replace the default tariff for these loads or apply in addition to the default tariff.

Thirdly, an essential choice for coverage of the mechanism is whether users can opt into the mechanism or not. We call these options for participation "by consent" and "by default."

2.4.4. PRICE FORMATION

There are two possible options by which prices for network access or buy-back can be set. The first one is regulated, where the DSO sets prices for network access and congestion-related buy-back of network access in agreement with the regulator. The regulated prices can be static and fixed in advance or dynamic and responsive to network condition forecasts (see Section 2.4.5). This approach is the most common for "Offer"-based CM approaches.

The second option for price formation is "auction-based." Auctions are used mainly in "Buy-back" market-based proposals but can also occur in some "offer" based proposals where the DSO auctions off network capacity [18, 21]. There are different formats by which the price in an auction can be set. The most commonly used ones are:

- Pay-as-bid [6, 22–26]: market participants bid for flexibility requests from the DSO. The DSO selects sufficient bids to remove the congestion problem and pays each accepted bid exactly at its bid size. Note that this may create an incentive to bid above marginal costs for the flexibility provider, as long as they anticipate their bid is still accepted [27, 28].

[8]This is envisioned in a current proposal by the Bundesnetzagentur, the German regulator for the network.. It foresees the installation of remotely controllable load-limiting devices, through which the network operator can curtail flexible loads to a maximum of 3.7 kW.

[9]In the North American context, the network price is typically integrated with the energy price itself. Thus, these considerations apply similarly to the complete energy price, not just the network tariff.

- Pay-as-cleared [6, 26]: Each market participant is paid the price of the marginal bid the DSO accepted.
- Dutch reverse auction [6]: Market participants do not submit bids in this type of auction. Instead, the DSO starts with a small offer price for flexibility, which gradually increases until market participants accept the bid.
- Vickrey-Clarke-Groves (VCG) auctions and modifications thereof [28]: In VCG auctions, participants submit sealed bids, meaning that the bids of other participants are not known. The market is cleared to minimize costs for the DSO, and each participant is reimbursed proportional to the benefit they bring to the system (see [28] for further details).

2.4.5. Time frame

CM methods differ regarding the time frame for determining network prices and access conditions. The options are:

- Long-term: e.g., monthly, seasonal, or yearly.
- Day-ahead or near-term (several hours ahead).
- Near-real time.

An important aspect here is the timing of determining the network access conditions relative to the wholesale energy market, especially the day-ahead market. This issue is particularly relevant for aggregators and other energy service companies active in the wholesale market on behalf of their customers. It may be easier for them to optimize their portfolio by knowing the network access conditions before trading on the wholesale market, as they can include the network constraints in their trading decisions. When network access conditions change after these entities have traded on the wholesale market, they may require intraday and balancing markets.

2.4.6. Spatial variation

In addition to temporal variation, there can also be spatial variation in network access conditions. The main advantage of using localized CM options is that network congestion can be targeted efficiently. On the other hand, introducing charges based on location introduces some degree of discrimination in network access (see [4]) and may adversely affect users in congested areas.

The spatial variation can also have varying degrees of granularity. In analogy to the congestion problems themselves (Section 2.2), the main options are:

- Whole network, transmission level
- Larger sub-zones of the network, e.g., behind the same HV/MV transformer station
- Neighbourhood level (several LV feeders)
- Single LV feeder level

2.4.7. FURTHER PRODUCT SPECIFICATIONS

There are many implementation details at a lower level of differentiation between different methods. We use the summary term "product specifications" for these.

Some of these specifications apply to all kinds of CM methods, while others are particular to the type of CM method. For the common ones, we identified:

Commodity: Network access conditions can be specified in terms of either the maximum capacity of network access in kW, energy transported through the network in kWh, or the cost of the connection itself[10]. In the case of capacity, there can be different bases for how it is determined. It can be the measured peak power at a user connection in a given billing period [30, 31], a contracted specific amount of network capacity (with a penalty for exceeding this amount) [32, 33], or the utilized capacity of a user at the times of highest coincident network peaks [34]. It is also essential to define the time over which power usage is averaged to determine network capacity usage, e.g., 5, 15, or 60 minutes. For example, a kettle or a microwave may have a relatively high power consumption of 1 kW over 3 minutes. This results in a total energy usage of 0.05 kWh. Over a 5-minute interval, this would be an average power usage of 0.6 kW, over 60 minutes, it would only be an average use of 0.05 kW.

Tiered pricing: This method refers to a price variation per unit of commodity based on *quantity* used, which can be implemented for energy and capacity. E.g., the price per kWh may increase (or decrease) when total yearly consumption exceeds 2000 kWh and then again at 4000 kWh, and so on [35, 36]. Similarly, the cost per kW of network capacity access may increase at 2 kW, 4 kW and so on [37, 38].

[10] The connection cost may vary by location to incentivize investments in less congested areas and recover costs for network upgrades in more congested areas [29]. However, this is outside the scope of this review as we are concerned more with operational congestion management, not investments.

Firmness: Connection agreements and flexibility products can be firm or non-firm. Firm means a guaranteed fixed network capacity is available for the end-user. In non-firm agreements, the network access capacity is dynamically dependent on the network state and may be reduced during network congestion. In this latter case, specifications may also include the maximal allowable number and duration of load reductions. Examples of non-firm products include option trades in buy-back-based proposals (see, e.g., [22, 39]) and activation of direct-control measures in [40].

In addition to these common ones, some specifications apply only to certain classes of CM mechanisms. These are discussed in the next section, where we review the different classes.

2.5. Review and classification of congestion management mechanisms

In this section, we review CM proposals from the literature. We use a classification based on two high-level design variables discussed in the previous section to structure the review. Firstly, the load-controlling party: DSO or aggregator/end-user (the interaction and contracts between aggregators and end-users are not considered here). Secondly, the DSO position is "offer" or "buy-back" for schemes not based on DSO control. Sorting CM mechanisms by these choices leads to 3 distinct categories: Network access prices, Local Flexibility Markets (LFMs), and Direct Load Control (DLC) schemes (Figure 2.2).

This classification was chosen because these categories are also commonly discussed in the literature as separate strands. A different distinction would also be possible, e.g., by time frame or commodity. However, different time frames and commodities are often discussed together in the reviewed literature, while mechanisms from different categories in the proposed classification are not. The following subsections discuss the lower-level design choices of different variations in each category.

2.5.1. Network access price-based methods

This category includes all CM proposals based on charges for network access by the DSO to users. There is no buy-back within these mechanisms; by default, the DSO does not directly control user loads (except for emergency curtailment). The

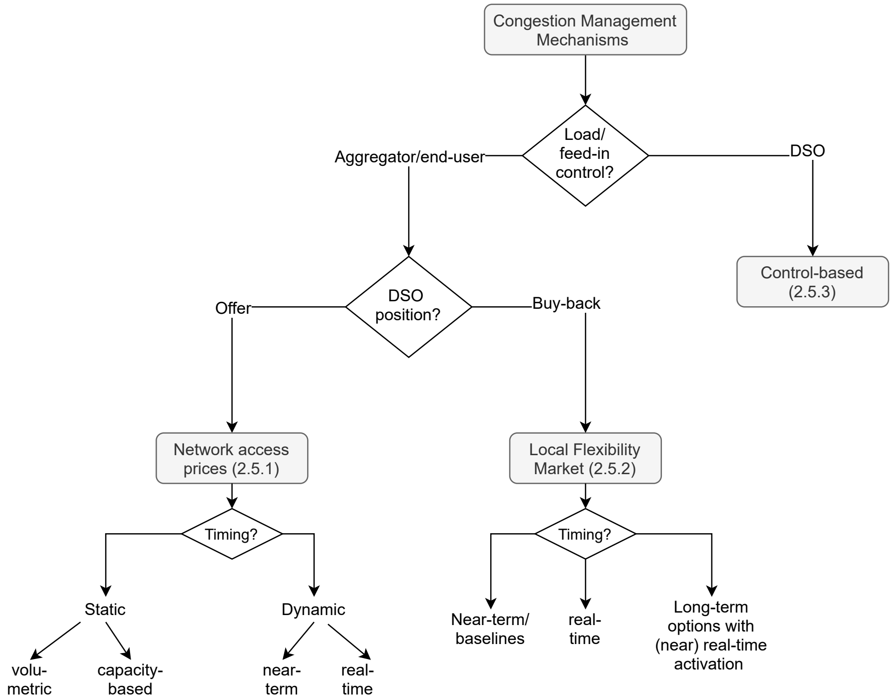

Figure 2.2: Classification of mechanisms

main distinction within this category is based on the time frame: network access prices fixed over the long term are also called "static tariffs", while those not fixed are called "dynamic tariffs".

STATIC NETWORK TARIFFS

Standard tariffs are periodically recurring payments the network operator charges for network use. Their primary purpose is cost-recovery for network-related activities [4, 41, 42]. However, these tariffs can also perform implicit congestion management. They are usually fixed over a billing period. All of the commonly proposed variations have the following additional design variables in common: they use regulated prices, apply over a long-term time frame, provide firm access to the network (except for emergency curtailment), and do not distinguish between flexible and non-flexible loads. However, they can distinguish between load and feed-in of distributed generation [30].

Being static does not mean that the charges do not vary: in Time-of-Use (ToU) tariffs, charges can vary according to a fixed schedule by time of day or season. However, this time dependence is known in advance and does not change over the billing period.

The primary distinguishing design variable for static tariffs is the commodity on which the tariff is based [3, 4, 31, 41]:

- Energy for volumetric tariffs: a fee per kWh of energy delivered through the network.
- Measured peak capacity: a fee per kW for personal peak usage.
- Contracted capacity for capacity subscription tariffs: the end-user can choose different power levels (kW). Energy consumption up to the selected level is free or at a low price, while consumption above the chosen level is penalized [33, 37, 43].

[44] and [45] give an overview of the current static tariffs in European countries.

Dynamic tariffs

Dynamic tariffs are network access prices adjusted dynamically based on expected or observed network conditions. In contrast to static tariffs, we find much more variation in other design variables.

Critical Peak Pricing (CPP) [41, 42, 46]: In CPP, Network prices are increased for an expected significant peak in network load, e.g., on particularly hot, cold, or sunny days. The network operator sends an advance notice a few hours to a day before the price spike occurs. The price spike is added to the default network tariff and applies to all loads equally.

Network Coincident Peak Charges (NCPC) [34, 47]: In this approach, charges are based on the network-coincident peak, not the personal peak of the end-user. Instead of a single network peak, it might also consider multiple network peaks. Furthermore, the network operator may send an advance notice before expected peaks, making this approach similar to CPP. [11]

[11] To list this as a dynamic tariff may seem strange: the network access conditions and price per kW of peak contribution are actually fixed over the long term, so this approach could also be seen as a static tariff. However, the final payments under this scheme depend on when the highest network peak(s) occurs, which is only truly known at the end of the billing period and could theoretically change in real-time at any moment until then. Therefore, we favor the categorization as dynamic.

Distribution Locational Marginal Prices (DLMP) [7, 31, 48]: This approach is an extension of locational marginal pricing (LMP) for wholesale power markets to the distribution level. LMP refers to price differentiation of electricity at different high-voltage transmission grid nodes. It has been applied in North American Regional Transmission Operator (RTO) grids[12]. In North America, integrated utilities deliver electricity by owning assets across the electricity supply chain: generation, transmission, and distribution. Thus, the LMP refers to the complete delivery price of electricity, including generation, transmission, and distribution charges. In the European context, DLMP is sometimes meant to include only the locational network costs [47], and sometimes the sum of locational network costs plus the wholesale price of energy [16, 49, 50]. The term "dynamic network tariff" sometimes refers to only the network-specific part, without the wholesale price component [21, 50].

DLMP can be set near real-time [31, 48], a day ahead [16, 21, 49, 50], or at intermediate steps, e.g. a few hours ahead [48]. As can be seen from the cited publications, near real-time DLMPs are more commonly discussed in the North American context with integrated utilities. There, they apply to all loads equally and include the energy cost. The day-ahead proposals typically apply to the context of unbundled electricity systems with wholesale day-ahead markets. Here, they replace only the network tariff component and presumably only apply to flexible loads, which can be inferred from the mechanism in these publications, where the day-ahead network prices are agreed between network operators and aggregators.

Capacity or "Double" Auctions [18, 51, 52]: In this approach, end-users or aggregators of flexible loads submit a bid curve with their willingness to pay for energy. The network operator can aggregate all these bid curves and clear them on the wholesale market, considering the network limits.

If the network limit is not binding, all bids are accepted, and the loads pay the market price plus a standard fee for network access. In case the limit is binding, all loads up to the free capacity in the network are accepted based on their bids, and they pay the price at which this market is cleared (pay-as-cleared), which is then higher than the wholesale price. The network operator collects the price difference as a congestion income.

The network capacity auction can be held a day ahead [16, 21] or near real-time. Network capacity auctions integrated with a wholesale energy market in real-time are also known as "transactive energy" approaches [51, 53]. Typically, capacity auctions

[12]See, e.g., PJM locational marginal pricing fact sheet.

Table 2.1: Design Space variables of dynamic access price variations

	Commodity	**Price Formation**	**Time-frame**	**Loads applied to**
CPP	Energy	Regulated	Near-term	All
NCPC	Capacity	Regulated	Network peak	All
DLMP	Energy	Regulated	Day-ahead or Real-time	Flexible or All
Capacity Auction	Capacity	Auction, pay-as-cleared	Day-ahead or Real-time	Flexible

replace the default network tariff and apply only to flexible loads.

An overview of the different variations and their design variables is given in Table 2.1. Note that all the proposals described above offer firm network access.

2.5.2. Local flexibility markets for CM

This category includes all CM proposals based on the DSO's buy-back of network access and end-user load control. Most CM proposals in this category also use auction-based pricing, which justifies the term "market." However, the literature also has some ambiguity around the term "flexibility market." For example, Radecke et al. [23] review 12 current European proposals. They observe that not every project called a "flexibility market" is a market in the traditional sense where prices are determined based on free bids of participants. Instead, some of the projects they investigated use regulated prices. Furthermore, local CM for the distribution grid is not always the only purpose of schemes labeled "Local Flexibility Market" (LFM) or similar. Ramos et al.
citeRamos2016RealizingFlexibility state that an LFM's purpose can be to help resolve localized network constraints and help with non-localized problems such as system balancing or portfolio optimization.

Nevertheless, even though the purpose of the trade and the details of the implementation can vary widely, the basic idea of the "flexibility market" concept is mostly the same: providers of flexibility in the distribution grid (e.g., aggregators of flexible residential loads) are paid to change their power profile. We found several additional design variables specific to this category:

- The choice of reference load relative to which the load profile change is realized. Choices are a baseline (agreed upon by both parties), the current consumption of the trading party (individual end-user or sum of connections managed by an aggregator), and a capacity limit to power usage in kW (see [22, 28]). The power limit may be either fixed contractually or variable, depending on the state of the network.

- Minimum bid size in kW or kWh of flexible load over particular time intervals.

- Matching mechanism of requests and bids for flexibility (see, e.g., [23]).

- Penalties: Since these proposals are based on end-user control, whether the contracted load reduction occurred should be verified. If the reduction did not occur, there may be penalties specified in the contractual agreements.

- Activation fees: (only for option trades) There may be an additional fee for activating an option.

- Activation lead time for option trades: the interval between the announcement of activation of an option and its activation. For example, the DSO may predict congestion in a specific time interval of the next day and inform the flexibility provider who sold the option that it will be activated at this time. Lead times would generally be one day but could also be a few hours or minutes ahead. The possible values must be defined in the contract agreement between the parties [22].

Additional design questions around the implementation and specifics of these markets are investigated in the reviews [6, 8, 12, 23, 26, 54–56].

As we can see, many different kinds of proposals for flexibility markets exist in the literature. Most of them have in common that they are based on auction-based price formation, capacity-based commodity (typically as deviation from baseline or current consumption or maximum network capacity) and that they operate in addition to the default network tariff. The most important distinguishing features are reference load, firmness, and trade time frame.

The terminology in the literature can sometimes be confusing: different names are applied to seemingly similar concepts in various proposals and vice versa. In the following, we attempt to give a standardized list of the types of proposed LFM products based on their design variables:

- Real-time flexibility [39], or “PowerCut Urgent” in [22]: reduction of power consumption below current consumption in near-real-time. This approach is typically only a last resort for unexpected congestion problems, as it creates unexpected portfolio imbalances for flexibility providers and would, therefore, likely be an expensive option.

- Flexibility-to-baseline [39] or "drop-by" in [20]: Flexibilty providers submit a baseline schedule. The DSO gathers these baselines and makes its forecasts to determine whether congestion will happen. When the DSO anticipates congestion, it contracts power reductions relative to the submitted baselines. As this might lead to a re-appearance of congestion at a different time step, some proposals require additionally the specification of a "pay-back" period during which the reduced power consumption is caught up on [39], or an iteration of adjusted schedules and additional trades until all expected congestion problems are resolved.[13] Because the baseline needs to reflect the actual anticipated power profile of the provider, this variant can only work in the near term, e.g., a day ahead.

- Flexibility option contracts: a contracted power reduction that may be activated during network stress, i.e., the network access is non-firm. There may be an additional activation fee and a penalty for inability to deliver. The contract specifies the time frame and reference load. The time frame can be day-ahead [39], long-term for a fixed recurring time interval with expected high loads[14], or a long-term reserve with no specific time ("PowerReserve" in [22]). The reference load can be relative to current consumption at the time of activation [22], relative to baseline [39], fixed capacity limitation [28] ("PowerMax" in [22], "drop-to" services in [20]), or variable capacity limitation ("PowerCap" in [22][15]

- Long-term capacity limitation: a flexibility provider agrees to always stay below a specific contracted network capacity (at all times or within specified times). The Dutch regulator has identified this as one of two market-based flexibility procurement options in the Netherlands[16].

[13] The Dutch GOPACS platform addresses this issue by matching only orders on existing electricity market platforms if they help resolve a local congestion problem.

[14] For example, between 16:30 and 18:30 on weekdays in a given year, as in the Piclo-Flex platform in the UK [57] or the "PowerCut Planned" product in [22].

[15] This proposal's capacity limitation is based on the available capacity at the congestion point. There is real-time feedback between load at the congested asset and capacity limits for flexibility providers, offering a higher degree of control for the DSO. This product is functionally almost equivalent to the direct load control mechanisms introduced in Section 2.5.3. The main difference is that the DSO buys the product on the market, whereas the DSO offers it for regulated prices in the proposals in Section 2.5.3.

[16] Alongside redispatch, see https://www.acm.nl/nl/publicaties/codebesluit-congestiemanagement (in

Moreover, the auction format plays a vital role in flexibility markets and can have a strong influence on how efficient the resulting mechanism is. The above product types can be sold with the auction formats listed in Section 2.4.

Table 2.2: Design Space variables of LFM products

	Firmness of network access	**Reference Load**	**Time-frame**
Flexibility to Current	Firm	Current	Near-real-time
Flexibility to baseline	Firm	Baseline	Near-term
Flexibility options	Non-firm	Current, baseline, capacity limitation	Long-term to near-term.
Long term capacity limitation	Firm	Capacity limitation	Long-term

2.5.3. CONTROL-BASED MECHANISMS

Direct-load-control (DLC) approaches are those where the DSO can directly control the power consumption of high-power end-user devices, like EVs, or of the maximal power capacity of the connection in times of network congestion. Thus, by definition, these approaches provide non-firm network access. In addition to loads, these mechanisms can also be applied to distributed generation. In addition, their common design variables are typically regulated prices, long-term contracts, and a commodity framed in terms of connection capacity.

Perhaps the most important distinguishing feature is the type of devices to which the scheme is applied. [40] discusses the "Connected Solutions" program in the US, where end-users can enroll their flexible devices and batteries. For a regulated fee, typically a few hundred USD per kW of device capacity, the utility purchases the ability to control these devices directly. As this is in the context of an integrated utility, this ability can help manage network bottlenecks and generation shortages. In the context of unbundled electricity systems, [58] also discusses how grid operators may take over limited control over flexible devices in exchange for reduced grid tariffs but mentions the lack of clear regulations and control technology as obstacles.

Dutch)

There are proposals for a limited grid connection of larger users, where the network operator has the right to curtail or reduce the connection capacity in exchange for a lower grid fee.[17] Bjarghov et al. [38] discuss a new tariff proposal that would apply to all loads: dynamic capacity subscriptions. These are a variation of the static subscription concept introduced in Section 2.5.1: here, there is no penalty for exceeding the capacity limit in times with no network stress, but when there is congestion, the grid operator can curtail the load at the connection down to the subscribed amount to resolve congestion. Control-based mechanisms have also been applied to distributed generation [8, 44, 59]

These mechanisms can also vary in whether they are applied based on user consent or by default. [44] gives an overview of use cases, design choices, and the status of current direct control agreements in European countries.

2.6. Discussion

This section addresses the following questions: How are the different CM mechanisms (Section 2.5) performing concerning the objectives (Section 2.3) for the different congestion problem types (Section 2.2)? What risks may occur? How do the design variables (Section 2.4) influence performance and risks?

Table 2.3 gives a summary of our findings. We first introduce the possible risks of CM approaches in Section 2.6.1 and discuss the influence of design choices on performance in Section 2.6.2. Finally, we give a detailed qualitative assessment of all the listed CM approaches in the remainder of this section.

2.6.1. Types and allocation of risks

Every CM approach comes with different kinds of risks that can jeopardize the fulfillment of the objectives:

- Residual risk of network overload: There is the potential that the mechanism does not entirely remove congestion. Static tariffs may be the most likely for this, as they are not adaptable to network conditions. However, it can also occur in other mechanisms: the inflexible load may have been underestimated

[17]For example, the Dutch regulator has recently introduced two such agreements: capacity limitation contracts ("Capaciteitsbeperkingscontract) for existing users who opt into a capacity reduction service in exchange for payments, and non-firm connection agreements ("flexibele aansluit-en transportovereenkomst") where mandatory capacity reductions are part of the connection agreement, in exchange for lower fees and sometimes a prioritization of the connection procedure.

Table 2.3: Summary of Performance of CM Approaches

	Suited for	Not suited for	Pros	Cons
Static Tariffs	Rough signals for structural congestion	Sporadic congestion	Simple, not discriminating	Not adaptable to sporadic congestion
Dynamic Tariffs	All types of congestion problems	Risk-averse or inflexible consumers	Adaptable, no price risk for DSO	Price discrimination, user price risk
Local Flexibility Markets	Large scale aggregation	Small scale	Theoretically efficient, use of flexibility for other purposes	Gaming of markets, price risk for DSO
Direct load control	All types of congestion problems	Must-run or tight constraint loads	High reliability and decent efficiency	QoS discrimination, curtailment risk

in day-ahead tariffs, and the tariff set too low. In LFMs, the DSO may not have purchased sufficient flexibility. In DLC methods, there may not be enough load signed up for the load control scheme. Generally, this risk can be reduced as the mechanism moves closer to real-time, making it more adaptable to network conditions. In DLC methods, this risk is also reduced by requiring all high-power flexible loads to sign up by default rather than by consent. In practice, there is always the fallback option of indiscriminate curtailment to avoid overloads leading to damage or safety concerns. However, DSOs may be penalized for these actions.

- User network price risk: In CM approaches where the price of network usage is not fixed in advance (i.e., dynamic tariffs), network users have a risk associated with this variability. They may be committed to using the network at this time, e.g., due to external constraints such as industrial schedules, heating, or EV charging requirements, or they may have purchased power on electricity wholesale markets for which they would have to pay additional imbalance fees. The risk is higher the closer the mechanism operates to real-time, as this reduces the chance to plan for alternatives.

- Network operator price risk: In analogy to network user price risk, there are

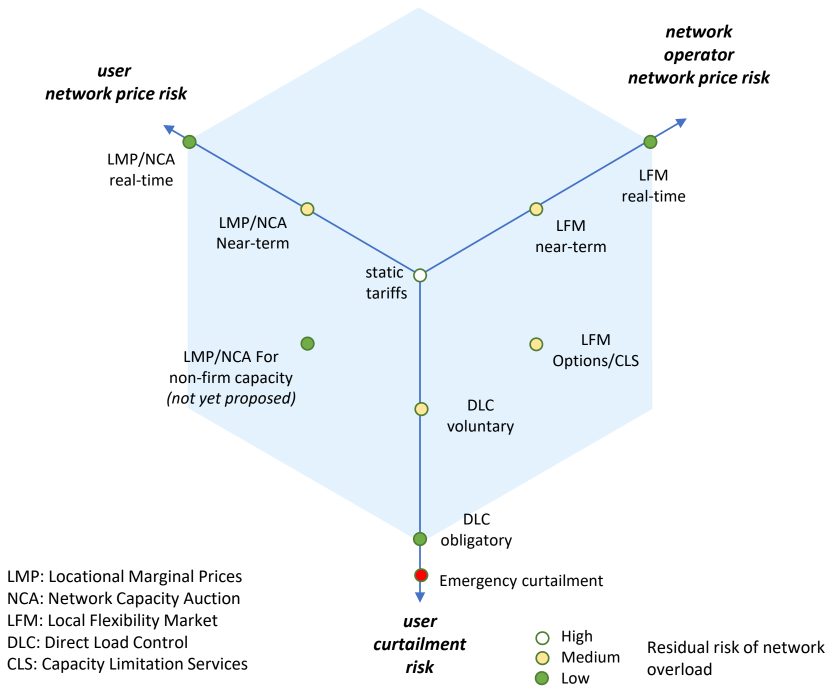

Figure 2.3: Risk mapping of CM mechanisms

approaches where the network operator carries the price risk. This situation applies to market-based methods where the DSO must buy back network access from users at prices based on user bids. Again, the price risk increases closer to real-time operation and can also be exacerbated by market failures [60].

- User curtailment risk: The end-user or aggregator risks being curtailed, which may be due to a feature of the mechanism, as in DLC, or as an emergency in case other CM mechanisms fail. The advantage of the targeted curtailment in DLC approaches is that it can specifically select high-power flexible loads.

> In contrast, indiscriminate curtailment typically comes with a high customer interruption cost, often represented by an assumed Value of Lost Load.

We visualize the risk allocation of different CM approaches qualitatively in Figure 2.3. In addition to the pure risk cases already discussed above, there are also possible mechanisms that can share risks: LFM option types, for example, come with a price risk for the DSO (like other market types) and a curtailment risk for the aggregator in case the option is activated. In this case, network overload is also a residual risk if the network operator does not procure sufficient options or limitation services.

In current practice, there is usually a combination of several mechanisms operating on different time horizons. E.g., LFMs are typically applied in addition to static tariffs. Emergency curtailment can always supplement static tariffs if nothing else is done for CM. Haque et al. [61] investigate a combining market-based mechanism and "graceful degradation" based on direct control methods. A novel mechanism could also combine near-term dynamic prices with a real-time LFM for emergency buy-back in case the DSO anticipated congestion wrongly. This approach would resemble an "airline" model of slightly overbooking flights.[18] This mechanism leads to sharing the network price risk between the end-user and DSO. However, there are also combinations of mechanisms that might not work well—for example, operating an LFM simultaneously as dynamic tariffs would introduce unnecessary complexity [41].

Figure 2.3 can also identify novel CM mechanisms in the "risk space" by identifying a desired risk allocation and constructing a mechanism that leads to this allocation. For example, for a mechanism with both a moderate price risk and curtailment risk for the end-user, this could be in the form of near-term LMP/NCAs for non-firm network access. The DSO may sell near-term network access based on a relatively loose estimate of load. In case congestion does occur, some of the load that purchased non-firm access will be curtailed, and the network price will be returned to them. We have added this option in Figure 2.3 in the lower left.

2.6.2. THE INFLUENCE OF DESIGN CHOICES

[18] This is typically done because some passengers are expected to miss their flight. If there are still too many passengers for the flight (the equivalent of "congestion" in that problem), airlines often auction off the overfilled seats by offering money in increasing steps until the congestion has been removed.

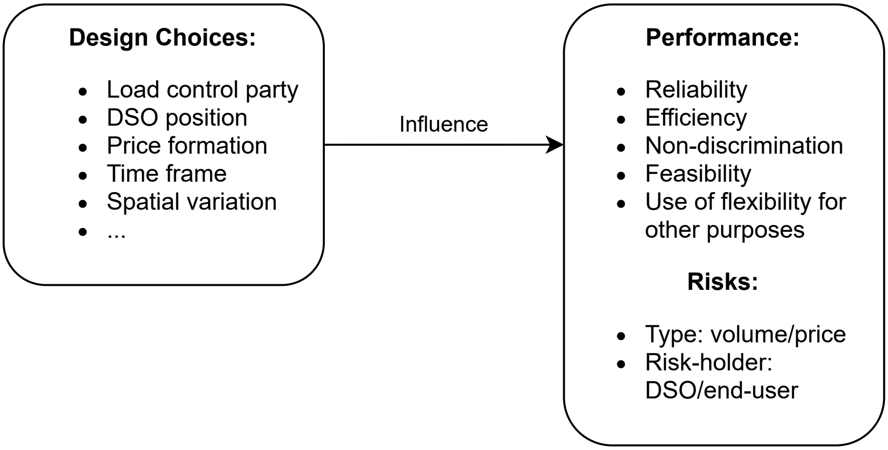

Figure 2.4: Design choices influence performance and risks

The design variables of congestion management mechanisms impact their performance. We visualize this relation in Figure 2.4 and give a few concrete examples in the following:

- The choice of load-controlling party influences who carries the “volume” risk associated with energy delivery: if the DSO controls loads, the end-user or aggregator has a risk of curtailment. If the end-user or aggregator controls loads, the DSO has a risk of network overload, meaning the mechanism may be less reliable.

- DSO position influences who shoulders price risk: in access price-based methods, the end-user may have a price risk; in buy-back-based methods, the DSO has it. Furthermore, buy-back-based approaches are susceptible to misrepresentation of information by private actors: they give an incentive to inflate baselines, maximal capacity or current consumption (based on the specific mechanism), and to employ strategic bidding, which leads to a decrease in efficiency.

- Price formation influences the degree of price risk: with regulated prices, there is no (network) price risk; with auction-based methods, there are varying degrees of risk, depending on the time frame and competitiveness of the market. Auction-based methods may increase efficiency in well-functioning competitive markets or decrease it in case of market failures. Further, they have a higher degree of complexity.

- Varying the time frame from static through near-term to real-time has multiple consequences: price risk increases, reliability increases, complexity increases, the usability of flexibility for other purposes decreases, and efficiency generally increases, though it may be compromised in near real-time as this only allows a shifting of loads to later times, not earlier ones.

- Spatial variation: Each of the CM mechanisms listed could be applied at different spatial granularity, tailored to the congestion situation in the network. Higher granularity could increase the reliability and overall efficiency of the mechanism (as [48] shows for LMP), as congestion areas can be targeted deliberately. However, it comes at the cost of introducing discrimination: users in congested areas pay more than those in non-congested areas[19]. This result may be considered unfair, as it depends on the state of the network, on which users have no influence[20].

2.6.3. STATIC TARIFFS

Static tariffs give rough incentives to reduce congestion but are not adaptable to network conditions. Thus, there is no guarantee that they will resolve it entirely. For example, the peak times in ToU tariffs can be tailored to expected structural congestion times but are not adaptable to deal with sporadic congestion. Capacity-based tariffs give further incentives to limit peaks, which can also be differentiated by time. However, a static price signal sometimes disincentivizes network access when there is spare capacity, limiting efficiency as the network is not used to the extent that would be economically desirable. The positive aspects are that static tariffs are simple and not discriminatory.

Note that we only considered the performance of tariffs concerning congestion management here. As this is not the primary purpose of network tariffs, other considerations are relevant when evaluating their performance [3, 4].

[19] This is different with flexibility markets, where users in congested areas may even benefit more from congestion by charging inflated prices

[20] see also [4] and [62] for similar discussions on network tariffs and nodal pricing respectively

2

2.6.4. Dynamic tariffs

The peak-based approaches CPP and NCPC can increase reliability, especially for expected structural peak events, e.g., during heat waves or cold spells [41]. As they specifically target these times and do not needlessly restrict network access at other times, this would also increase efficiency. On the other hand, since they typically apply to all loads equally, they may not be a good solution for situations with many sporadic congestion events driven by flexible loads.

More dynamic proposals like DLMP and NCA can react better to network conditions and thus may potentially improve reliability and efficiency even further. On the other hand, they come with their own set of problems. Firstly, their effectiveness increases with spatial granularity [48], allowing them to be tailored more to the specific congestion problem. However, this also introduces price discrimination. It could be interesting to investigate tariffs with the same price on average but higher variations in congested areas to yield a stronger control signal. Secondly, they require sophisticated communication interfaces to transmit the price signal, which means they have a higher implementation burden. Thirdly, vulnerable consumers may be unable to react to them and be hit with unexpectedly high charges[21].

Network Capacity Auctions can resolve the network price-risk problem by simultaneously clearing the energy market, as in the transactive energy proposal by [51]. Theoretically, this setup may have the potential for the highest reliability and efficiency. However, this comes at a high system implementation burden where every device must communicate its bid function continually.

An alternative could be a dynamic tariff where it is not the price that varies in response to network conditions but the available network capacity of users, i.e., a tariff with non-firm access conditions. This approach would remove the price discrimination problem for network access and protect vulnerable customers against price spikes. We will investigate this type of tariff in more depth in future work.

An additional important consideration with dynamic prices is what happens with the generated revenue. As their prime purpose is not cost recovery but congestion avoidance, they might not be counted towards the normal operating income of the DSO. Otherwise, this may create a perverse incentive for the DSO not to upgrade the network to collect more congestion rent. Therefore, these revenues should be

[21] This problem was demonstrated in Texas, where marginal pricing is already applied to many households. When, in February 2021, a major winter storm caused very high electricity prices, some consumers faced extremely high bills as they were unaware of the costs. [63]

collected as a separate budget item and could, e.g., be used for network upgrades.

2.6.5. LOCAL FLEXIBILITY MARKETS

LFMs for CM have been proposed to deal with structural congestion problems in extended period option markets [22, 57] and sporadic congestion events [22, 39]. Theoretically, the advantage of a market is that it could remove congestion in an economically efficient way by paying flexibility providers at their marginal cost of shifting loads. This approach would also remove the price discrimination in dynamic price schemes. However, the theoretical optimum could only be reached if flexibility providers submit truthful information about their available flexibility and costs. Unfortunately, the basic premise of these kinds of markets, paying providers for adjustment of their energy consumption, is prone to manipulation by withholding private information and misrepresenting costs and flexibility [64]. This situation might even lead to a form of "reverse" price discrimination: flexibility providers in congested areas may be able to collect greater rents on congestion by behaving strategically. Furthermore, this discrimination is also socially regressive in terms of wealth. As Ribó-Pérez et al. [65] showed, the wealthier members of the population can invest in flexible devices and obtain rents from these kinds of markets. In the following, we discuss a few potential problems that can occur.

The auction format and strategic bidding. As mentioned before, the choice of auction format significantly impacts the outcomes: In a pay-as-bid market, congestion could theoretically be removed at the lowest cost if all participants bid truthfully. However, there are well-known problems in pay-as-bid markets [6, 27, 28], as it incentivizes participants to bid higher than their actual costs.

In uniform (pay-as-cleared) price markets, flexibility is traded at the marginal supplier's price. All bidders below this price collect additional rents equal to the difference between their bids and the clearing price, meaning congestion is no longer removed at the lowest possible cost for the DSO. The incentives to over-represent costs are not as strong as in pay-as-bid because bids above the clearing price would not be accepted. In contrast, below the clearing price, it does not matter whether the provider bids at its marginal cost or not, as it will always be accepted. However, flexibility providers that control many flexible loads may be able to manipulate the clearing price by bidding their whole fleet above marginal costs. In highly localized markets, an aggregator might easily acquire market power at a single LV feeder by controlling only a few dozen EVs. A further illustration of this problem can be found in [60].

Heinrich et al. [28] propose a modified VCG auction as an alternative that pays each flexibility provider according to the benefit they bring to the system. However, this would still be more than the marginal cost of shifting loads, which implies that flexibility providers still collect rents on congestion. Additionally, it is still possible for individual actors or cartels of actors with a large share of flexible loads to inflate the price artificially.

Strategic bidding may be mitigated by having a large pool of potential providers, so acquiring market power becomes more difficult. Thus, LFMs might be a better solution for larger-scale congestion problems, such as MV substations, rather than individual LV feeders.

Manipulation of baselines and real-time consumption. In addition to the problem of strategically bidding above marginal costs, there is another problem in LFMs: the strategic adjustment of consumption, either in supposed baselines or in real-time, to collect higher rents from LFM payments. These strategic adjustments typically even worsen the original congestion problem. For profit-maximizing actors in the market, it is rational to adjust their consumption so that they consume *more* when there is a congestion problem. In this way, they also get paid more.

Ziras et al. [66] have comprehensively discussed this problem concerning baselines and showed that it exists irrespective of the method used to construct baselines. A possible exception to this is large industrial consumers where the baselines pertain to specific processes and can be easily verified.

In real-time LFMs, a similar problem exists when market participants realize that there is a congestion problem and that they can benefit from artificially increasing their load to be paid to reduce it[22]. This problem is similar to the problem of "inc/dec" gaming in redispatch markets identified by Hirth et al. [67].

In capacity-limitation LFMs like those proposed by Heinrich et al. [28], the payments increase in line with the maximum potential power consumption of flexible loads, as the limitations have to be computed relative to this theoretical maximum power consumption. Thus, this practice incentivizes them to over-represent this number,

[22] A particularly striking real-world example has been given by the case of a baseball stadium in Baltimore and a demand response program by the regional grid operator PJM: When PJM sent out a declaration of an emergency event as part of the demand response program, the baseball stadium switched *on* the stadium lights, even though there were no games or practice scheduled, to collect payment for reducing the demand by switching off the lights again.

akin to the issue of inflated baselines.

There are also specific problems in option-type LFMs. Proposals based on long-term contracts for load reductions at particular times can lead to a commitment problem: the provider is committed to being able to supply the load reduction given in the agreement. Thus, it has to schedule loads at these times. Otherwise, it would not be able to fulfill the contract, even when it would be disadvantageous to do this based on wholesale prices and network conditions, as otherwise, the aggregator would be faced with a penalty. Eliminating the penalty is also not an option, as it would allow the aggregator to sell an indefinite amount of products it does not have to supply.

Feasibility. Setting up an LFM requires sophisticated communication and control infrastructure, which might be why there are only small pilots and demonstration projects [54]. As Dronne et al. [8] observe, the size and capabilities of DSOs can differ widely, and for smaller DSOs, setting up the required technology can pose a significant resource challenge. Even for larger DSOs, it is questionable whether setting up an LFM for every potentially congested LV feeder is possible, further suggesting that LFMs might be more applicable to larger-scale congestion problems, not to highly localized congestion.

Use of flexibility for other purposes. Perhaps the most significant advantage of LFMs is that they are not limited to resolving congestion problems; flexibility may also be offered for other purposes. Coninx et al. [68] investigate a setup where it is offered to multiple potential buyers: DSOs, TSOs, and BRPs. Ramos et al. [12] discuss how flexibility products could be traded on a larger, location-agnostic market and localized sub-markets. They stress that for flexible products offered on the larger market, it is essential that they do not violate any localized constraints. Hence, the market mechanism needs to take this into account. An example is the Dutch platform GOPACS[23]

2.7. CONCLUSION

Electric distribution networks have various congestion problems and potential mechanisms to resolve them. The main categories of CM mechanisms are static and dynamic access prices, Local Flexibility Markets, and direct control methods. Some of these mechanisms are variations of network tariffs, while others are specialized mechanisms on top of a default tariff.

The design choices of these mechanisms influence their performance and risks. For example, market participants' potential for undesirable strategic behavior should be carefully considered. It may turn out that this may point towards abandoning market-based approaches in favor of methods with lower price risk for the DSO. In general, mechanisms should be fitted to the problem they are intended to solve by carefully considering all possible design choices.

Academic studies and proposals of new CM solutions should include a precise problem analysis as a starting point. What kind of congestion are they attempting to solve regarding localization, timing, predictability, and network limitation? There is no one-size-fits-all, so it is essential to know the specifics of the problem to judge the merits of the proposed solution.

Network operators should collect data on existing and anticipated congestion problems: at what local scale do they appear? Is the timing at regular hours, or does it fluctuate due to external factors like weather and wholesale prices? Are they related to thermal overloading or power quality due to load or feed-in? This information and a clear regulatory framework could help significantly to find applicable solutions.

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3

Market Failures in Local Flexibility Market Proposals for Distribution Network Congestion Management

The previous chapter noted the potential dangers of using Local Flexibility Markets (LFMs) for congestion management, as these can be susceptible to gaming. In this chapter, we expand on this discussion by providing specific examples of how gaming can lead to unintended consequences and excessive payments for the network operator in such markets.

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Abstract

The steady uptake of PV cells and high-power flexible loads such as electric vehicles (EVs) and heat pumps can lead to localized network congestion if their power consumption or feed-in is not controlled well. One potential way that has been proposed to manage this congestion is so-called Local Flexibility Markets. It is often argued that these proposals are theoretically efficient as they are market-based. However, some of these proposals may suffer from design flaws that allow market participants to obtain undue profits at the expense of the network operator. In this contribution, we discuss which kinds of market failures can occur based on theoretical reasoning and demonstrate them in a toy model. Based on this, we argue for a more careful consideration of congestion management options.

3.1. INTRODUCTION

Congestion is becoming a problem in electric distribution networks. It is often due to high-power flexible loads like electric vehicles and heat pumps or excessive feed-in of distributed generation. To deal with this problem, several families of solutions have been proposed: new forms of distribution tariffs [2], [3], direct load control schemes [4], [5], and different forms of Local Flexibility Markets (LFMs) [6–9]. In this analysis, we focus on the LFM proposals for congestion management. Some of these market-based proposals are structured in a way that may lead to perverse incentives for profit-maximizing market parties. Rather than helping to relieve congestion, they may lead to more congestion and market participants may collect undue profits for their participation in the market. This is worrying, as LFMs are currently widely discussed as a potential remedy for distribution-level congestion and a careless application of the concept may lead to high inefficiencies and excessive costs for network operators. The chapter is structured as follows: in Section 3.2, we describe the versions of LFM proposals that we analyze here and give examples from the literature. In Section 3.3, we explain why these proposals can lead to market failures. In section 4 we demonstrate these failures in an illustrative toy model of an LV network. In section 5 we discuss the consequences of these findings and implications for policy making and academic work. Section 6 concludes.

3.2. LFM PROPOSALS IN THE LITERATURE

Many LFM proposals are based on the idea of baseline schedules [10–12]. In this implementation, aggregators of flexible loads submit schedules for the loads that they control, typically on a day-ahead time frame. The Distribution System Operator (DSO) collects these schedules and also forecasts the anticipated inflexible load at the congestion point. If the sum of the schedules and inflexible loads leads to congestion problems at any time step, it requests flexibility offers from the participating aggregators. The aggregators then submit bids for reducing load at the selected time steps. As Esmat et al.[11] point out, it is important also to consider the time step at which this reduced load is then added again (called the "payback time" in [11]). Thus, a bid can include:

- The time step for reducing load
- The time step at which this load is added instead
- The maximal load reduction in kW

- A price, e.g., per kWh of shifted load.

Congestion can occur at many different points in the grid: e.g., at LV transformers, cables or HV/MV substations. Unfortunately, many proposals do not clearly state for which congestion point they are intended to be applied which makes it hard to assess how they would work in practice. The USEF framework [10] specifies: “A congestion point is a set of connections which (directly) relate to a part of the grid where grid capacity might be exceeded because it may be insufficient to distribute the requested amount of energy; e.g. the secondary side of an LV transformer.” Thus, it explicitly includes LV transformers, which we will use as a case study in the toy model in section IV.

An important aspect of the LFM is the clearing process by which bids are selected. [10–12] all propose to use pay-as-bid pricing. Other methods, such as pay-as-cleared [6] or Vickrey-Clarke-Groves auction types [13] have also been suggested.

In the discussion above and the case study, we focus on proposals with products that are based on a baseline schedule. Other “product types” that could be sold in LFMs have also been suggested:[1]

- An option-type trade where load reduction is only activated by the DSO if necessary [11, 12]
- An emergency load reduction that is activated in real-time relative to the current consumption of the market participant rather than relative to a baseline [12]
- A power limitation product, where load is limited to a maximum power rather than reduced relative to a baseline or current consumption [12, 13].

3.3. Pathways of possible market failures

In theory, these flexibility markets could lead to perfectly efficient solutions: this holds if all market participants are completely transparent about their costs and baseline schedules and submit flexibility bids in accordance with their true marginal cost of shifting loads and if the market operation has no unintended consequences.[2] However, firms in competitive markets behave in profit-maximizing ways. This can become a problem in poorly designed markets. In the proposals described in the

[1] Discussed in further depth in Chapter 2 of this thesis.
[2] Such as altering the schedule that a purely profit-maximizing market actor submits.

previous section, there are several potential avenues by which profit maximization would not result in managing congestion in the most cost-efficient way for the network operator. In this section, we describe the reasons behind two types of such market failures in managing congestion with LFMs. They are based on the ability of aggregators to control either the price or the volume of traded flexibility.[3]

3.3.1. PRICE CONTROL: MARKET POWER

Distribution level congestion can be highly localized, e.g. at the single LV feeder level, as suggested by the USEF framework [10]. Thus, it may be possible for an aggregator of flexible loads to acquire market power in a local market: if it has control over a sufficient amount of flexible loads it can effectively hold a monopoly over the congestion on that feeder, in the sense that congestion cannot be removed without participation of this aggregator. Therefore, this aggregator can influence the clearing price of the market at this feeder, a concept known as strategic bidding. It can charge prices for adjusting its consumption that are significantly higher than its marginal cost of shifting loads. This problem is analogous to the pivotal supplier problem in wholesale electricity markets [15]. A similar case has been assessed in [16] for wind power operators in coupled local and central (wholesale) markets. Strategic bidding may also occur when it is not only a single aggregator holding market power, but rather an oligopoly of a few aggregators. They may collectively bid at higher-than-marginal prices. This can happen either due to explicit collusion between them, or due to implicitly learning that they can obtain higher profits in this way on average.

Market power can be avoided in highly liquid markets with many bidders. In the case of distribution level congestion management, this would be the more likely case at higher network levels in the distribution grid, e.g. at a substation which serves in the order of 10.000's of customers. This suggests that LFMs for local congestion management may be more suited to application at the substation level, rather than at LV feeder level.

3.3.2. VOLUME CONTROL: MODIFIED SCHEDULES

The presence of an additional revenue stream due to an LFM for local congestion management may influence the schedules that aggregators submit in proposals such as [10]. The schedules may be modified relative to the case without the LFM because

[3] In the meantime, additional research studying this problem has been published, e.g. [14].

of expected payments in case of congestion. We can distinguish two subcases of schedule modification:

1. "Fake" schedules: These are schedules that the aggregator does not actually intend to fulfill. It submits them in the expectation that it will not have to do so because it will be paid under the LFM mechanism to reduce load anyways. This behaviour is more likely if the aggregator expects congestion with near certainty, or when there are low penalties for not sticking to the submitted baseline if no congestion occurs. In those circumstances, submitting fake schedules could become a low-risk winning strategy for a profit-maximizing firm.

   One could assume that the network operator should be able to detect falsified baseline schedule, but this is difficult because the network operator cannot know the true constraints of the aggregator. The aggregator could argue that the flexible loads, e.g. EVs charged at a home charger, are really only available during the submitted times. This might lead to a situation where there is a large burden on DSOs to prove that aggregators use manipulated schedules, and aggregators try to find ever more elaborate methods of manipulation for which they can argue that these are their true baselines due to availability constraints.

2. "True" profit-maximizing modifications of schedules: In this case, the aggregator submits schedules that it actually intends to adhere to, even when congestion does not materialize and it is not paid for shifting loads. The presence of payments to shift loads during those times when flexibility is requested offsets the additional costs of modifying the schedule. Note that this is also a possible avenue of profit maximization in proposals that operate in near-real time, rather than relying on pre-submitted baseline schedules (e.g. in [11, 12]). In this case, aggregators could increase their consumption when they anticipate high-network load in real-time, in order to be paid to reduce it again.

   Note also that this doesn't have to entail the malign intent of employees of the aggregator themselves; it might simply be the outcome of an optimization algorithm that has been programmed to take all available revenue streams into account. Lastly, note that modified baseline schedules can have negative repercussions beyond network operation itself: they often imply that the aggregator has to charge more vehicles during high consumption hours, where market prices may be higher and added electricity demand is likely served by conventional electricity generators based on coal and gas.

Both cases of modified baseline schedules can aggravate the congestion problem relative to the case without LFM. They often occur in conjunction with market power: a market participant may modify its schedule in order to obtain a position where congestion cannot be removed without them and then charge inflated prices in an LFM. But even without market power, a market participant can add to an expected pre-existing congestion problem in order to get paid to subsequently reduce its consumption. While pure market power alone could be addressed by diversifying markets, modified baseline schedules cannot so easily be avoided.

The fundamental market failure that enables both types of scheduling problems is that in many LFM proposals there is no cost associated with submitting a baseline schedule that targets times of likely congestion. Contrast this to energy markets: there, forward and day-ahead markets for energy at peak demand hours have already priced in the high expected cost of marginal generation. It is therefore costly to take a position that allows one to profit from high intra-day prices. Although in some cases, the long-term costs of the energy market can reduce the benefits of submitting modified schedules in LFMs, the objectives of both markets do not always align. For example, an EV charging aggregator can optimize their entire fleet for the energy market, and can submit modified schedules for EVs in a congested area of the network, balancing those changes with modified schedules for EVs in other areas of the network.

3.4. Demonstration of market failures in a toy model

In this section we demonstrate the kinds of market failures described in the previous section in a toy model. The model consists of a simplified neighbourhood with a typical LV feeder that supplies 50 households and 24 charging EVs. The 24 EVs are controlled by 3 different aggregator companies, called A, B and C. We model 6 time steps of length 1 hour each, which exemplify a typical night from the evening peak through a drop of traditional loads during the night and then a rise in load in the morning. Table 1 gives the chosen values for inflexible loads and wholesale market prices (not to be confused with the LFM clearing prices). These are motivated by real world data, such as those used in our modelling in [17]. Each EV requires 12 kWh of energy overnight and has a maximal charging power of 11 kW. The LFM is modelled based on the proposals described in section Section 3.2: aggregators submit a baseline schedule to the DSO and submit bids for reducing consumption. Each bid contains the possible amount of reduction, the payback time period and the price per kWh. The market is cleared pay-as-bid based on the lowest possible cost of resolving congestion.

We begin with a situation in which the 24 EVs are evenly split over the 3 aggregators and there is perfect competition. We assume that aggregators spread out charging schedules for EVs over all time steps, due to availability requirements. However, the lowest price time steps are preferred, leading to some expected congestion due to the scheduled EV charging at hour 3. This initial situation is shown in the top panel of Figure 3.1.

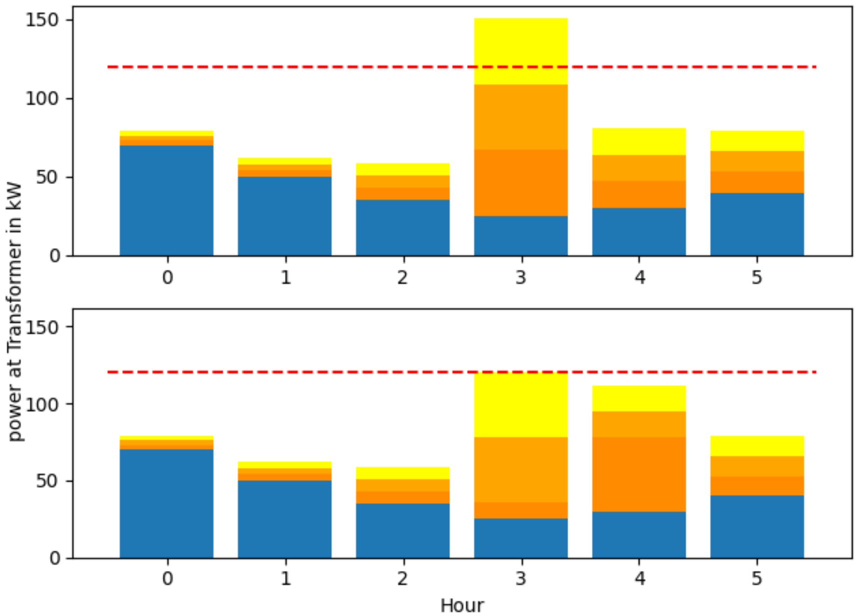

Figure 3.1: Initial and final schedules in a perfect competition market with efficient outcomes. Blue: inflexible load. Dark orange, orange, yellow: Aggregators A, B and C. Red dashed line: rated transformer capacity.

3.4.1. Scenario 1: Perfect competition, efficient outcomes

In the first scenario, we assume all aggregators submit their true original schedules (the same schedules as in the absence of the LFM) and submit truthful bids at

	Time Step [hour]					
	0	**1**	**2**	**3**	**4**	**5**
Inflexible Load [kW]	70	50	35	25	30	40
Market Price [Euro/kWh]	0.15	0.1	0.05	0.01	0.025	0.032

Table 3.1: Load and price time series for case study

their marginal cost of shifting from the congested time step to other time steps. The DSO selects these bids to remove congestion at the lowest possible cost, which lead to a cost-efficient outcome for the DSO. For aggregators the schedule change is revenue-neutral, as they are reimbursed at their marginal cost of shifting. See Figure 3.1 bottom for the final schedules.

3.4.2. SCENARIO 2: AGGREGATOR A IS DOMINANT AND CHARGES INFLATED PRICES

In the second scenario, we assume that aggregator A controls 20 of the 24 EVs. This means that congestion at hour 3 cannot be removed without participation of this aggregator and it can therefore charge higher prices. We assume that it charges the marginal prices of shifting to another time step (based on wholesale price differences), plus an additional mark-up of 1 Euro/kWh. Now the DSO first clears the cheaper bids of aggregators B and C and then also has to accept 11 kWh from aggregator A in order to fully remove congestion. See Figure 3.2 for the initial and final situations in this scenario.

Note that the choice of the mark-up price that aggregator A charges is somewhat arbitrary here. Theoretically, the upper limit for this mark-up is given by the DSO's cost of the alternative of removing congestion with an LFM. This could be the Value of Lost Load (VoLL) in the short term or the cost of upgrading the transformer in the long term. However, this cost would be many orders of magnitude higher than the marginal cost of shifting for the aggregator, and in practice, it would be quite easy to prove market power abuse at these values. Therefore, an aggregator would like to choose a lower value that could be considered realistic and for which it would be hard to prove an abuse of market power.

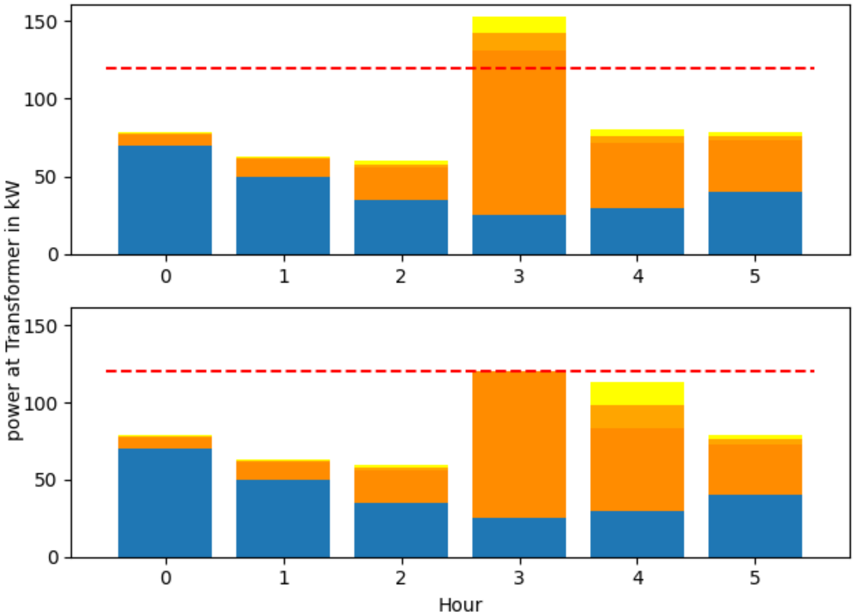

Figure 3.2: Network load schedules before and after LFM operation in case of market power and inflated prices by Aggregator A

3.4.3. Scenario 3: Aggregator A submits a fake schedule

In this scenario, each aggregator controls 8 EVs again. Aggregator A anticipated that the *inflexible* load (the blue bar in the figures) in time step 1 will be high and that it can cause a congestion problem by scheduling all of its available loads in this time step. In reality, it may not even have all EVs available for charging at this time. But since it expects to be paid for shifting loads, it does not intend to actually fulfil this schedule anyways. We again assume it charges an additional mark-up price of 1 Euro/kWh for shifting. The DSO has to accept this bid to avoid overload at hour 0. The before- and after LFM operation schedules are depicted in Figure 3.3. Note that due to aggregator A moving all of its load to hour 0, there is no longer any congestion at hour 3.

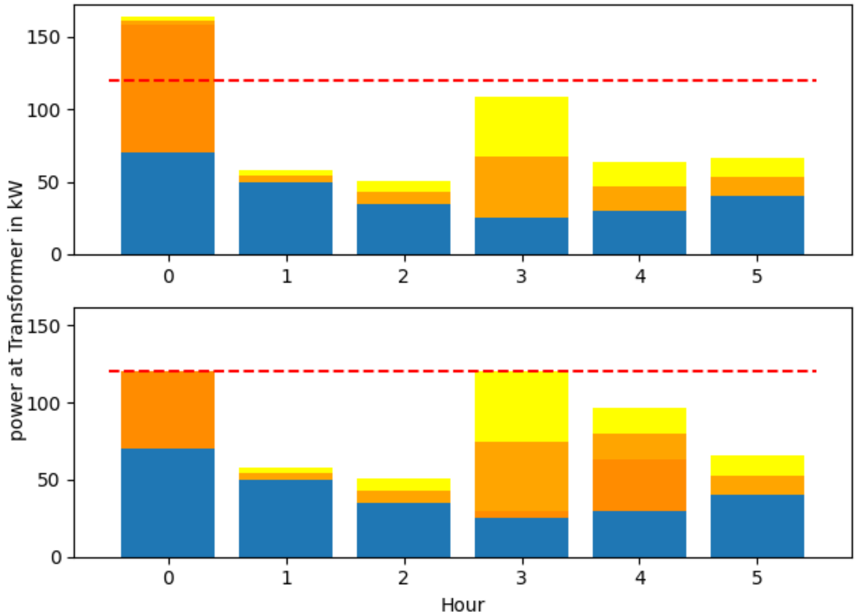

Figure 3.3: Network load schedules before and after LFM operation in case of fake schedule by Aggregator A

3.4.4. SCENARIO 4: AGGREGATOR A SUBMITS A TRUE MODIFIED PROFIT-MAXIMIZING SCHEDULE

Similar to the previous scenario, Aggregator A anticipates that inflexible load is typically high in time step 1. However, rather than submitting a fictional schedule that it may not be able to fulfil, it submits a realistic schedule that can be fulfilled even if it is not called to shift loads.

In some cases it will be called and paid according to its bids and in some cases not. As long as the expected value for the profit of this strategy is higher than submitting the truthful (without LFM payments) schedule, it has an incentive to follow this strategy. We assume that Aggregator A is certain that it has 5 out of its 8 vehicles available for charging at hour 0. Further it assumes that in 50% of all days, the load at the LV feeder in hour 0 will be 90 kW, so that congestion occurs when all 5 of the available EVs are charged at full power and for simplicity we assume no congestion occurs in the remaining 50% of days. If these assumptions are correct and it charges

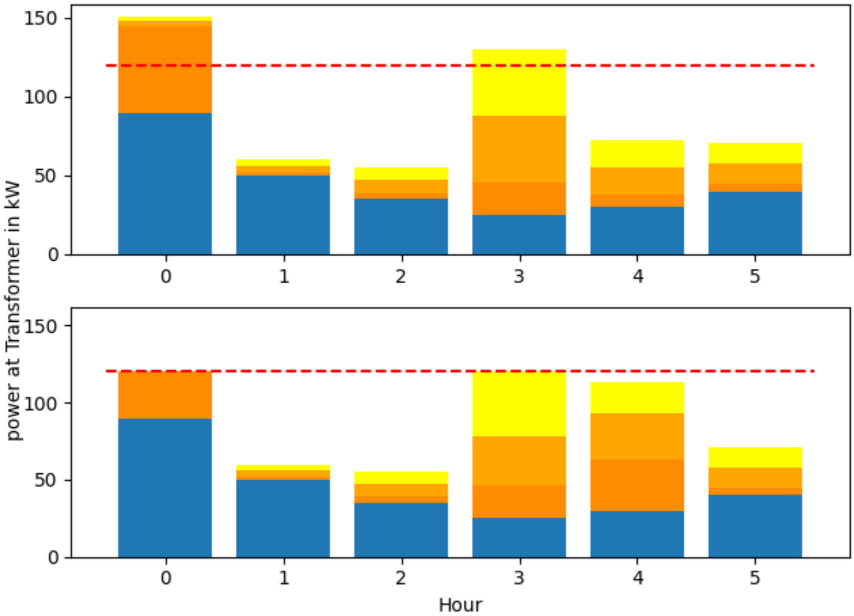

Figure 3.4: Modified schedule by Aggregator A, case of high inflexible load at hour 0: inflexible load is 90 (compared to 70 in other scenarios)

a price higher than a certain threshold value, this is a profit maximizing strategy. It can be calculated that with the given values, the threshold value for the price it must charge is around 0.476 Euro/kWh (see Appendix A). We again assume that it charges an additional 1 Euro/kWh mark-up to the wholesale price difference for shifting. The initial and final schedules are shown in Figure 3.4 for the situation with high load.

	Scenario			
	Perfect Comp.	**Market Power**	**“Fake” Schedule**	**mod. Schedule**
DSO Costs [Euro]	0.47	11.47	32.34	10.64 (exp. value)

Table 3.2: DSO costs of LFM operation in Euro

Table 3.2 gives an overview of the costs of removing congestion for the DSO in the different scenarios. In a perfect market with truthful schedules and bidding, the DSO can remove congestion for the low price of 0.47 Euro. In the scenarios with market failures on the other hand, the DSO ends up paying significantly higher prices. The aggregator who exerts market power and submits non-truthful schedules benefits from these payments. In scenario 2, where schedules are truthful but bidding is not, all of the extra costs of the DSO accrue as profits for the aggregator. In scenarios 3 and 4 the schedules themselves have been modified by the presence of LFM payments. In our toy model, we observe that the modified schedule actually helps in the cases where there is no congestion at hour 0, because aggregator A removed some load from the other congested hour (3) so that congestion is not as severe there anymore. However, as shown in Table 3.2, these savings are offset by the times when there is congestion at hour 0.

3.5. DISCUSSION AND POLICY RECOMMENDATIONS

As we have seen, LFM proposals that are based on baselines can lead to inefficient outcomes, where aggregators collect undue profits at the expense of the DSO. Since the DSO will typically pass on these costs through network tariffs, this also comes at the expense of other network customers. This creates strong fairness concerns: aggregators and their customers may benefit by behaving in network-burdening ways rather than network-serving ways. This is worrying from an income inequality perspective as well: owners of high-power flexible loads are typically more wealthy [18, 19]. Some of the problems that we demonstrated can be partly remedied by regulation: fake schedules can be discouraged by imposing strong penalties and disqualification from further trades when they are detected. Market power can be diluted by imposing market diversification requirements (which is easier at a larger aggregation level). However, the exercise of market power may be difficult to detect. True profit maximizing schedule modifications may also be difficult to detect and are not technically illegal.

Therefore, we recommend to counteract these problems in one of the following ways:

1. Use of other congestion management methods that are more targeted to the problem.[4]

2. In case the LFM method is still the preferred method by the DSO and other stakeholders, there should be a careful consideration of the possible market failures before implementing an LFM at large scale. LFM designs based on

[4] Such as direct control methods and network tariffs, see Chapter 2 and Section 5.2.2.

the submission of baselines and pay-as-bid market clearing should be avoided and other product types, such as capacity limitations Section 3.2, should be considered. Strong regulatory oversight is necessary.

Academic and regulatory proposals that advocate for LFM type solutions should give a clear and precise problem definition for the kind of congestion that the solution is intended to resolve, and demonstrate how it does so without creating undue profit opportunities for aggregators. Other possible CM solutions should be taken into account as well. Network operators, regulators and other involved stakeholders should be aware of the possible unintended consequences of LFM type proposals and be informed about other possible solutions.

3.6. Conclusion

We have reviewed a class of distribution congestion management proposals with Local Flexibility Markets and demonstrated how they may lead to inefficient solutions. These inefficiencies can occur because the private incentives of aggregators for profit maximizations are not aligned with the DSO objective of removing congestion at lowest societal cost. We identified market power and modified baseline schedules as two of the main market failures for LFMs that are based on baselines. The impact of market power can be reduced by increasing the number of market participants. Modified baseline schedules can pose a problem even in situations with many participants. We therefore recommend stakeholders to carefully consider possible market failures before attempting to implement LFM type solutions and to also consider using alternative congestion management mechanisms.

Appendix

In this appendix we derive the threshold value for the price of shifting load in scenario 4 in Section 3.4. Beyond this threshold value, submitting a modified charging schedule, which worsens the original congestion problem, becomes a winning strategy for the aggregator.

In the following, we assume that the aggregator originally would schedule load at time step t_2, which has a lower day-ahead wholesale market price π^{DA} than time step t_1. There is a Local Flexibility Market for congestion management, which pays a price $\pi^{\mathrm{LFM}}(t_1, t_2)$ for shifting loads from t_1 to t_2. Congestion at t_1 happens with likelihood $p(\text{cong})$. This may induce the aggregator to schedule some additional load $\tilde{q}$ (relative to the original schedule) at t_1. In the case of congestion and subsequent operation of the LFM, some of this load will be paid to shift by the LFM, and the rest will not: $\tilde{q} = q^{\text{shift}} + q^{\text{not-shift}}$. With these quantities, we can write the expected profit of the modified schedule, S^{mod}, relative to the original schedule as:

$$\begin{aligned}\text{EV}\left(S^{\text{mod}}\right) = p\left(\text{cong}\right) * \left(q^{\text{shift}} * \pi^{\text{LFM}}\left(t_1,\ t_2\right) - q^{\text{not-shift}} * \left(\ \pi^{\text{DA}}\left(t_1\right) - \ \pi^{\text{DA}}\left(t_2\right)\right)\right) \\ - p\left(\overline{\text{cong}}\right) * \tilde{q} * \left(\pi^{\text{DA}}\left(t_1\right) - \ \pi^{\text{DA}}\left(t_2\right)\right)\end{aligned}$$

The first line gives the profit from congestion events: the payments from the LFM for the shifted load minus the cost of higher wholesale prices for the not-shifted load, and the second line gives the losses in case no congestion occurs: higher costs from the wholesale market for the load that has been added at t_1. The profitability condition $\text{EV}(S^{\text{mod}}) > 0$ yields:

$$\pi^{\text{LFM}}\left(t_1,\ t_2\right) > \frac{1}{q^{\text{shift}}} * \left(\frac{p\left(\overline{\text{cong}}\right)}{p\left(\text{cong}\right)} * \tilde{q} + q^{\text{not-shift}}\right) * \left(\pi^{\text{DA}}\left(t_1\right) - \ \pi^{\text{DA}}\left(t_2\right)\right) \tag{3.1}$$

Using the values from scenario 4: $\tilde{q} = 55\,\text{kW}$, $q^{shift} = 25\,\text{kW}$ (we assume that some of the congestion can be removed with the help of the other aggregators who charge lower prices), $q^{\text{not-shift}} = 30\text{kW}$, $p\left(\text{cong}\right) = 0.5/\text{kWh}$, $p\left(\overline{\text{cong}}\right) = 0.5/\text{kWh}$, $\pi^{DA}\left(t_1\right) = 0.15$ Euro/kWh, $\pi^{\text{DA}}\left(t_2\right) = 0.01$ Euro/kWh. This yields a threshold price of 0.476 Euro/kWh for $\pi^{LFM}\left(t_1,\ t_2\right)$.

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4

What's a Good Distribution Network Tariff? - Developing Indicators for Performance Assessment

Based on the previous chapters, network tariffs emerged as a promising tool for managing network congestion. This chapter focuses on the question of how the performance of these tariffs can be evaluated objectively. This objective evaluation may help in accelerating the uptake of new network tariff proposals.

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Abstract

The adoption of distributed energy resources such as PV cells, electric vehicles and batteries in electric grids is increasing steadily. This brings new challenges for distribution networks. The current network tariffs were not designed for these types of usage and, in many cases, they are not adequate anymore. Thus, many new tariff frameworks have been proposed. In this chapter, we focus on the question of how to assess whether a given tariff framework fulfills its objectives. We propose to use quantitative indicators for performance assessment. We give examples of indicators for common objectives and demonstrate how they can be derived from a cost-accounting methodology for distribution networks.

4.1. INTRODUCTION

The problem

The energy transition leads to an increasing penetration of solar photo-voltaic (PV) cells and high-power flexible loads, such as electric vehicles (EVs) and heat pumps in electricity networks. Users of these networks are charged a tariff for the cost of building and operating them. However, most tariffs were established in a time when power was generated in large, predictable generators and household loads were rather inflexible and easy to predict in aggregate. With the increasing penetration of variable renewable energy sources, distributed generation and high-power flexible loads, these preconditions are no longer true. Therefore, current network tariffs are outdated.

We need new tariffs that are able to deal with the current challenges, while also fulfilling the traditional objectives, such as cost-recovery and easy understandability for consumers. How to design such tariffs has been the subject of much debate recently. However, two important questions that have not received much attention in the literature are: how can we systematically assess whether a tariff fulfills the required objectives, and how can we estimate the trade-offs between different objectives when designing new tariffs? In this chapter, we provide a framework to help answer these questions. We propose quantitative indicators for this purpose and demonstrate how they can be used in practice.

Difficulties in network regulation

Power system operation in Europe has been subject to *unbundling* since the 1990s, meaning that that the processes of electric generation, transmission and distribution were no longer done simultaneously by the same vertically integrated utilities [2, 3]. Generation has been opened up to competition among generators on power markets, while transmission and distribution are regulated monopolies. In most cases they are handled separately by distinct legal entities, the transmission/distribution system operators (TSOs/DSOs). The idea behind this process was that competition in power generation would be beneficial for consumers as markets were assumed to provide cost-efficient outcomes. But how can we ensure that network tariffs are also set in a way that leads to beneficial outcomes for transmission and distribution, given that networks are not subject to market competition?

The framework for tariffs in European countries is typically set by a National Regulatory Agency (NRA) [2]. This is done in consultation with network operators and other stakeholders, which include: electric utilities, consumer groups and special interest groups like smart charging, battery storage and PV companies. The regulator's objective is a tariff framework that recovers network costs at fair prices and that is acceptable to the involved stakeholders and the public.[1]. Given the number of stakeholders involved in the discussion, it is clear that finding a tariff that satisfies everyone is a difficult task.

This is compounded by the problem that no theoretical optimum for network price regulation exists. [5] traces the history of the theoretical developments on network pricing and utility regulation. Since marginal cost pricing is not able to recover network costs, he ultimately comes to the conclusion that there is no strict optimum for price regulation. Rather, network pricing and utility regulation should be made for "practical application" and fulfill a list of desired objectives.

Objectives for network tariffs

There is some variation in the academic and regulatory literature on what the main objectives for network tariffs should be. Most sources agree that their primary function is to recuperate operating expenses and investments for the network operator. In addition, the most commonly cited objectives are [6–8]:

- They should give signals for efficient use of the network, i.e. ideally limit congestion. Congestion can be caused both by high load, and high feed-in from distributed generation;
- Tariffs charged to a given user should be reflective of the costs the user generates for network operation and future investment;
- They should not be *unduly* discriminating among users (more on this and the meaning of the word undue in Section 4.3.3);
- They should be easy to understand and predict by users and not change too much from one billing period to the next.

However, the specific choice of objectives and their relative weighting depends strongly on the context and the view of the stakeholders. Consumer groups and smart charging companies may place a higher value on consumer freedom and simple tariffs that do not restrict consumption too much, while network operators care more about the safe operation of the grid and keeping costs under control. Many such trade-offs and value judgements exist, and therefore discussions about

[1]Once a tariff framework is agreed upon, it typically remains in place for the duration of a period of 4-7 years [4] Minor parameter changes within the framework can happen more often, e.g., on a yearly basis.

new tariff systems can be quite contentious. There are many proposals for new tariff systems in the literature and ongoing national discussions, but there has not been much discussion about best practices for processes to decide on new tariff systems and objective evaluations of them.

Increased urgency for new tariffs

In recent years, installations of new distributed energy resources like PV cells, EVs, batteries and heat pumps have been strongly increasing [9, 10]. These resources create new challenges for the grid, as they can draw or feed-in power at very high rates and at the same time, i.e., they can show strong simultaneity. This is because these resources follow the same drivers, e.g., sunshine in the case of PV cells, or low prices in the case of high-power flexible loads. This is contrary to traditional household loads, which typically had rather low average power with peaks that were spread out randomly over time. On the other hand, the flexibility of these new resources could also be used to resolve congestion in the distribution grid and even help with reducing problems at transmission level, if they receive the right incentives [11]. However, current grid tariffs typically do not provide incentives that align the use of flexibility with network objectives.

4

For example, the current tariff in the Netherlands is a standard fixed tariff that is the same for all households with a connection of up to 3 x 25 Ampere[2]. This was reasonable as long as the large majority of households were heated by gas and did not have EVs. It is a simple tariff, without any data transfer requirements, and variation in energy consumption between households was limited. However, this tariff does nothing to limit EV charging or PV feed-in when there are network problems. Furthermore, consumption profiles of users with and without these resources are now very different, so this tariff effectively subsidizes heavy consumers as they have to pay less relative to the energy they receive through the network and relative to the problems they cause for the network.

Performance assessment of network tariffs

In light of these difficulties, we propose a quantitative method for assessing the performance of tariffs with the help of indicators. The complete process of assessing a proposed new tariff is depicted in Figure 4.1: first, objectives for tariffs are clearly identified. Second, indicators for assessing these objectives are agreed upon. Third, data is collected in real-world field trials or simulated and used in

[2] https://www.energievergelijken.nl/energieprijzen/energierekening/capaciteitstarief

simulation environments. Lastly this data is processed in order to obtain the chosen indicators. The main advantage of this process lies not necessarily in providing exact performance scores, but rather in demonstrating the inherent complexities and trade-offs involved in tariff setting. This helps increase clarity and objectiveness of the discussions. The main contribution of this chapter lies in proposing a sample of possible indicators for the main objectives and demonstrating a framework for their usage.

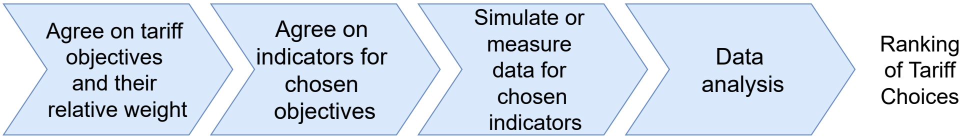

Figure 4.1: Assessment process for network tariffs

Contribution of this chapter

Many studies have proposed new tariff frameworks to deal with the aforementioned challenges. Typically, studies focus on highlighting the benefits of these proposals with respect to how well they reduce network stress and discuss potential fairness issues. For example, the Utilities of the Future report [12] demonstrates how a tariff based on locational marginal prices at LV transformer level lead to cost optimal outcomes in the study system. They note that the resulting situation may not be fair, as users in a congested area are charged higher LMP's than users in not-congested areas. Furthermore, users who invest in flexible thermal loads bring down prices for everyone, while carrying the investment costs themselves. Thus, this setup also creates a "free-rider" problem. Schittekatte et al. [13] investigate the problem of "grid-defection" in some tariffs, where active users may invest in PV cells and batteries to avoid grid charges. They compute total system cost as a proxy for efficiency and allocation of sunk grid costs as a proxy for fairness. Neuteleers et al. [14] investigate fairness in terms of public perceptions. Ansarin et al. [15] look at total social welfare and wealth transfers, based on assumptions about the price elasticities of network users. Fridgen et al. [16] present a model for estimating the impact of different tariff systems in the specific case of residential micro-grids. They focus on total system cost, cost-allocation and network peak shaving services. Savellie et al. [17] propose a novel ex-ante dynamic network tariff and assess it in terms of cost-recovery and social welfare maximization, taking into account the network planning problem.

Many more examples of investigations like these exist, but what we found missing is a comprehensive assessment framework for general distribution networks that looks at all of the main regulatory objectives and trade-offs between them.[3] Brown et al. [19] present a score sheet of different tariff options for performance with respect to: simplicity, economic efficiency, adaptability, affordability and equity. However, the scoring of performance in this case is done based on the subjective judgement of the authors and not based on measured or simulated data.

In light of these gaps, the main contributions of this chapter are:

- to propose indicators for the comprehensive assessment of the performance of tariffs with respect to a set of commonly used objectives;
- to develop a cost-accounting methodology for distribution networks including network cost factors and revenues from tariffs;
- to demonstrate the proposed framework in a case study.

Chapter organization

The rest of the chapter is organised as follows: Section 4.2 presents a conceptualization of a cost-accounting methodology for distribution networks and tariffs, Section 4.3 proposes indicators for the main regulatory objectives that tariffs are expected to fulfill and discusses connections and trade-offs between them, Section 4.4 presents a case study for the application of some of the indicators for a selection of tariffs, Section 4.5 gives a critical discussion of the approach, the limitations and remaining knowledge gaps and Section 4.6 concludes.

4.2. TARIFF COST ACCOUNTING METHODOLOGY

In order to be able to evaluate the performance of network tariffs, we need to have a holistic picture of the determining factors of the costs that are allocated by them, the impact that the tariffs have on these costs and the manner in which they are allocated. To this end, this section introduces a proposed assessment framework for these issues. We begin by noting that there is a feedback in networks between the usage parameters of network users, network costs associated to these usage

[3] During review of this thesis we were made aware of a study that performs a similar analysis as this chapter [18].

patterns and the tariffs by which the costs are allocated back to network users (see Figure 4.2). We now discuss each of these topics in detail.

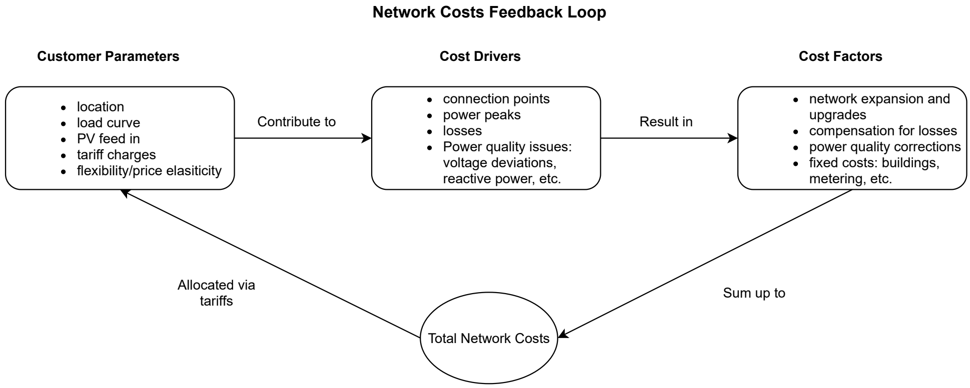

Figure 4.2: Feedback between network costs and tariffs

4.2.1. USER PARAMETERS

We consider a set of network users $\mathscr{U}$. Each user $u \in \mathscr{U}$ has a power curve $P(u,t)$. Loads are represented as positive values of P and PV feed-in can be represented as negative values. For computations relevant to tariffs, we typically consider all times t in one billing period T, where T is most often taken to be one year and time is discretized in time steps Δt, the most commonly used choices for Δt being 5, 15 or 60 minutes.

The network tariff NT interacts with a user's power consumption in several ways: first, flexible loads are able to change their consumption profile based on the price signal π^{NT} that they receive from the tariff. The network tariff price combines with other price components to give the effective price seen by users. The implication of this is that a user's total power consumption profile can be a function of the network tariff: $P(u,t,\mathrm{NT})$. Thus, the tariff can be used to give incentives for efficient network usage.

Second, based on the realized power consumption of the user, the tariff charges are computed as presented in Section 4.2.3.

Lastly, performance indicators for the tariff can be computed based on the power consumption and contribution to network costs (Section 4.2.2), as described in Section 4.3.

4.2.2. NETWORK COSTS

The costs of building and maintaining a distribution network are composed of several cost factors: asset and installation costs for grid infrastructure like transformers, power lines and switch gear, compensation for losses, repairs, power quality maintenance and fixed costs, e.g. for buildings and employees.

These cost factors can be related to cost drivers: number of connections and contracts, network peaks (which may necessitate network upgrades before the end of the designated lifetime of the upgraded assets), energy losses and power quality issues. The cost drivers in turn depend on the behavior of network users: power consumption and generation of existing users and siting choices of new property developments which require a network connection (see also Figure 4.2).

In order to use the indicators proposed in Section 4.3, we need to have an estimate for how the network usage of users relates to the costs they incur for the network operator.

In the following, we base our assumption on a simplified model of a single neighborhood. We take into account only the losses and potential replacement of the LV transformer at which this neighborhood is connected to the grid. We use this to demonstrate how the proposed indicators can be applied in the real world or in more elaborate simulation studies that can include line losses, power quality issues and higher network levels.

Losses

For transformer losses, we follow the methodology given in [20]. Load-related losses, also called copper losses, grow quadratically in the loading of the transformer, multiplied by the nominal copper loss factor $P^{\mathrm{Tr}}_{\mathrm{cu}}$, which depends on the rated capacity of the transformer $P^{\mathrm{Tr}}_{\mathrm{RC}}$:

$$P^{\mathrm{Tr}}_{\mathrm{Loss}}(t) = \left(\frac{P^{\mathrm{Tr}}(t)}{P^{\mathrm{Tr}}_{\mathrm{RC}}}\right)^2 \times P^{\mathrm{Tr}}_{\mathrm{cu}} \tag{4.1}$$

The power at the transformer $P^{\mathrm{Tr}}(t)$ can be computed as the sum of power used of all households over this time step:

$$P^{\mathrm{Tr}}(t) = \sum_{u \in \mathscr{U}} P(u,t) \tag{4.2}$$

We compute the cost of losses using the energy price at the wholesale day-ahead market and a constant mark-up for transmission grid fees, taxes, and other transaction costs:

$$\mathrm{C}_{\mathrm{Loss}}(t) = \left(\pi^{\mathrm{WS}}(t) + \pi^{\mathrm{markup}}\right) \cdot P^{\mathrm{Tr}}_{\mathrm{Loss}}(t) \cdot \Delta t \tag{4.3}$$

Total losses for billing period T are obtained by summing over all times t in T:

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$$\mathrm{C}_{\mathrm{Loss}}(T) = \sum_{t \in T} \mathrm{C}_{\mathrm{Loss}}(t) \tag{4.4}$$

Network upgrades due to peaks

An increase in network peaks may necessitate an upgrade of network infrastructure in order to avoid overloading of assets. This may also be triggered by feed-in peaks of distributed generation [21]. For evaluating tariff performance, it is therefore necessary to consider the impact of tariffs on flattening demand and feed-in peaks and to estimate how contribution to network peaks may be related to the costs required for these network upgrades.

Several methods for computing cost-causation with respect to network expansion exist in the literature [22–25]. Typically these are based on the idea of having a Reference Network Model (RNM) [26, 27], with respect to which cost differences due to new load or distributed generation are estimated.

In our simplified one-transformer model we follow a similar approach and assume that the transformer will have to be replaced once network load reaches 95% of the transformer's rated capacity. We define an indicator variable for whether or not this replacement happens in billing period T:

$$\mathrm{I}_{\mathrm{Repl}}(T) = \begin{cases} 1, & \text{if } P^{\mathrm{Tr}}(t) > 0.95 \cdot P^{\mathrm{Tr}}_{\mathrm{RC}} \text{ for any } t \in T \\ 0, & \text{otherwise} \end{cases} \tag{4.5}$$

Replacement before the end of the designated lifetime of the transformer results in a financial loss due to the foregone remainder of lifetime. This loss is proportional to the fraction of lifetime remaining and the sum of asset and installation cost:

$$C_{\text{Repl}} = \frac{T_{\text{remain}}}{T_{\text{Life}}} \cdot \left(C^{\text{Tr}}_{\text{Asset}} + C^{\text{Tr}}_{\text{Installation}}\right) \cdot I_{\text{Repl}}(T) \tag{4.6}$$

Where we multiplied by the indicator variable from Equation (4.5), to ensure these costs are only taken into account when replacement is actually triggered.

This cost can be annualized for billing period T using the equivalent annual cost formula[4]:

$$C_{\text{Repl}}(T) = C_{\text{Repl}} \cdot \frac{r}{1-(1+r)^{-T_{\text{Life}}}} \tag{4.7}$$

where r is the interest rate paid.

In our model, the total network cost of billing period T then consists of the sum of these factors and fixed costs:

$$C^{\text{Network}}_{\text{Total}}(T) = C_{\text{Loss}}(T) + C_{\text{Repl}}(T) + C_{\text{Fixed}}(T) \tag{4.8}$$

More realistic models could take into account the costs for power quality corrections, line losses, replacements and higher network levels.

4.2.3. NETWORK TARIFF STRUCTURES

The total network costs are allocated to the end-users via recurring network tariffs (and one-off connection charges for new developments). The choice of these tariffs may in turn influence the behavior of network customers, i.e., their power consumption, thus closing the cost feedback loop (Figure 4.2). It may, for example, give incentives in order to reduce total network costs $C^{\text{Network}}_{\text{Total}}$ and fulfill other objectives, which are discussed in Section 4.3.

Network tariffs generally have three main components: fixed, volumetric and capacity based [6, 28]:

- **Fixed component π^{fixed}:** typically paid on a monthly or yearly basis to recover recurring fixed costs. They can also be used to recover residual costs, which are defined as the difference between actual network costs and “the revenues collected through the application of allocation methodologies based

[4] see, e.g., https://xplaind.com/143298/equivalent-annual-cost

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on cost-causality" [29]. This difference exists in networks due to the difficulties in (or impossibility of) establishing a cost-function based on cost-causality [5].

- **Volumetric component π^{vol}:** to be paid per kWh of energy delivered. In the most general formulations, this can be time and location dependent. E.g., in Time-of-Use (ToU) tariffs, this component varies according to a fixed schedule each day. For Locational Marginal Prices (LMP), it can vary in near-real-time and location. Additionally, for some variants of contracted capacity tariffs, a volumetric fee may be applied to users when they exceed a certain power threshold. This is, e.g., the case for the proposed capacity subscription tariffs in the Netherlands [30, 31] and Norway [32], which are also studied in the case study in Section 4.4. Therefore, our formulation of the volumetric component also includes a dependency on power demanded.[5]

- **Capacity component π^{cap}:** payment associated to peak power drawn from the network. The idea behind charging for peak power is that this correlates more with the actual degree of network usage, as networks have to be designed to accommodate peak power and infrastructure investments are a major cost factor [7, 13, 34]. I.e., building a network that accommodates an additional 100 kW of peak demand may be much more expensive than delivering an additional 100 kWh of energy during non-peak hours. These payments can be applied to measured demand peaks, or by contracting a maximum capacity, which limits the maximum power available to the consumer or establishes a threshold to activate financial penalties, as described in the capacity subscription proposals cited above.

The network tariff NT is the set of parameters and functions $\pi^{\mathrm{fixed}}, \pi^{\mathrm{vol}}, \pi^{\mathrm{cap}}$. When this tariff is applied to a users power usage $P(u,T)$, it yields a tariff charge π^{NT}:

$$\pi^{\mathrm{NT}}(u,T) = \pi^{\mathrm{fixed}}(T) + \sum_{t\in T} \pi^{\mathrm{vol}}(t, P(u,t)) \cdot P(u,t) \cdot \Delta t + \sum_{\tau\in T} \pi^{\mathrm{cap}}\left(\tau, \overline{P}(u,\tau)\right) \tag{4.9}$$

where $P(u,t)\cdot\Delta t$ is the energy consumed by the user u in the time step from t to $t+\Delta t$ and $\overline{P}$ is the peak power (measured or contracted) used as a basis for the capacity charge over time period τ. The accounting periods for peak power τ may, for example, distinguish between seasons or day and night time, similar to a ToU

[5] Another option are network coincident peak charges [33, 34].

volumetric charge.

This tariff charge results in a cost for the user and a revenue for the network operator. Total network revenue TNR can then be computed as the sum of all revenues over the user set for a given tariff:

$$\mathrm{TNR}(T, \mathrm{NT}) = \sum_{u \in \mathcal{U}} \pi^{\mathrm{NT}}(u, T) \tag{4.10}$$

4.3. OBJECTIVES AND INDICATORS FOR NETWORK TARIFF PERFORMANCE

4

In this section, we build on the network cost model introduced in the previous section to develop performance indicators for network tariffs. Besides recovering costs for network operation and sending signals for efficient network usage, tariffs are expected to ideally also fulfill a range of other objectives [4, 6–8, 35]. Among them: they should reflect the costs users are incurring on the network (cost-reflectiveness), they should be non-discriminatory between users, easy to understand (simplicity), not vary too much from one year to the next (stability) and easy to predict for users (predictability).

We formalize performance indicators (PIs) as sets of functions for a given network tariff NT:

$$\mathrm{PI} = \{\mathrm{PI}^{\mathrm{CostRec}}, \mathrm{PI}^{\mathrm{CostRefl}}, \mathrm{PI}^{\mathrm{CostEff}}, \mathrm{PI}^{\mathrm{NonDis}}, \mathrm{PI}^{\mathrm{Simpl}}\} \tag{4.11}$$

Where each of these sets consists of multiple indicators for the respective objective. We focus on the objectives of cost-recovery (CostRec), cost-reflectiveness (CostRefl), efficiency (CostEff), non-discrimination (NonDis) and simplicity (Simpl) here, as these are the most commonly found objectives. Given the abstractions involved in the cost model presented in the previous section, the numbers obtained from computing these indicators should be seen as indicative of relative performance, rather than precise values. The main advantage of the proposed framework is that it enables better understanding of the complexities and the principal trade-offs between performance with respect to different objectives. The choices of which indicators to use and how to weigh objectives relative to each other should be adapted to the specific context in which tariffs are investigated. In the following sections, we discuss each of these individually, with an emphasis on considerations for quantifying performance. A summary of the proposed indicators is given in Table 4.1.

Objective	Possible Indicators
Cost recovery	Expected value and variance of expenses and revenues, based on plausible distribution of consumption patterns
Cost Reflectiveness	Tariff charges relative to individual contributions to short- and long-term marginal costs and fixed costs
Non-discrimination	Difference of tariff charges for the same load curve in different pricing locations Variations in tariff that are not explained by total consumed energy and personal peak
Cost-Efficiency	Network operation and infrastructure costs Other user costs: e.g., cost of charging EV at wholesale prices Congestion management: peaks relative to network capacity, average loading of network assets
Simplicity	Degree of temporal and spatial variation Complexity score: 1. Fixed or flat volumetric tariffs; 2. vol. ToU with 2-3 time periods; 3. capacity based or vol. ToU with >3 periods; 4. mix of vol. and capacity, or near real-time. Implementation burden score: 1. No change required; 2. Smart meters required; 3. Near real-time communication required; 4. New market platform required.

Table 4.1: A selection of possible performance indicators for the chosen objectives

Note that we do not have separate indicators for "fairness", which is also often cited as an objective for network tariffs. This is because "fairness" is an ambiguous term, which can have different meanings depending on the individual viewpoint. For example, for tariff setting it could mean charging users according to the costs they incur (cost-reflectiveness), charging everyone according to the same rules (non-discrimination), or even using tariffs for wealth redistribution purposes (equity concerns) to support vulnerable groups. Therefore, we use the more clearly defined concepts of cost-reflectiveness and non-discrimination here, while we consider equity concerns out of scope for this chapter.[6]

[6] They are addressed, e.g., in [36].

4.3.1. COST-RECOVERY

Cost-recovery, i.e., financial sustainability of network operation [37], is a requirement, rather than merely a desired outcome. The network operator needs to recover costs to guarantee continued delivery of the service: “Cost recovery is the core objective of tariffs.” [35].

An equality of revenues and costs needs to hold on average, across billing periods over the network under consideration. Due to the complexity of building and operating a network and setting charges on its use, revenues and expenses will not exactly balance out every year. Thus, we formalize this principle in terms of expected values:

$$\mathrm{E}\left[\mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}(\mathrm{NT})\right] \simeq \mathrm{E}\left[\mathrm{TNR}(\mathrm{NT})\right], \tag{4.12}$$

where we treat total network costs and revenues as random variables over different usage patterns of the user set $\mathcal{U}$. How to compute them for a given usage pattern was discussed in Section 4.2.

Equation (4.12) leads us to define the performance indicators for cost-recovery as the (absolute) expected value and variance respectively, of the difference of costs and revenues:

$$\mathrm{PI}^{\mathrm{CostRec}}_{\mathrm{E}}\left(\pi^{\mathrm{NT}}\right) = \left|\mathrm{E}\left[\mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}(\pi^{\mathrm{NT}}) - \mathrm{TNR}(\pi^{\mathrm{NT}})\right]\right| \tag{4.13a}$$

$$\mathrm{PI}^{\mathrm{CostRec}}_{\mathrm{Var}}\left(\pi^{\mathrm{NT}}\right) = \mathrm{Var}\left[\mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}(\pi^{\mathrm{NT}}) - \mathrm{TNR}(\pi^{\mathrm{NT}})\right], \tag{4.13b}$$

Where the support of the random variables $\mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}$ and TNR is given by a range of plausible usage patterns across the user set of the network.

Note that better performance corresponds to a lower indicator value in this formulation, but this could be changed by adding a minus on the right side of the equation, if desired. While large deviations from a balanced budget are undesirable in any case, a large revenue shortfall may be potentially more severe than a large surplus, as it may threaten the financial stability of the network operator. To reflect this, it would also be possible to make the indicator asymmetric and penalize revenue shortfalls more than surpluses.

As demonstrated above, tariffs impact both sides of Equation (4.12): they obviously determine the revenues from network charges. But on the other hand, they also can gives incentives for efficient network usage patterns that lead to lower overall costs, e.g., due to reduced losses and required network upgrades. Thus, when moving to a new tariff system, estimates should be made on how the new system influences both sides of the budget. This may lead to adjustments of the parameters of the new tariff system to avoid excessive revenue shortfalls or inflated prices. In order to reflect the uncertain nature of customer behavior patterns, it is beneficial to simulate this over a range of possible load patterns, e.g. based on different weather patterns or behavioral assumptions, in order to get a more robust picture.

As a side note, a good performance with respect to cost-recovery is also beneficial for the stability of tariffs over billing periods. The closer that revenues and costs are together, the less need there is for an adjustment of the parameters of the tariffs between billing periods. An example for a threat to stability is the so-called "death spiral" of distribution grids. It occurs, e.g., when grid tariffs only account for net consumption and active users can largely avoid them by investing in PV cells and/or batteries. In this case, the network operator would have to increase charges more and more in order to satisfy cost-recovery, which leads to highly instable tariffs (see, e.g., [13, 38]).

Connections to other objectives

Cost-reflectiveness and non-discrimination: Equation (4.12) imposes cost-recovery for the whole network. If network charges were also highly cost-reflective, this equation would hold not only for the network as a whole, but for all sub-parts of the network down to LV-feeders. For perfect cost-reflectivity, it could even hold for the single household level contributions (see Section 4.3.2). The degree to which cost-recovery varies over different neighborhoods may be seen as a form of cross-subsidy from areas where costs are over-recovered to those where they are under-recovered (note that these could also be intentional cross-subsidies in tariffs that are meant to subsidize certain groups of users, see e.g. [39]). On the other hand, if charges are perfectly cost-reflective at every sub-part of the network, they will likely also be highly discriminatory (see Section 4.3.3), as they would vary strongly by location. [7]

Cost-efficiency: As mentioned above, tariffs that give efficient price signals help to reduce the total cost side of the revenue balance. Thus, tariffs that give efficient signals score higher for cost-efficiency and they also need to recover fewer costs for the network operator (on average).

Simplicity: The simpler the tariff structure the easier it is to estimate total network

[7] There are also discriminatory tariffs which are not based on cost-reflectiveness. For example volumetric net-metering [28] of PV owners: it makes cost-recovery harder as less revenues are obtained from them, it is not based on cost-reflectiveness and it is discriminatory in terms of price-per-kWh delivered through the network.

revenue and to set charges such that total revenues equal total costs.

4.3.2. COST-REFLECTIVENESS

According to EU law: "Charges applied by network operators for access to networks, including charges for connection to the networks, charges for use of networks, and, where applicable, charges for related network reinforcements, shall be cost-reflective (...)"[8]. I.e., network charges should reflect the costs that a users network usage incurs for the network operator:

$$\pi^{\mathrm{NT}}(u,T) \simeq \mathrm{C}^{\mathrm{Contr}}(u,T), \tag{4.14}$$

The main difficulty in assessing cost-reflectiveness is to establish a cost causation function: how does a given usage profile by user u impact the total network costs $\mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}$? I.e., what is their cost contribution $\mathrm{C}^{\mathrm{Contr}}(u,T)$?

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Network users contribute to the costs of building and operating the network in several ways (see also Figure 4.2):

- Having a network connection: contributes to fixed costs and residual costs. A distribution network and a company managing it have to exist in order to supply users with electricity from wholesale markets. The costs for running this company include, for example: costs for owning and managing company buildings, employee wages and ancillary costs, maintenance costs of network infrastructure. Additionally, there is a one-off connection cost for new customers to build and maintain the physical connection to the network and set up a metering device.

- Consumption of energy: contributes to the short-term marginal cost of delivering energy through the network. Losses and power quality issues (e.g. voltage deviations) depend on the energy consumed by a consumer, their location and the total electricity flow in the network at a given time. E.g., thermal losses grow quadratically in the loading of an asset.

- Contribution to network peaks: contributes to the long-run marginal costs for investments in network infrastructure. Network assets have to be sized in order to safely supply the highest network peaks without failing. Thus, peaks are considered to be the main cost-driver for long-term investment decisions and replacement of assets which are at risk of being overloaded [6, 40].

[8] see Article 18(7) of Regulation (EU) 2019/943

Note that these contributions map approximately on the typical tariff components presented in Section 4.2.3: fixed, volumetric and measured or contracted power (though personal power peaks generally do not align with network power peaks, see [34]). We now discuss each of these contributions in turn.

Contributions to fixed and residual costs

Since fixed and residual costs are driven by the need for having a network connection and are largely unrelated to short and long-term marginal costs, one obvious way of allocating contributions to fixed costs is to simply divide them evenly among all network users:

$$\mathrm{C}^{\mathrm{Contr}}_{\mathrm{Fixed}}(u,T) = \mathrm{C}_{\mathrm{Fixed}}(T)\cdot\frac{1}{n_{\mathcal{U}}} \tag{4.15}$$

where $n_{\mathcal{U}}$ is the number of users connected to the network. Some authors also discuss approaches to recover these costs by means that attempt to charge wealthier households more than less-wealthy households (see, e.g., [41]). However, this introduces distributional considerations unrelated to cost-reflectiveness. This can be identified as an additional objective for tariffs (as in [42]), but in the following we use Equation (4.15) as the definition of the cost-reflective contribution to fixed and residual costs.

Contributions to short-term marginal costs

In the simplified network cost model introduced in Section 4.2.2, we use losses at the transformer as a proxy for short-term marginal costs. We allocate contributions to losses proportionally to power usage at each moment:

$$\mathrm{C}^{\mathrm{Contr}}_{\mathrm{Loss}}(u,t) = \mathrm{C}_{\mathrm{Loss}}(t)\cdot\frac{P(u,t)}{\sum_{u'\in\mathcal{U}}P(u',t)} \tag{4.16}$$

More elaborate models could also take into account power lines, higher network levels and power quality issues such as voltage support in short-term marginal costs. Furthermore, in realistic power flow models these costs also depend on a users location within the network.

It may be useful to define an auxiliary performance indicator to judge how well a tariff reflects these losses (or analogously for other short term marginal costs). This could, for example, be the Pearson correlation of tariff charges with contributions to losses:

$$\mathrm{PI}^{\mathrm{CostRefl}}_{\mathrm{Loss}}(\mathrm{NT}) = \mathrm{corr}\left(\pi^{\mathrm{NT}}(u,T),\, \mathrm{C}^{\mathrm{Contr}}_{\mathrm{Loss}}(u,T)\right) \tag{4.17}$$

Contributions to long-term marginal costs

A precise relation between contribution to peaks and contribution to long-term costs in networks is not possible. This is because the long-term cost function also depends on:

- other developments in the network, like demand growth and new connections,
- the prior situation in the network, i.e., the size and age of existing network assets,
- the planning of the network operator, which may or may not anticipate demand growth correctly,
- the location of the tightest constraint, i.e., whether it is at the LV transformer, a power line or an MV/LV substation. This would determine which peak contribution should actually be taken into account.

Furthermore, marginal costs are difficult to determine as network investment costs are typically step-functions: the marginal cost of adding additional demand is zero as long as the limit of safe operation with existing equipment is not reached, and it has a large jump once an additional unit of marginal demand pushes total demand over this limit. Lastly, a user's previous contribution to network peaks may also not necessary imply that the user will have the same peak contributions in the future. This could perhaps be resolved by treating a users load as a random variable, which is influenced by certain user parameters. Based on this, one could compute the most likely contribution to future network peaks.

However, a precise relation may also not be necessary in order to gain general insights into tariff performance. What is important here, is that network peaks are an important cost driver for network operators. Therefore, this should be reflected in the tariff. The degree to which we relate contribution to peaks to costs is a parameter that should be varied in a sensitivity analysis in order to obtain a more robust picture.

We approximate this relation by using the transformer replacement condition Equation (4.5) to establish a degree to which a given consumer contributed to the replacement. [34] show that in order to get a better estimate of a users true contribution to peaks one should take not just the single highest peak into account, but a range of peaks. This may better reflect the true nature of how often a given user contributes to critical or near-critical network peaks. Thus, we approximate this contribution by calculating the average contribution of each user to the n_{peaks}

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highest network peaks:

$$\mathrm{C}_{\mathrm{Repl}}^{\mathrm{Contr}}(u,T) = \mathrm{C}_{\mathrm{Repl}}(T) \cdot \frac{1}{n_{\mathrm{peaks}}} \sum_{t \in \mathrm{T}_{\mathrm{peaks}}} \frac{P(u,t)}{P^{\mathrm{Tr}}(t)} \tag{4.18}$$

where $\mathrm{T}_{\mathrm{peaks}}$ is the set of the n_{peaks} highest network peak times. Note that the contribution in Equation (4.18) is zero if the replacement condition Equation (4.5) has not been met.

In analogy to Equation (4.17), we define a performance indicator for the contribution to replacements as:

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$$\mathrm{PI}_{\mathrm{Repl}}^{\mathrm{CostRefl}}(\mathrm{NT}) = \mathrm{corr}\left(\pi^{\mathrm{NT}}(u,T), \mathrm{C}_{\mathrm{Repl}}^{\mathrm{Contr}}(u,T)\right) \tag{4.19}$$

Total cost contribution performance indicators

Based on these contributions, we propose a combined performance indicator for cost-reflectivity as:

$$\mathrm{PI}_{\mathrm{Total}}^{\mathrm{CostRefl}}\left(\pi^{\mathrm{NT}}\right) = \mathrm{corr}\left(\pi^{\mathrm{NT}}(u,T), \mathrm{C}_{\mathrm{Fixed}}^{\mathrm{Contr}}(u,T) + \mathrm{C}_{\mathrm{Loss}}^{\mathrm{Contr}}(u,T) + \mathrm{C}_{\mathrm{Repl}}^{\mathrm{Contr}}(u,T)\right) \tag{4.20}$$

Note that the correlation coefficient here refers to the standard Pearson correlation. This coefficient tracks how strong a linear relationship between the two variables is. However, it does not measure the *slope* of the linear relationship. That is, a perfect linear relationship with a flat increase of variable y with x has the same coefficient as a perfect linear relationship with a very steep increase, both have a correlation coefficient of 1. On the other hand, perfect cost-reflectiveness would mean that cost contributions are exactly equal to tariff charges. Thus, an increase in cost contributions should be met by the same increase in tariff charges, i.e., the slope of the linear relationship would be 1. Thus, we propose as an additional indicator the slope of the linear regression function:

$$\mathrm{PI}_{\mathrm{Slope}}^{\mathrm{CostRefl}}\left(\pi^{\mathrm{NT}}\right) = \beta_1, \tag{4.21}$$

where β_1 is the linear coefficient of the regression function

$$\hat{\pi}_{\mathrm{cost-contr}}^{\mathrm{NT}}(u,T) = \beta_0 + \beta_1 \cdot \mathrm{C}_{\mathrm{Non-fixed}}^{\mathrm{Contr}}(u,T) \tag{4.22}$$

and we include only non-fixed cost contributions in independent variable. Fixed costs in perfectly cost-reflective tariffs should be exactly equal to the offset parameters β_0.

Note that this indicator should always be assessed in conjunction with either the correlation coefficient, or the R-squared metric of the regression function. This is because non-linear relationships can also produce a slope coefficient close to 1 in linear regression, even though the true relationship is very different, see, e.g., [43].

Connections to other objectives Non-discrimination: There is a fundamental friction between these two objectives. Perfectly cost-reflective charges would be highly dependent on a user's location, time of usage and interuptibility of loads. Thus, they would be highly discriminatory.

Cost-efficiency: Theoretically, fully cost-reflective charges would send perfectly efficient price signals which could lead to highly efficient network outcomes. However, cost-reflective charges are not in themselves a sufficient condition for cost-efficient outcomes. In order for them to be effective, there also needs to be an abundance of price-elastic, flexible loads that can react to them, as well as a communication interface that reliably transmits price signals (and perhaps also control signals for interuptible loads), see Figure 4.3.

Simplicity: As already discussed, fully cost-reflective charges would be strongly dependent on time, location and interuptibility. Thus, they would also be highly complex and require elaborate interfaces to be implemented.

4.3.3. NON-DISCRIMINATION

Perhaps the biggest challenge with this objective is, to define what discrimination means, and when it may be permissible. For example, the Council of European Energy Regulators (CEER), in its summary of tariff design principles, states: “there should be no undue discrimination between network users” [6]. But what is *undue* discrimination and how can we distinguish it from *due* discrimination?

There are three main factors on which discrimination in tariffs charges can occur: time, location and flexibility of loads.

Discrimination based on time, e.g. in ToU or real-time tariffs, affect everyone equally and thus may be seen as *due* discrimination. However, there may be large differences

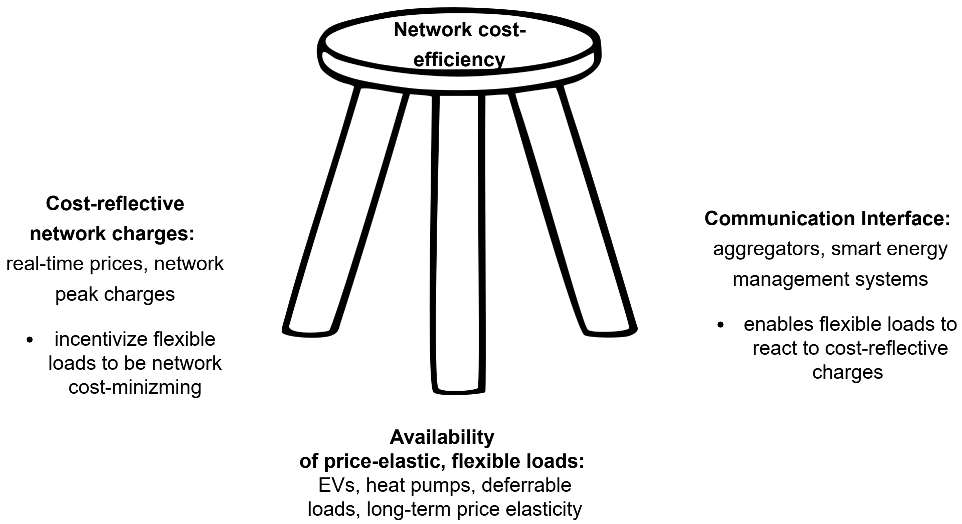

Figure 4.3: 3-legged stool model for cost-efficiency in networks

in how well users can react to these varying prices. Thus, care should be taken to help vulnerable groups to adapt to these changes or offer easier tariffs for them.

Discrimination based on flexibility can occur when flexible loads (or generators) are charged differently than inflexible, must-run loads. In return, these loads may be curtailed in times of high network stress by the network operator. As flexible loads give up their right to run at any time and help reduce network problems, this may also be seen as *due* discrimination. However, again some users may be able to profit more from this than others (see, e.g., [44]). Thus, care should be taken to design tariffs in ways that do not lead to unintended wealth redistribution.

Discrimination based on location is more difficult to judge, as it depends strongly on the granularity of the variation in charges. Currently, many network operators apply "postage-stamp" pricing [8], whereby all consumers in the operating area are charged the same tariff, in analogy to the price of postage stamps for sending mail. In this approach there is no variation in location and therefore no discrimination based on location. On the other hand, problems related to network stress are typically highly localized. For example, the "Utility of the Future" report [12] shows how applying the same tariff system wide, or even at an MV substation level does nothing to resolve a localized network problem (p. 124 and following). Only applying an LMP-based tariff that targets the specific neighborhood feeder resolves this localized congestion problem. But does this mean that this is a *due* form of discrimination? Which feeders are congested and which not depends on factors that are outside of a user's control, like network planning failures by the operator or congestion due to a localized rise in energy consumption, e.g., because of a new commercial establishment or higher consumption of other users at the same feeder. Thus, this form of discrimination may be seen as *undue*. A further example is the distinction between rural and urban users: rural grids are typically spread out further and benefit less from economies of scale. Thus, costs for rural users will typically be higher. Furthermore, whether to live in an urban or rural area may be a choice that a user has some degree of control over, but then again it also may not be. Thus, a tariff that makes a general distinction between urban or rural may or may not be considered *due*. We do not make a judgement here on which forms of discrimination are *due* or not. The main point is that all of these considerations may be important when judging the degree of permissiveness of discrimination.

We propose the following performance indicators for non-discrimination:

Location-based discrimination
Due to the complexities related to location-based discrimination described above, we propose specific indicators for this issue. These are the maximum and average of differences in tariff charges for two different pricing locations a and b:

$$\mathrm{PI}^{\mathrm{NonDis}}_{\mathrm{loc,max}}\left(\pi^{\mathrm{NT}}\right) = \max_{\mathrm{u,loc_a,loc_b}} \left|\pi^{\mathrm{NT}}(u,T,\mathrm{loc_a}) - \pi^{\mathrm{NT}}(u,T,\mathrm{loc_b})\right| \tag{4.23a}$$

$$\mathrm{PI}^{\mathrm{NonDis}}_{\mathrm{loc,avg}}\left(\pi^{\mathrm{NT}}\right) = \frac{1}{n_{\mathscr{U}} \cdot n_{\mathscr{L}}(n_{\mathscr{L}}-1)/2} \sum_{u,loc_a,loc_b} \left|\pi^{\mathrm{NT}}(u,T,\mathrm{loc_a}) - \pi^{\mathrm{NT}}(u,T,\mathrm{loc_b})\right| \tag{4.23b}$$

where the set over which to find the maximum and average includes each observed or simulated user profile u for each price-location difference. I.e., this set is $\mathscr{U} \times \mathscr{L} \times (\mathscr{L}-1)/2$, where $\mathscr{L}$ is the set of distinct pricing locations and the factor of one half is added to avoid double counting.

General non-discrimination
In the most general sense, discrimination means that users are charged differently for using the network in a similar way. But as discussed above, it is difficult to define precisely what using the network "in a similar way" means. Arguably, the

the two parameters that perhaps best summarize how much a user uses the grid are their total energy consumption and peak load. Thus, one option to determine discrimination between users in a quick and rough way could be to look at the variance of charges per kWh of energy consumption and per kW of peak usage respectively:

$$\mathrm{PI}^{\mathrm{NonDis}}_{\mathrm{energy}}\left(\pi^{\mathrm{NT}}\right) = \mathrm{Var}\left(\frac{\pi^{\mathrm{NT}}(u,T)}{\sum_{t\in T} P(u,t)\cdot\Delta t}\right) \tag{4.24a}$$

$$\mathrm{PI}^{\mathrm{NonDis}}_{\mathrm{peak}}\left(\pi^{\mathrm{NT}}\right) = \mathrm{Var}\left(\frac{\pi^{\mathrm{NT}}(u,T)}{\overline{P}(u,T)}\right) \tag{4.24b}$$

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Another option to measure discrimination indirectly could be to look at how much of the variance in network charges is explained by total energy use and peak load. This can be done by using the R^2-metric of a linear regression for network charges based on these two parameters:

$$\mathrm{PI}^{\mathrm{NonDis}}_{\mathrm{general}}\left(\pi^{\mathrm{NT}}\right) = R^2 \tag{4.25}$$

with the standard R^2-metric of the regression function:

$$\hat{\pi}^{\mathrm{NT}}_{\mathrm{energy,peak}}(u,T) = \beta'_0 + \beta'_1\cdot\left(\sum_{t\in T} P(u,t)\cdot\Delta t\right) + \beta'_2\cdot\overline{P}(u,T) \tag{4.26}$$

where we included apostrophes in the regression parameters to indicate that they're different from the ones used for the cost-reflectiveness regression function Equation (4.22). Note, however, that this indicator would not be well defined for a pure fixed charge, which has no relation to either energy consumption or peak load at all.

Connections to other objectives

Cost-efficiency: As explained in the discussion on cost-reflectiveness (Section 4.3.2), discrimination that is based on cost-reflectiveness may lead to efficient outcomes. On the other hand, there may also be discriminatory effects which are not based on cost-reflectiveness and thus do not lower network costs, like net-metering of PV cells.

Simplicity: Typically, simpler tariffs are less discriminating, as they tend to vary less. But it also depends on the viewpoint of what constitutes a discriminatory charge. E.g., an identical fixed charge for every user is a very simple tariff and it may be seen as non-discriminatory as everyone is charged the same. On the other hand, the charge-by-kWh and charge-by-peak measures (Equation (4.24a) and

Equation (4.24b)) for this tariff may be highly discriminatory.

4.3.4. COST-EFFICIENCY

As previously discussed, network tariffs can give incentives for efficient network usage which reduces total costs for the network operator and hence reduces the charges that need to be recovered from network users. As demonstrated in the network cost model Section 4.2.2 and the discussion of cost-reflectiveness, Section 4.3.2, the main cost contributions which are under the control of users are those to short- and long-term marginal costs (e.g., contributions to losses and to network peaks). By lowering these costs, total network costs and costs per kWh of delivered energy can be reduced, which are two obvious choices for performance indicators:

$$\mathrm{PI}^{\mathrm{CostEff}}_{\mathrm{network}}\left(\pi^{\mathrm{NT}}\right) = \mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}(\pi^{\mathrm{NT}}) \tag{4.27a}$$

$$\mathrm{PI}^{\mathrm{CostEff}}_{kWh}\left(\pi^{\mathrm{NT}}\right) = \frac{\mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}(\pi^{\mathrm{NT}})}{\sum_{u,t} P(u,t)\cdot\Delta t}, \tag{4.27b}$$

On the other hand, perhaps minimizing network costs should not be the only objective. When tariff charges are applied that lead to minimal network costs, the total cost of energy consumption of all users may still be higher. This could occur, e.g., in a situation where the tariff disincentivizes consumption during times of low wholesale prices to restrain network peaks. Thus, another objective for cost-efficiency could be to minimize total system costs, taking into account also the effective prices paid by users (Equation (4.32)):

$$\mathrm{PI}^{\mathrm{CostEff}}_{\mathrm{total\ system}}\left(\pi^{\mathrm{NT}}\right) = \mathrm{C}^{\mathrm{Network}}_{\mathrm{Total}}(\pi^{\mathrm{NT}}) + C^{\mathrm{Other}} \tag{4.28}$$

where other costs would mainly be made up of wholesale prices. In more elaborate schemes, they could also include foregone revenues from not being able to trade on other markets, e.g. balancing, due to restrictions of the tariff.

Since other costs are quite hard to obtain or realistically simulate, a middle ground may be to use congestion-management related measures to judge performance with respect to cost-efficiency. Ideally the tariff should lead to some flattening of peaks, so as to not threaten overloading of grid assets, but preferably the tariff should not restrict usage too much during times in which there is no network congestion, in order not to constrain users to make use of low wholesale prices during these times. Thus, possible performance indicators could be the size of peaks relative to the rated

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capacity of assets and the load factor of critical assets. The load factor is defined as average power divided by peak power. If it is close to 0, the load curve is dominated by large spikes and long times of comparatively low load. This indicates inefficient usage of assets. On the other hand, a load factor close to 1 may indicate that the asset is too often used at its limit and may have to be replaced soon. For the single transformer in our cost model, these indicators are obtained as:

$$\mathrm{PI}^{\mathrm{CostEff}}_{\mathrm{PeakSize}}\left(\pi^{\mathrm{NT}}\right) = \frac{\overline{P^{\mathrm{Tr}}(t)}}{P^{\mathrm{Tr}}_{\mathrm{RC}}}, \tag{4.29a}$$

$$\mathrm{PI}^{\mathrm{CostEff}}_{\mathrm{LoadFac}}\left(\pi^{\mathrm{NT}}\right) = \frac{\mathrm{avg}\left(P^{\mathrm{Tr}}(t)\right)}{\overline{P^{\mathrm{Tr}}(t)}}, \tag{4.29b}$$

These indicators have also been proposed by a study on tariff design for the European Commission [8]. Peak load has also been used in tariff assessment by [16]. They also proposed an indicator similar to the load factor, the "crest factor" which is defined as "the quotient of absolute peak to root mean square of all loads".

4.3.5. Simplicity and implementation burden

Users should be able to easily understand their network tariff in order not to be hit with unexpected charges and to be able to follow the price signals sent by the tariff in order to reduce impact on network costs. A highly cost-reflective tariff may not be effective in reducing costs if it is too difficult for users to adapt their usage to the price signal, or if the signal cannot reliably be transmitted. Therefore, it can be helpful to have a measure for how easy or difficult it is to understand the tariff.

Of course it is difficult to judge what users may consider simple or complex tariffs, as it strongly depends on traits of the individual users - e.g., their willingness and time availability to concern themselves with their network tariffs, or whether they have a smart homer energy management system, which can automatically follow price or control signals sent by the network operator. We propose a categorization based on 4 levels of increasing difficulty, as defined in Figure 4.4. Based on this, we define a categorical indicator:

$$\mathrm{PI}^{\mathrm{Simpl}}\left(\pi^{\mathrm{NT}}\right) = \mathrm{I}_{\mathrm{Simpl}} \in \{1, 2, 3, 4\} \tag{4.30}$$

Similarly, it is possible to define an indicator for the implementation burden of a

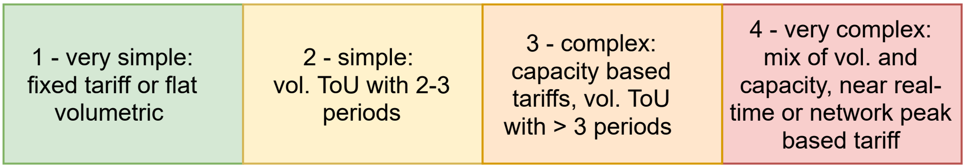

Figure 4.4: Complexity score for the simplicity of tariffs

tariff based on the infrastructure requirements that must be met in order for the tariff to be implementable. Many new tariff proposals like capacity subscriptions and highly variable time of use tariffs require at least smart meters. More advanced tariffs that send price or control signals in near-real time require a communication interface capable of transmitting these signals. And even more advanced solutions might require new market platforms between network operators and users (not considered in this study).

4.4. CASE STUDY

In this section we present a case study of tariff assessment to demonstrate how the proposed framework can be applied in practice. We keep the scope limited to a single neighborhood, four types of network tariffs and a selection of a few of the most important indicators, as this is intended only as a demonstration of the framework. We leave as future work an in-depth discussion of many different tariff variants, using a more comprehensive set of indicators and larger networks with multiple neighborhoods.

4.4.1. MODEL DESCRIPTION

We developed the ANTS-model[9] (Assessment of Network Tariff Systems) to investigate the performance of tariffs. The model implements the network cost model presented in Section 4.2.

We account for the increasing penetration of distributed energy resources by separating users load into a flexible and inflexible component:

$$P_{\text{total}}(u,t) = P_{\text{flex}}(u,t) + P_{\text{inflex}}(u,t) \tag{4.31}$$

[9] publicly available at https://gitlab.tudelft.nl/rhenning/ANTS-model

Inflexible loads are "traditional" household loads like lighting, electric stoves and power outlets, which should be served at any given time. In our framework, these loads are not assumed to be able to respond to price or control signals. Flexible loads (or generation) include EVs, heat pumps and PV feed-in (which can be curtailed), and are assumed to be able to respond to price and control signals in near-real time. This responsiveness to external signals may be achieved through control by a Smart Energy Management System (SEMS) or an aggregator.

We assume that the effective price seen by these flexible loads is composed of different components, in euro/kWh:

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$$\pi^{\mathrm{eff}}(t) = \pi^{\mathrm{NT}}(t) + \pi^{\mathrm{WS}}(t) + \pi^{\mathrm{other}}(t) \tag{4.32}$$

where π^{WS} is the whole-sale price in the electricity market and other charges may include, e.g. transmission fees and taxes.

A complicating factor is that network operators do not have precise information about how consumers respond to price and control signals. Even the loads that we consider inflexible here may, over the long run, have some elasticity of demand and the loads that are flexible may not at all times be able to follow external signals. Moreover, there is another category of devices that does not cleanly fall into either of these two categories: deferable loads with fixed power consumption profiles like smart dishwashers lie somewhere in the middle. These details could be included in future work.

For the purpose of demonstrating how the indicator framework developed in the previous sections can be applied in practice, we limit our analysis here to EVs as a proxy representation of flexible loads. Their scheduling is based on the tariff charge in combination with a wholesale market day-ahead price. We assume that they have perfect knowledge of wholesale prices and optimize charging over a 2-day time horizon. Their charging flexibility is limited by their driving behavior, which is represented as deadlines by which time a vehicle's battery must hold enough energy for a certain trip.

The model can be divided into two phases (see Figure 4.5): in the first phase, EV charging is scheduled optimally, based on tariff signals and wholesale market prices. In the second phase, the proposed indicators are evaluated based on household load curves, the transformer loading and the given tariff charges. The model execution logic is presented in Section 4.6

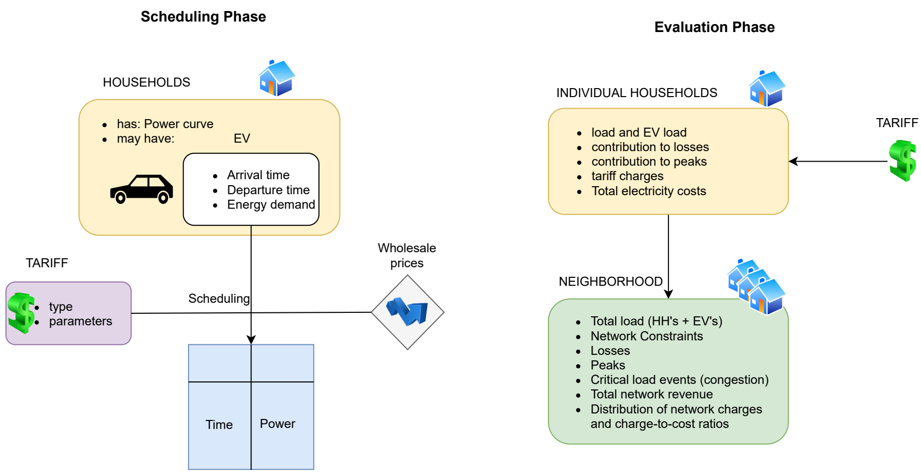

Figure 4.5: Scheduling and evaluation phases in ANTS-model

Please note that the proposed cost-measures are strongly influenced by the existing situation at the given network location. Transformer replacement is triggered earlier if the LV transformer does not have a lot of headroom at the beginning of the simulation and the costs of losses also critically depend on the size of the transformer. Therefore, we sample over a range of existing situations with different transformer sizes for each EV scenario. Once a transformer upgrade has been triggered, we use the upgraded transformer size for loss computations and the initial transformer size for peak contributions.

4.4.2. INPUT DATA AND PARAMETERS

For household load profiles (without EVs), we used the publicly available load profile generator by [45][10]. We simulated 50 German household load profiles for one year at a 15-minute time resolution. For electric vehicle charging needs, we use parameters based on the 25 profiles derived by [46]. For each tariff and EV number, we randomly draw out of the 25 profiles (up to a maximum of 25 EVs), and randomly assign the profiles to households. The random seed is reset for each tariff choice, so that the same values are used for each tariff in order to be able to compare results across tariffs. Wholesale market prices were obtained from the ENTSO-E

[10] https://www.loadprofilegenerator.de/

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transparency platform[11] for Germany in 2020.

For our computations of losses according to Equation (4.1), we make the simplifying assumption that the loss factor is always 10% of the transformer size. This is larger then it generally is in real transformers (and in reality it also does not grow linearly with size), but in this way we can use the single transformer as a proxy for network losses in general. Network losses are generally around 5% of total power served [6], but since the first factor in Equation (4.1) is mostly below 1, the second factor needs to be accordingly larger in order to approximate total losses closer to this percentage. We also assume costs for losses and transformer replacements to be a bit higher than is often done in the literature (e.g., in [25]), in order to account for the fact that we are omitting losses and replacements in lines and higher network levels. A summary of all main parameter choices can be found in Table 4.2.

Tariff choices

We chose four different tariff types for the assessment, which cover a range from very simple traditional tariffs to more complex newer tariff types:

- A fixed tariff with a charge of 250 Euro per customer per year, which resembles the "Capaciteitstarief" (capacity tariff) currently in place in the Netherlands.

- A volumetric day-and-night tariff with a charge of 5 ct/kWh during day-, and 2.5 ct/kWh during night time.

- A capacity subscription tariff, as described in [30]. The possible subscription levels are at 2, 4, 8 and 17.3 kW, for a yearly charge of 192, 252, 480 and 900 Euro and a penalty of 0.5 Euro for every kWh of exceeding the subscriped capacity. This is inspired by values currently used in discussions for a new tariff system in the Netherlands, also used in [31].

- A mixed measured capacity and ToU volumetric tariff with parameters resembling the current distribution tariff for low-voltage users in Spain [47]: the measured capacity peak charge is 19.318 Euro/kW per year and the volumetric charges are 0.0559 ct/kWh from 12am to 8am, 1.7076 ct/kWh from 8am to 10am, 2pm to 6pm and 10pm to 12am, and 2.2658 ct/kWh from 10am to 2pm and 6pm to 10pm.

[11] https://transparency.entsoe.eu/

Parameter	Values
Number of households	50
physical connection limit	17.3 kW
Number of EVs	0-25
n_{peaks} for peak contribution	10
Transformer	
Initial size	80, 100, 120, 140, 160 kW
Age	20 yrs
Lifetime	40 yrs
Replacement limit	95% loading
Upgrade size	2 times current capacity
Loss factor	10%
Costs	
Fixed	100 Euro
Loss markup per kWh	0.1 Euro
Transformer asset	10.000 Euro
Transformer installation	20.000 Euro
Interest rate	3%

Table 4.2: Parameter values for simulation case study. Note: For transformer sizes, only 100 kW and 160 kW are commercially available. The other sizes in 20 kW increments were added to simulate differing initial levels of congestion for computing averages and percentiles of the resulting indicators.

4.4.3. RESULTS

For this case study we focus on results for cost-reflectiveness, efficiency and simplicity, to demonstrate how the methodology can work in practice. For each of these, we use indicators proposed in Section 4.3.

Cost-reflectiveness

In Figure 4.6 we show an intermediate result from a single model run to provide insight in the way in which cost-reflectiveness and efficiency indicators are derived. The Y-axis shows the tariff charges for different network users, while the X-axis represents the contributions to the network costs of these individual users. We see that with a fixed tariff, (by definition) all users are charged the same, while the cost contributions differ widely, so cost-reflectiveness is zero. High cost-reflectiveness would be expressed in a linear relation between cost contribution and paid tariffs

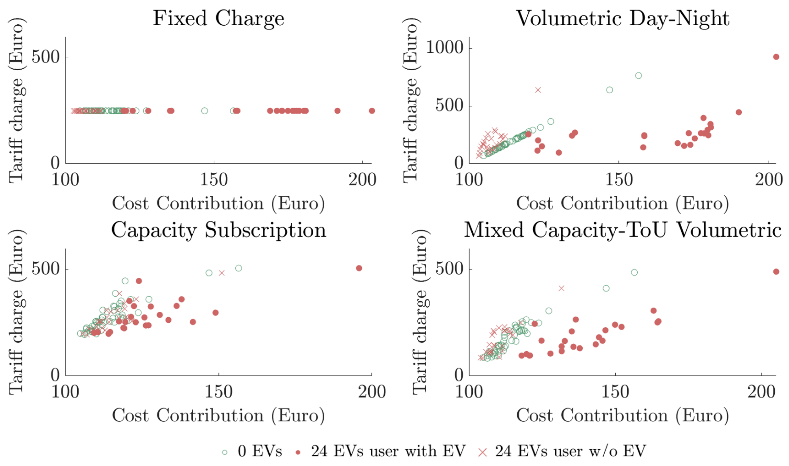

Figure 4.6: Relation of tariff charges with cost contributions for different tariffs in a single model run with a transformer size of 120 kW. We show two situations: one with no EVs (green) and one where 24 households have an EV (red). Empty circles are households without EV, full circles are households with an EV. Note the different y-axis scale for volumetric day-night tariffs, as these can result in much higher charges than the other tariffs.

per household. For volumetric tariffs, there appears to be a strong linear relation between the two for users without EVs. This is understandable as these users do not contribute much to peak-related costs. Their main cost contribution comes from losses. Like the volumetric tariff charges, these are proportional to total energy consumption. The linear relation is weakened a bit by the fact that losses actually grow quadratic in line loading (Equation (4.1)), and that the volumetric tariff has two different cost levels for day and night. When we go to a situation with many EVs, we can see that the linear relationship breaks down completely for volumetric tariffs. Users with EVs have much higher cost contributions now, as transformer replacement becomes necessary in this situation because of higher peaks. However, with this tariff, users are not charged according to their peak contribution. For the partly power based tariffs in the bottom row, we can see that the initial linear relationship between costs and tariff charges is not as strong. On the other hand, for higher EV numbers, these tariffs prevent the cost-contributions of most users from becoming very high. This is because these tariffs incentivize users to limit their maximal charging power, thus reducing network peaks and limiting the need for costly network upgrades.

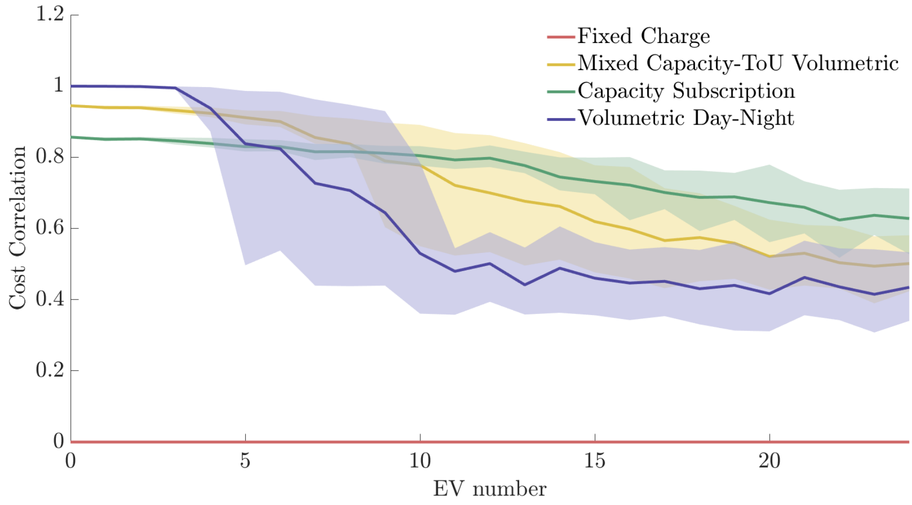

Figure 4.7: Correlation coefficient between users cost contribution and their tariff charges for varying number of EVs with uncertainty bands from 20th to 80th percentile.

In Figure 4.7 and Figure 4.8 we show the cost-correlation between tariff charges and cost contributions, which was identified as a performance indicator for cost-reflectiveness in Equation (4.20). The random choice of EVs out of the 25 profiles and random assignment to households leads to some variability in results. Thus, we also show uncertainty bands that result from the sampling over different transformer sizes and EV profiles. This is particularly pronounced for the capacity-based tariffs, where for very low choices of EV numbers the correlation shows quite a large spread. This is due to the fact that at these low EV numbers costs are only due to losses in our model, and losses are proportional to volumetric consumption. Thus, the tariffs that charge based on maximal capacity have a much larger spread here. As in Figure 4.6, we can see that:

- fixed tariffs have no relation between tariff charges and cost contributions whatsoever.
- volumetric tariffs perform quite well initially in a situation without EVs, but quickly deteriorate with higher EV numbers.
- capacity subscriptions and mix power-ToU volumetric tariffs do not start out quite as well as volumetric tariffs, but also do not drop off as much. Among

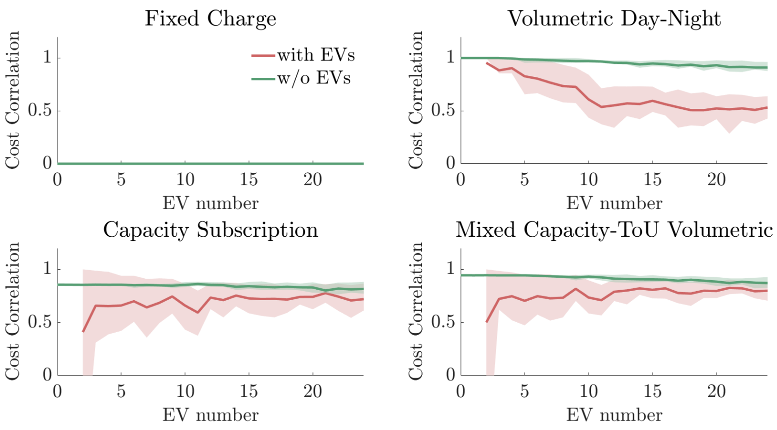

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Figure 4.8: Correlation coefficient between users cost contribution and their tariff charges, broken down by households with (red) and without (green) EVs with uncertainty bands from 20th to 80th percentile. Note: the difference to Figure 4.7 is that here the correlation is computed separately for the households sets with and without EVs respectively. The line with EVs only starts at 2 EVs, as the correlation coefficient can only be computed for a set of at least 2 observations.

these two, capacity subscriptions remain the more cost-reflective tariff at higher EV numbers.

Figure 4.8 breaks down the results for users with and without EVs. We can see that in all cases, the performance of the tariffs for users without EVs remain quite stable, also once the network is becoming more congested due to EVs of other users. For EV owners, cost correlation drops off quickly in volumetric tariffs, and remains relatively stable for the capacity-based tariffs. Note that the total cost correlation in Figure 4.7 may be worse than both the non-EV and the EV cost-correlation in Figure 4.8. This is because while each of the two groups individually may have a near-linear relation in a result like the one shown in Figure 4.6, they have different slope factors. Thus, the strength of the linear relation and consequentially the correlation, is worse for the combined results.

Efficiency In Figure 4.9 we show another intermediate result to aid understanding of efficiency results: the highest-load part of the load-duration curve in model runs with a 120 kW transformer. We can see that fixed and volumetric tariffs do not limit high load peaks. The transformer gets overloaded at low numbers of EVs

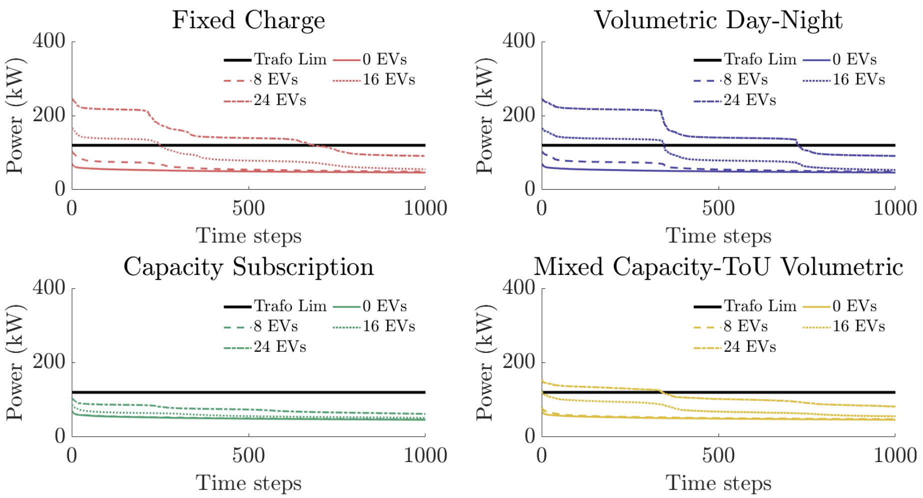

Figure 4.9: The 1000 highest load time-steps of the load duration curve for selected EV numbers and transformer size of 120 kW

(around 8) already. The capacity-based tariffs again perform better: for the mixed tariff, overloading happens only at very high EV numbers. The capacity subscription manages to reduce peaks to below this transformer size, even up to very high EV numbers.

These insights translate directly into the performance assessment of efficiency with the indicators total network cost, peak size and load factor (Equation (4.27a), Equation (4.29a) and Equation (4.29b)). Capacity-based tariffs limit peaks (Figure 4.10), which leads to more efficient network loading at higher EV numbers (Figure 4.11). Thus, they also reduce the need for transformer upgrades and lead to lower network costs (Figure 4.12).

Table 4.3 shows an example of "other costs" that could be taken into account for total system costs in Equation (4.28). For EVs, one important consideration might be how much EV owners will have to pay for the charging of their vehicles under different tariffs. To investigate this, we look at the price of charging EVs at wholesale prices (for Germany in 2020) under different tariffs. The differences are low: for 24 EVs over the whole year, the difference between the smallest value for fixed charges and largest value for capacity subscriptions is 89 Euro. For EVs that drive only up to 30 km there is almost no difference at all. These EVs can easily fulfill their charging

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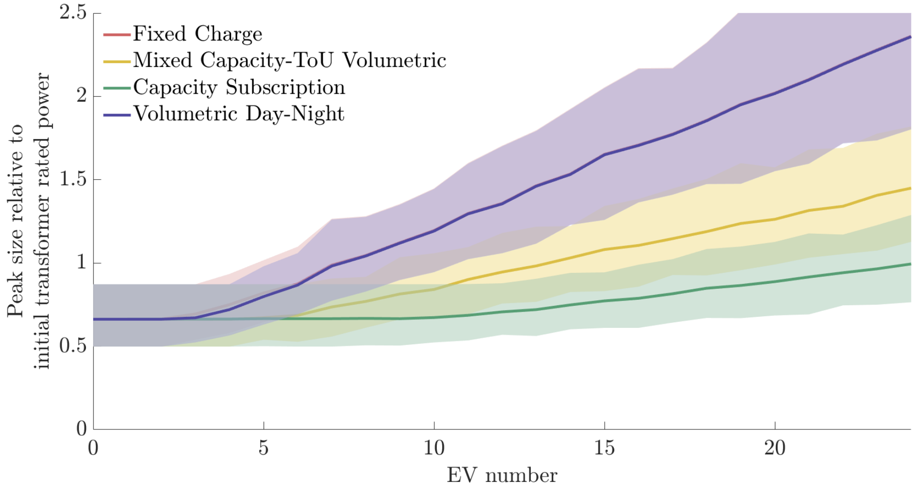

Figure 4.10: Network peaks by tariff type relative to initial transformer size. Note: the spread in results is due to the range of different transformer sizes used and, for higher EV numbers, also due to the random selection of EVs.

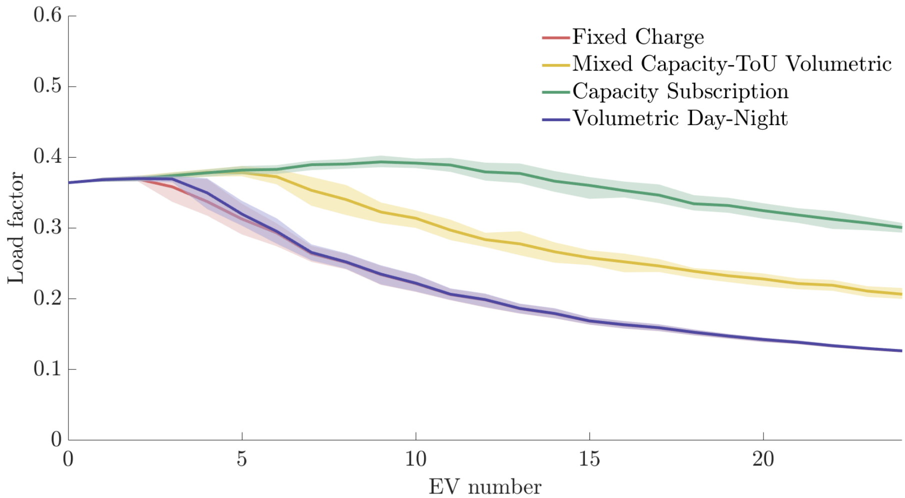

Figure 4.11: Network load factor (average load divided by peak load) for different tariffs and varying number of EVs

at the lowest prices also in the capacity-constrained tariffs, as they need only a few kWh every night. Only for heavy users with over 60 km driving distance per day

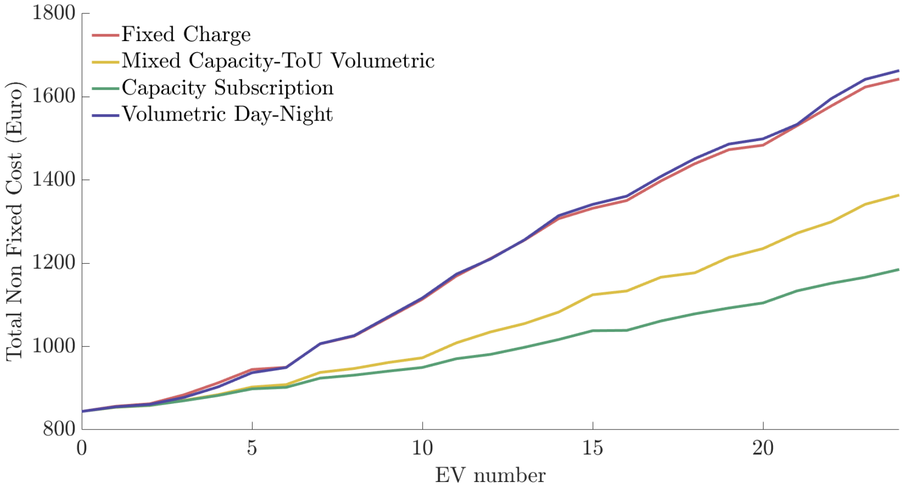

Figure 4.12: Total non-fixed costs for different tariffs and varying number of EVs

there is a noticeable difference. At this amount, the constraints given by the capacity based tariffs restricts charging at the lowest price hours considerably. The resulting difference for a whole year of charging is still not very big: it is on average 25 Euro per year for heavy users. Note however that these results were obtained with wholesale prices in 2020. At the end of 2021, wholesale prices in Germany showed unprecedented spikes.[12] These prices spikes also led to bigger arbitrages between high and low price hours. This in turn would increase the differences in charging costs presented above.

Simplicity

Performance with respect to simplicity is assessed according to the complexity score in Figure 4.4: the fixed tariff is the simplest one, the volumetric day-night tariff the second simplest, capacity subscriptions the second most complicated and the mixed capacity-ToU tariff the most complicated.

Comparative assessment

Table 4.4 shows a comparative assessment of tariff performance for the four tariffs. We rank tariffs based on their relative performance to each other for the chosen indicators. For cost-reflectiveness, we look at both the situation with low and high EV numbers, as the results change considerably. For efficiency, according to our

[12]see, for example: "German energy prices hard to tame", 21.12.2021, Thomas Kohlmann for Deutsche Welle

	Fixed Tariff	Vol. Day-Night	Cap. Subs.	Mix Cap.-ToU Vol.
Total for all EVs	1062	1090	1151	1117
< 30 km per day avg.	16.2	17.2	16.7	17.0
30 – 60 km per day avg.	68.3	69.5	72.5	71.1
> 90 km per day avg.	131	133	156	139

Table 4.3: Summed wholesale price costs in Euro for charging of all 25 EVs under different tariffs and average yearly charging cost per car by driving distance. The numbers of cars are 16 for lowest, 6 for medium and 3 for highest driving distance.

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Tariff	Cost-refl. low EV	Cost-refl. high EV	Efficiency high EV	Simplicity
Fixed	- -	- -	- -	+ +
Vol. Day-Night	+ +	-	- -	+
Capacity Subscription	+	+ +	+ +	-
Mixed Capacity-ToU Vol.	+ /+ +	+	+	- -

Table 4.4: Comparative assessment of the performance of the four tariffs relative to each other.

proposed indicators and the considerations in Figure 4.3, a tariff can only lead to efficient network usage if there are also flexible loads that can react to the tariff signals. Thus, we assess efficiency performance only for high EV numbers (it would be the same for all tariffs at 0 EVs). We can see that both the volumetric and the fixed tariff score very badly for high EV numbers. Interestingly, these are two tariff systems that are still commonly used nowadays. This underscores the point made in the introduction: many current tariffs are outdated and not well suited to deal with grids where there is a high amount of flexible loads. In terms of efficiency and cost-reflectiveness, the capacity-based tariffs perform much better in grids with high amounts of flexible loads.

4.5. DISCUSSION

This section critically reflects on the approach presented here. We discuss insights that can be drawn from this method, limitations and areas for future research.

4.5.1. INSIGHTS

What can we learn from the methodology described above? First and foremost, it clearly demonstrates the many complications in the process of tariff setting. There is no perfect solution that optimally meets all criteria and there are trade-offs between performance with respect to different objectives.

For example, one might wonder: the leading purpose of tariffs is to recover costs for the network operator in a cost-reflective way. So would it be possible to create a tariff that uses a framework similar to the one presented here and allocates network costs solely based on cost-contributions? This tariff would score perfectly based on the cost-recovery and cost-reflectiveness indicators presented here. However, there are two major problems with it: first, the practical difficulty of calculating and allocating network costs. This is theoretically impossible, see [5] and Section 4.3.2. Even if this could be overcome, the framework presented here demonstrates another objection: such a tariff would score very badly in terms of non-discrimination and would also be extremely complex, as the relation between network usage and cost contributions is quite difficult to establish and would be hard to communicate to users.

There are many trade-offs like this in tariff setting. The proposed methodology helps to demonstrate and quantify them. A tariff is a complicated construct and its implications are not immediately obvious, while objectives and indicators are easier to understand. Thus, the assessment process laid out in Figure 4.1 can clarify the underlying complexities and can lead to better understanding of the pros and cons of each tariff model.

Additionally, the methodology shows that tariff performance is highly context-dependent. The size and age of the existing infrastructure, the electricity wholesale market prices (for losses and user costs), the number of EVs and PV cells, the typical user load patterns and many other parameters have a strong influence on the performance assessment. Furthermore, the overall tariff performance depends on the weights of the different objectives relative to each other. This shows that there is no one-size-fits-all tariff system. The assessment should be done in consultation with all involved stakeholders and adapted to the local context. The case study also demonstrates that, especially in situations with increasing high-power flexible loads such as EVs, the performance of tariffs can change quickly. Thus, the urgency to change outdated tariff frameworks is growing.

In terms of the specific tariffs that we assessed in the case study, the methodology clearly showed that power-based tariffs are superior to fixed and volumetric tariffs for high numbers of EVs. On the other hand, they are also more complicated and may increase EV charging costs a little bit for heavy users. This further demonstrates the need for integrating this objective assessment with discussions among involved stakeholders.

The methodology can also be used to investigate specific concerns, like the impact of tariff proposals on a specific user group. For example, one might think that a capacity subscription tariff would be bad for EV owners. It restricts their charging power to the subscribed capacity, even when there is no congestion in the network. This might lead to higher costs for EV owners as they can not make full use of the lowest-price hours at the wholesale market. However, our model shows that for most EV owners with a moderate driving range of up to 30 km per day, this effect is almost negligible and the resulting cost differences are less than a Euro per year (for wholesale prices in 2020 in Germany), assuming they are able to make use of smart charging. Only for very heavy EV use, above 60 km per day, does the capacity restriction make a significant impact. And for these users the price increase may also be justified by cost-reflectiveness.

4.5.2. Limitations

The indicator framework presented in Section 4.3 is of a general nature and therefore largely independent of the specific model implementation that is used.[13] However, in the case study presented here, there are many limitations in our current model. We only consider losses for short-term operational costs and transformer replacements for long-term investment costs. At the moment, we do not consider power quality issues like voltage deviations, line losses and replacements and higher network levels beyond the neighborhood LV transformer. This also prevents us from using more realistic network expansion models and power flow simulations. We only modeled EVs as a proxy for new kinds of high-power flexible loads, but future studies should also take into account heat pumps, PV cells and deferrable loads like

[13] Though intermediate steps, such as cost contributions to short and long term losses, have to be adapted to the sepcific network cost model that is used.

smart dishwashers. The binary split of load into “flexible” and “inflexible” could be improved by considering the elasticity of demand of network users. Lastly, for consumer behavior, we assume that users optimize according to price signals. In reality, they may respond in different ways.

Apart from the model, there may also be concerns about the *validity* of the indicators [48]: do they measure what they’re intended to? And are the indicators presented in Section 4.3 sufficient to judge the performance of any tariff? It is an important step in the process of translating the chosen objectives into indicators, which can be obtained from measurements or simulations. It can be up for debate whether a given indicator measures an objective. Therefore, indicators should ideally be agreed upon in a coordinated effort by all stakeholders. For example, there may be a concern by EV interest groups that capacity-based tariffs are too restrictive for EV owners and incur excessive costs for them. This could violate the cost-efficiency objective when considering not just network costs but related consumer costs as well, as in Equation (4.28). In this case, an indicator that measures the costs of charging EVs under different tariffs may be an obvious choice to add, as demonstrated in the case study.

4.5.3. RESEARCH GAPS

Some limitations of the proposed methodology are inherent to the use of stylized models for complex technical systems. However, we also identified a number of areas where future research could make a significant improvement in terms of modeling:

- The combination of more sophisticated network expansion models with a feedback loop of network costs. Costs should be allocated back to consumers through tariffs, and the reaction of consumers to these tariffs should be taken into account for the expansion modeling.[14]
- The use of more realistic power flow modeling in electricity networks to determine the cost-factors and cost-contributions.
- Implementation of advanced pricing mechanisms to resolve network congestion: locational marginal prices (LMP), dynamic tariffs, flex markets, smart curtailment solutions.

[14] See, e.g., [49] for a case study with different tariffs, an RNM model, and demand reactions by customers with heat pumps.

- Studies on consumer responsiveness to and understanding of different tariff types.

The indicator framework itself might also be improved by suggesting additional indicators for objectives that we did not treat in depth here, such as equity, third-party neutrality, and incrementalism. Adapting to specific local contexts and concerns could also be an area for further research.

Lastly, an issue that has not received much attention in the literature is the political process of tariff setting. When a tariff system needs to be updated, a wide variety of stakeholders are involved, each with their own objectives. This process often creates disagreements and is difficult to understand for the public. How do we agree in the face of these difficulties, and how do we make sure that an acceptable compromise is produced? The governance and organization of this transition process is an important piece of the puzzle that deserves further attention. The framework presented here may help with this process.

4.6. Conclusion

We propose quantitative performance indicators for the objective assessment of electricity network tariffs and a cost-accounting methodology for network costs. We demonstrated the benefits of evaluating tariffs with this methodology in a case study.

With the steady increase of distributed generation and high-power flexible loads, the urgency to improve tariffs is rising. For networks with high volumes of distributed energy resources, cost-reflectiveness and economic efficiency are particularly relevant performance indicators. However, cost recovery, non-discrimination and simplicity should not be neglected, as poor performance of any of these may lead to public or political resistance or failure of the tariff system to work as intended.

The proposed framework helps to understand the performance of network tariffs and the trade-offs between the different objectives of network regulation. This can improve the decision-making process for new tariff systems. Currently, this process is to a large degree based on subjective judgements and assumptions. With the presented methodology, which is as much as possible based on quantifiable indicators, the discussion can be moved to arguments about which objectives the tariff should fulfill and how to weigh the different objectives. It may be easier to agree on these questions, rather than immediately try to find agreement on a new tariff. Therefore, we recommend that stakeholders who are involved in tariff setting, agree on a set of objectives and indicators which can be assessed in simulations or real-world measurements.

The methodology demonstrates the complexities and trade-offs in tariff setting. As performance depends strongly on the context and the weighting of different objectives, there is no one-size fits all tariff. In future work, we plan to perform an in-depth study of the performance of tariffs in different European countries and to evaluate dynamic methods of congestion management.

Appendix: Model Execution Logic

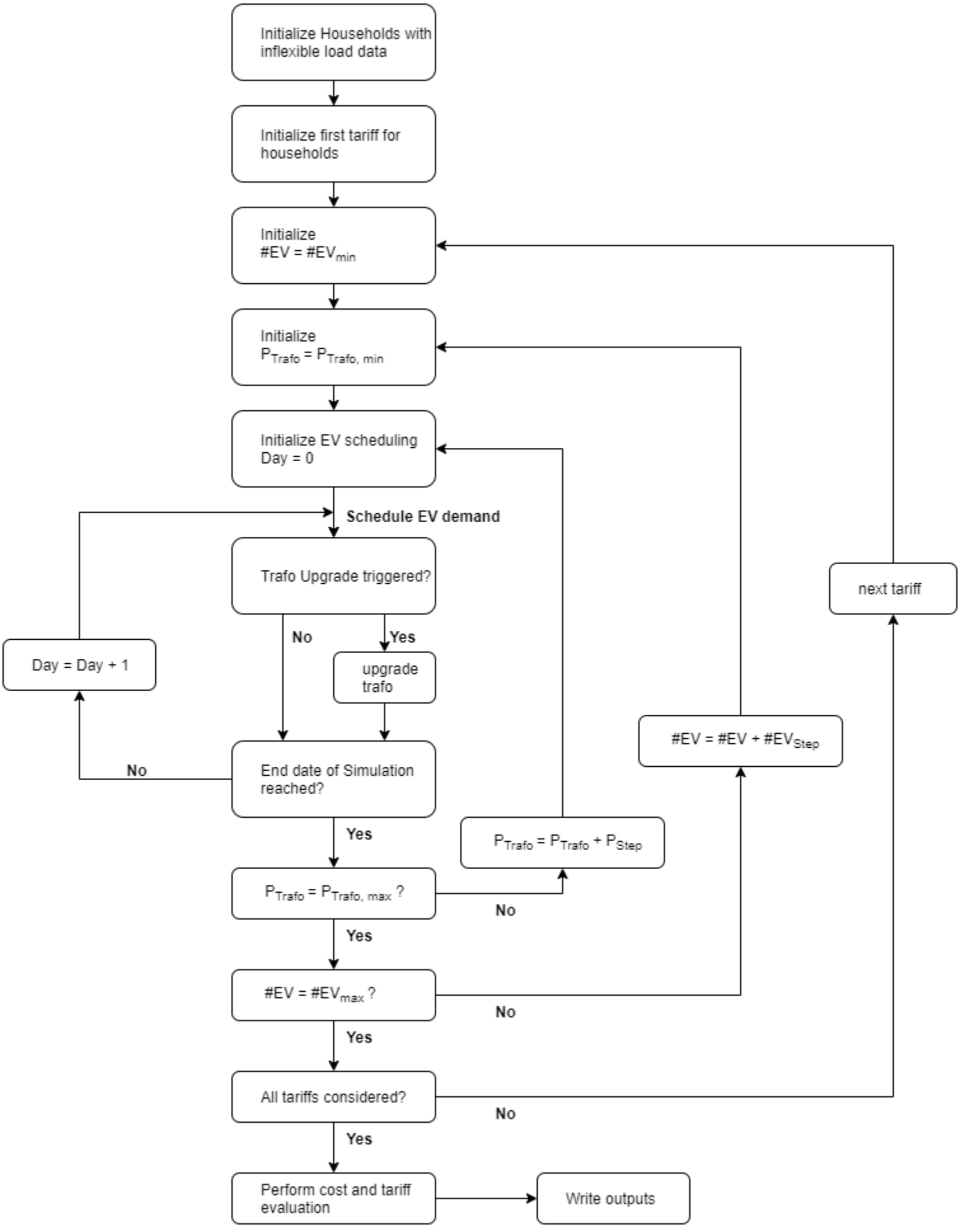

Figure 4.13: Model Execution Logic

Explanation of steps:

1. Load external household data and create household objects.

2. Load tariff parameters from tariff input file.

3. Load EVs at the given current EV number, from the minimum to maximum number in the given step size. EV profiles are loaded from an external file.

4. Set the transformer capacity to the given current capacity, from the minimum to maximum capacity in the given step size.

5. For each EV, schedule the charging based on required demand and optimized according to day-ahead wholesale prices and the tariff price signal.

6. If the sum of household load and all EV loads exceeds the current transformer capacity, a transformer upgrade is triggered.

7. Repeat scheduling for each day of the year.

8. Once the end of the year is reached, repeat steps 5-7 with the next higher transformer size. Store network indicators for each transformer size.

9. Once all transformer sizes have been used, repeat steps 4-8 with the next higher EV size. Store the averages and variances of network indicators over all transformer sizes.

10. Once all EV numbers have been used, apply the next tariff and repeat steps 3-9.

11. Once all tariffs have been considered, write output files (one for each tariff). Outputs can also be written at the household level if this option is chosen, as in the data for Figure 4.6.

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5

Risk vs. Restriction - An Investigation of Capacity-limitation Based Congestion Management in Electric Distribution Networks

As a result of the previous chapter, we found that network capacity-based tariffs perform particularly well in situations with many high-power flexible loads, as they give an incentive for these loads to reduce their peak consumption. Other congestion management methods based on limiting network capacity for flexible devices have recently been proposed by regulators in Germany and the Netherlands. This chapter compares the long-term capacity tariff from the previous chapter with these new proposals, which limit capacity at shorter lead times: day ahead or even near real-time.

This chapter has been published in Energy Policy as R. J. Hennig, S. H. Tindemans, and L. J. de Vries. "Risk vs. restriction—An investigation of capacity-limitation based congestion management in electric distribution grids" [1]. Spellings and formatting have been standardized throughout this thesis.

Abstract

Electrification of energy end-uses brings an increasing load on electric distribution grids with load peaks that can cause network congestion. However, many new end-uses like electric vehicles, heat pumps, and electrified industrial processes have some flexibility to move their power consumption away from peak times. Congestion management mechanisms can harness this flexibility. This chapter investigates congestion management mechanisms based on limited available network capacity for flexible loads during peak times. A case study discusses and investigates real-world examples of such mechanisms from proposals in Germany and the Netherlands. They differ concerning the lead time at which the capacity limitation is announced, with options from near real-time and day-ahead to long-term. These mechanisms are suited to remove network congestion, but there are significant trade-offs concerning the lead time. A shorter lead time leaves more room for using the network during non-congested times but creates a risk of curtailment for end-users, which may come with associated balancing and re-procurement costs. Longer lead times give more certainty on network access conditions but often restrict network usage even when there is no network congestion.

5.1. INTRODUCTION

The energy transition to renewable energy sources brings an increasing electrification of final energy consumption, such as heating, transport, and industrial processes. This increase in electrification can lead to congestion of the electric grid infrastructure, which was not designed with such high loads in mind. In the Netherlands, large parts of the electric grid are already considered to be in danger of congestion.[1] Consequently, some Dutch network operators have a adopted a strategy of refusing new network connections until the problem is resolved.[2] Similar concerns are raised in Germany.[3]

However, many of these new types of electricity consumption are also highly flexible. EVs typically only need to charge a specific minimum demand over the whole night, and heating can also be spread out over a longer time when houses are well insulated. Industrial processes may have flexibility at longer lead times. Thus, excessive load peaks could be avoided by using this flexibility and coordinating loads in a smarter way [2, 3]. This process is also called *congestion management* [4] and many possible methods for this have been proposed in the literature, e.g., market-based methods [5–10], dynamic prices [11–14], and network reconfiguration [6, 7, 15, 16]. In the long run, network reinforcement [6, 17–19] is also a possible solution, but it takes time, and often, it is not possible to reinforce the network as quickly as flexible loads are increasing.

This special issue is focused on future electricity tariffs that provide solutions to challenges like congestion from high power flexible loads and that help to reduce the need for network expansion. In this chapter, we take a wider lens than looking only at tariffs by considering a family of congestion management mechanisms that limit end-user network capacity to reduce peak size. Some of these mechanisms can also be considered a network tariff, while others operate in addition to a network tariff but do interact with the design of the tariff. We focus on three current proposals from practitioners in regulation and network operation:

- interruptible network connections that can be curtailed by the network operator close to real-time, which has been proposed by the German regulator (Bundesnetzagentur, BNA) [20], henceforth called “interruptible connection”.

[1] see, e.g., https://capaciteitskaart.netbeheernederland.nl/(assessed December 2023)
[2] https://www.meterinsight.com/en/blog-and-news/the-electricity-grid-is-full, https://fd.nl/bedrijfsleven/1468954/nog-jarenlang-wachtlijsten-voor-aansluiting-op-het-stroomnet
[3] https://www.br.de/nachrichten/deutschland-welt/e-autos-und-waermepumpen-mueller-warnt-vor-stromnetz-ueberlastung,TSvmR3C

- a day-ahead capacity limitation contract (CLC) proposed by the Dutch regulator ACM [21]. This proposal makes network capacity available without restrictions when no congestion is expected. Still, on the day ahead, the network operator can activate a clause in the contract by which this available capacity is reduced to a pre-contracted value.

- a static capacity subscription network tariff [22], which is considered a candidate for a new network tariff for residential consumers in the Netherlands [23, 24].

These proposals are based on a limitation of available capacity for network users. But there are also major differences: one important distinction concerns the lead time at which the capacity limitation is activated and the risk associated with this activation. In interruptible connections, the activation of the limitation happens close to real-time. This leaves network capacity available for use with no restrictions when no congestion occurs, but it does place a risk on the network user because usage can be restricted unexpectedly. The day-ahead capacity limitation is activated the day before real-time, which reduces the risk for the network customers but shifts some risk to the network operator, who now has to anticipate congestion correctly. The static capacity subscription is a long-term contract. Thus, the lead time is typically weeks to months in advance. This eliminates the risk of being curtailed for users and the mis-anticipation risk for network operators. The downside is that it is inflexible and restricts network access when there is no congestion. It is, therefore, less efficient.

Thus, one of the central trade-offs between the approaches appears to be between *risk* of curtailment for the network user and *restriction* of available capacity, especially during non-congested times. Both of these may lead to concerns and even resistance of network user groups to the implementation of these new proposals.[4] In this regard, some critical questions that are not yet well understood are:

1. What are the combined impacts on end users of these mechanisms and electricity market prices?

2. Can the impacts of restricting network capacity and the risk of curtailment be quantified?

3. How can these mechanisms be improved?

[4] This is shown by the array of responses to the calls for responses on the German and Dutch congestion management strategies.

The chapter describes the three proposals' benefits, drawbacks, and potential costs. We base our analysis on both a qualitative assessment, which is informed by our previous work on congestion management [4] and network tariffs [25], and a small case study for a residential congested feeder in which all three approaches are simulated and resulting costs and capacity restrictions are estimated.

Section 5.2 introduces the proposed mechanisms in detail. Section 5.3 discusses the criteria used for evaluating the approaches in a case study: different kinds of costs and restriction of network capacity. Section 5.4 describes our modeling setup and shows results for the different mechanisms. Section 5.5 provides a discussion of the strengths and weaknesses of each proposal that is partially qualitative and partially based on the simulation case study. Chapter 8 concludes and provides policy advice.

5.2. PROPOSED CONGESTION MANAGEMENT MECHANISMS WITH CAPACITY LIMITATIONS

5

We briefly summarize the proposals that will be investigated in this chapter. They can roughly be ordered by the lead time at which the capacity limitation is set: from near real-time in interruptible connections to pre-day-ahead in capacity limitation contracts to long-term static capacity subscriptions.

5.2.1. INTERRUPTIBLE CONNECTIONS FOR RESIDENTIAL LOADS

The German Federal Agency proposed this solution for network regulation (BNA) in 2023 (draft proposal [20] and final decision [26]). It envisions a reduced network charge for end-users with high-power flexible loads in return for the ability and authorization of the network operator to exert limited control over the power consumption of these devices. The targeted loads are EVs, electric heating and cooling systems, and batteries. Thus, when congestion occurs in the grid, the network operator can curtail them to a limited capacity to avoid network overload. This proposal extends the idea of non-firm connection agreements, traditionally discussed only for distributed generators and larger industrial consumers [27–29], to residential loads. In the US, similar schemes have also been employed on a voluntary basis for flexible residential loads in demand response programs [30].

The devices covered by the German proposal are non-public electric vehicle chargers, heat pumps, electrical cooling devices, and electrical storage devices; if they have a maximal power consumption of more than 4.2 kW (up from 3.7 kW in the first version of the proposal) and are connected after January 1^{st} 2024. There is an obligation to participate in this model for distribution system operators (DSOs) and customers with newly connected qualifying loads.

In case of congestion, the network operator can curtail participating devices close to real-time down to a minimum of 4.2 kW. If the device cannot reduce power consumption to this level, it is entirely curtailed to a consumption of 0. The proposal also envisions a second variant of control, in which the network operator does not control the individual device but limits the power consumption of the network connection point. In this case, the control is implemented by an intelligent energy management system. This is intended to allow for smarter energy management if the consumer has installed PV panels or batteries, which it can use behind the connection point to keep using the device with a power consumption above 4.2 kW.

Currently, the reduction of network costs is envisioned as a lump-sum payment given to all customers with participating devices. This is irrespective of:

- whether curtailment of these devices is ever activated,
- how much above 4.2 kW (or 5 kW, for the connection point-based variant) their maximal power consumption is,
- how much these devices are used.

An adaption of this cost reduction structure that is more reflective of the power and energy use of the device is considered for the future.

The near real-time curtailment of devices will likely incur additional balancing costs (Section 5.3.1) for balancing responsible parties who supply the users of these devices. The current version of the proposal explicitly states that the network operator does not have to provide compensation for balancing (2.2. in [20]). This means the balancing responsibility remains entirely with the energy supplier.[5] This contrasts with the situation in the Netherlands, where it is envisioned that the network operator is responsible for preventing the need for any adjustments of balancing responsible parties that occur due to close-to-real-time congestion management actions (Section 5.2.2).

[5] It is likely assumed that curtailment will not happen too often and, thus, not incur excessive costs. Furthermore, energy suppliers who supply multiple service areas may be able to shift energy from one area where devices are curtailed to another where no curtailment takes place or anticipate the statistical occurrence of curtailment in the service areas.

5.2.2. DAY-AHEAD CAPACITY LIMITATION CONTRACT

A day-ahead capacity limitation contract is currently proposed by the Dutch regulator ACM [21] with the first deployment planned for the second half of 2023. It envisions a long-term contract between the network operator and network users where the operator can announce a reduction of the capacity of the user's connection on the day-ahead, *before* closing of the day-ahead market. Currently, it is only envisioned as an option for large consumers with connection capacities above 1 MW, but it may be extended to smaller connections in the residential section as well. There, the contracts could be either with individual end-users, or with aggregators as proposed in [31].

Specifications in this contract can include the maximal capacity of the connection and maximal allowable reduction, the price per kW of reduction, the number of times it can be activated, and, optionally, for which times the reduction can be activated. It is envisioned that the price per kW of reduction is determined through a market platform where large consumers bid for the smallest required price per kW of flexible capacity. These bids need to include information on the location of the Point of Common Coupling (PCC) of the involved market parties to address the location-specific nature of congestion.

5.2.3. STATIC CAPACITY SUBSCRIPTION

The capacity subscription is a proposal for a network tariff for residential consumers that performs implicit congestion management [22, 32, 33], which has been extensively discussed as a model for the next round of network tariffs in the Netherlands [23, 24]. In this mechanism, network users sign up for a fixed amount of network capacity (in kW), within which they can use the network at no or low volumetric charges. A low charge for consumption within the subscribed capacity is used to reflect better the cost of network losses [25, 33], which typically have to be recovered by the network operator at market prices.[6] Customers must pay a significantly higher volumetric charge if they exceed their subscribed capacity. For this, an averaging time step over which to compute the exceedance has to be defined: exceeding the capacity for only a few minutes, e.g., due to using a kettle or induction stove on boost function, may not trigger a higher fee if it averages out over the settlement time step, which is typically 15, 30 or 60 minutes [4]. Often, the main problem of network congestion is an overload of the thermal capacity

[6] see, e.g., https://www.acm.nl/en/publications/when-setting-2023-tariffs-acm-takes-account-high-costs-connected-grid-losses-due-higher-energy-prices

of critical components such as transformers and lines. As these can typically withstand short-duration peaks above their rated capacity, it is reasonable to define the averaging time step slightly longer, such as on the order of one hour.

The subscribed capacity is guaranteed to be available, apart from unforeseen outages which may occur in rare cases. A minimum service level (e.g., 1 or 2 kW) may be mandatory to guarantee basic services. Above that, users can select a capacity level that satisfies their "standard" consumption needs, e.g., lighting, cooking, wet appliances, and entertainment for household consumers. Users with additional high-power flexible loads, such as EVs or heat pumps, may have to choose a higher subscribed capacity to satisfy their needs for these devices without incurring high fees for exceeding the bandwidth.

Note that this proposal integrates capacity limitation into the network tariff. In contrast, the other two proposals described above typically function additionally to an underlying network tariff, but as part of the connection agreement.

5.2.4. Comparison

Figure 5.1 gives an overview of the timeline in the three approaches. We distinguish between tasks for the network operator (top bar in blue) and for the end-user (bottom bar in orange). As described above, the main difference between the mechanisms concerns the lead time at which the capacity reduction is announced. In the interruptible connection, this happens very close to real-time during the delivery phase of electricity. In contrast, in the day-ahead CLC, it happens shortly before the closing of the day-ahead market, and in the capacity subscription, it is agreed in a long-term contract.

Furthermore, we present additional design choices of the three mechanisms in Table 5.1. The metering point at which the capacity limitation is applied can be either at a specific device itself or at the overall network connection point of the customer, e.g., a household connection. As discussed, the BNA interruptible connection proposal offers both options. Both options are also possible for a day-ahead variable capacity limitation. The limitation is typically applied to the overall connection in the static subscription, as it is part of the network tariff. The interruptible connection proposed by the BNA is envisioned to be applied in addition to a network tariff, while the capacity subscription replaces the former tariff. The day-ahead CL can be both additional to or replacing the former tariff. The contracted capacity during non-congested times is the full technical capacity

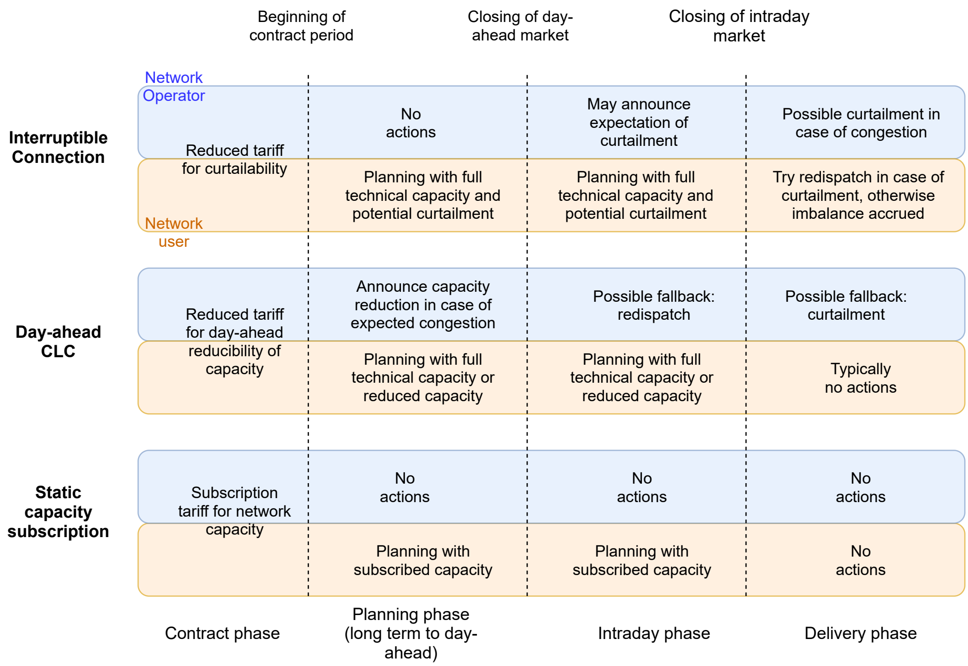

Figure 5.1: Timeline of capacity limitation approaches

of the device or connection in interruptible connection and day-ahead CLs. In the capacity subscription, it is a subscribed capacity, which is typically less than the total technical capacity. When there is congestion, the interruptible connection foresees the reduction of available capacity to a fixed value (e.g. 4.2 kW). The day-ahead CL can also reduce to such a fixed value, but it would also be possible to allow for a variable reduction, based on anticipated network conditions. The capacity subscription has no variation of available capacity based on network conditions. Lastly, "firmness" concerns whether or not the capacity limit is hard, i.e., whether a user can exceed it for a higher price or exceedance is prohibited. In the BNA proposal, the limit during activation of the limitation is hard and can be enforced through a remote switching operation by the network operator. In the capacity subscription, exceeding the subscribed capacity is possible for a higher per-kWh price. In the day-ahead CL both options are possible, based on the contractual specifications. When there are multiple possible choices for a mechanism, the boldface option indicates the choice we modeled in the case study, Section 5.4.

Table 5.1: Comparison of capacity-limitation-based congestion management approaches. In bold: choices implemented in the case study, Section 5.4

	Interruptible connection	**Day-ahead capacity limitation**	**Static capacity subscription**
Lead time for variation announcement	Near real-time	Day-ahead	Contract period
Metering point	Flexible device or **network connection point**	Flexible device or **network connection point**	Network connection point
Relation to network tariff	Additional to default tariff	Additional to or replacing default tariff	Replaces previous tariff
Contracted capacities when not congested	Full technical capacity	Full technical capacity or **subscribed variable capacity** (e.g. 8, 10, 12, ...kW	Subscribed fixed capacity (e.g. 2, 3, 4...kW)
Possible variation of contracted capacity when congested	Reduction to fixed value (binary)	**Reduction to fixed value (binary)** or variable	None
Firmness of capacity limit	Hard	**Hard** or soft	Soft

5

5.3. Evaluation criteria for case study

We introduced different capacity-based congestion management approaches in the previous section. In the present section, we describe our evaluation criteria for comparing them in a case study (Section 5.4). These are augmented by a qualitative discussion in Section 5.5.

5.3.1. Costs

Congestion management requires shifting or shedding loads, relative to a situation without congestion. Users may incur additional costs due to these adjustments related to the procurement of electricity that depend on user preferences, energy market prices, and how close to real-time the adjustment is required. We can distinguish several kinds of costs:

- Day-ahead market: When users would like to use low prices on the day-ahead electricity market, but cannot due to the congestion management mechanism in place, there is a cost related to purchasing power at higher prices. For this to happen, the mechanism needs to specify network access conditions before the gate closing time of the day-ahead market.
- Intra-day market: In analogy to the first point, costs are also associated with the inability to exploit low intra-day market prices. This is particularly interesting for flexible load types with potential load shifting times of several hours, which residential flexible loads typically have. These load-shifting potentials could be used to exploit price spreads on the intra-day market and price spreads between day-ahead and intra-day markets.
- Balancing costs: in vertically unbundled electricity systems [34] with independent markets, energy suppliers, and network operators, all major network users have a balancing responsibility to the transmission system operator (TSO).[7] When they fail to meet their balancing program they incur balancing costs, which TSO charges for keeping power balance in the system.

All the costs discussed above are related to electricity procurement at wholesale markets and the corresponding balancing responsibility for energy suppliers. In addition to these procurement-related costs, there may be other costs, depending on the congestion management mechanism. In particular, some congestion management mechanisms are based on varying network prices [4]. Thus, in those cases, these also need to be considered. In the present chapter, however, all of the investigated mechanisms are based on variations of network capacity limitations rather than price variations. Additional costs include taxes, transmission fees, and subsidy schemes. However, these are mostly unrelated to the congestion management method and are not discussed here.

Furthermore, installation costs are associated with implementing a new congestion management mechanism. For example, the interruptible connection requires installing a load-limiting device that the network operator can remotely control. The day-ahead capacity limitation requires the setup of communication channels through

[7] see, e.g., https://www.next-kraftwerke.be/en/knowledge-hub/balancing-responsible-party-brp

which the network operator can send information about expected congestion and available capacity. The day-ahead capacity limitation and the capacity subscription also require installing smart meters. These costs can also be significant and should be considered when a new congestion management mechanism is considered. However, they are not considered in this study.

5.3.2. Capacity restriction and user discomfort

In addition to the costs of electricity procurement, there may also be discomfort costs for the users from not being able to use the total technical power capacity of devices, e.g., not being able to charge an EV to the desired amount on time or not being able to heat to the desired comfort level. These are harder to quantify in monetary terms, as they depend on the user's specific willingness to pay (or willingness to accept reduced capacity). However, they can be quantified regarding users' available capacity for using flexible loads, as we will do in the case study (Section 5.4.3).

5.4. Case study

In this section, we explain the modeling setup for investigating differences in costs between the different proposals for the case of a residential neighborhood.

5.4.1. Parameters

General:

$t \in \mathcal{T}$:	Time interval set
$u \in \mathcal{U}$:	User set
$s \in \mathcal{S}$:	Scenario set
Δt:	power settlement time step in minutes
$P(t)$:	Power over time interval
$\pi^{\mathrm{DA}}(t)$:	day-ahead electricity price at time t
c^{Bal}:	cost assumption for power imbalances
q^{EVUD}:	EV (U)nsatisfied (D)emand
c^{EVUD}:	cost assumption of EV (U)nsatisfied (D)emand
$\lambda^{\mathrm{activation}}(t)$:	activation level of capacity subscriptions at time t

Electric Vehicle Specific quantities:

t_u^{arr}:	Arrival time
t_u^{dep}:	Target departure time
q_u^{start}:	Charge at beginning of simulation in kWh
q_u^{target}:	Target charge at departure time in kWh
q_u^{daily}:	Daily energy demand in kWh
$\overline{q_u}$:	Maximum charge of battery in kWh
$\underline{q_u} = 0$:	Minimum charge of battery in kWh
$\overline{P}_u^{\text{EV,max}}$:	Maximum rate of charge in kW
$\eta_u^{\text{eff}} \in (0,1]$:	Charging efficiency

5.4.2. MODEL DESIGN

We use a modification of the Assesment of Network Tariff Systems (ANTS) model, previously used in [25]: the ANTS-CS (Capacity Subscription) model[8], to model a single, potentially congested, residential neighborhood with customer set $u \in \mathcal{U}$. We assume that customers have a certain inflexible power demand $P^{\text{inflex}}(u,t)$ at each time t. In addition, some users have EVs, which can be controlled remotely by an energy supplier (ES). We assume that the ES employs optimization for the scheduling of EV charging based on market electricity prices and that EVs can be continuously controlled. The ES also knows the parameters of the charging constraints of each user: their arrival and departure times, battery size, efficiency, charger capacity, and daily demand for electric energy.[9]

The optimization problem that the ES faces is the following: given expectations about the inflexible demand and the required energy for EV charging, choose the optimal quantity of power purchased at the day-ahead market and optimal dispatch schedules of power to consumers. A complication for this objective is the inherent uncertainty of the problem. The energy supplier doesn't know how much inflexible load customers will require and how much network capacity they will have available for charging EVs. In the interruptible proposal (Section 5.2.1), the available network capacity for EVs will be either the total technical capacity or 4.2 kW in case of curtailment. In the day-ahead capacity limitation (Section 5.2.2), the network operator can set constraints on network usage before the day-ahead planning stage.

[8] available publicly at https://gitlab.tudelft.nl/rhenning/ants-cs

[9] This assumption of remote controllability is strong and may not currently hold for most loads. In the future, however, we expect these devices to become smarter and more easily controllable, as this will unlock many operational benefits for the power system, which can be translated into financial benefits for their owners

In the static capacity subscription (Section 5.2.3), the available network capacity for flexible loads is the subscribed capacity minus whatever inflexible loads a user has at each time (additionally, exceeding the subscribed capacity may be possible for a higher charge during times of no congestion).

As the inflexible loads and resulting available network capacity are not known in advance, we assume that the ES employs a set of potential scenarios for its planning, over which it optimizes jointly. To formalize the optimization problem, we introduce the net power balance of the ES as the difference between purchased power and dispatched power in each scenario s:

$$P^{\text{net}}(s,t) = P^{\text{disp}}(s,t) - P^{\text{pur}}(t), \tag{5.1}$$

where dispatched power at time t is the sum of all flexible and inflexible loads supplied by the ES:

$$P^{\text{disp}}(s,t) = \sum_{u \in \mathcal{U}} \left(P_u^{\text{flex}}(s,t) + P_u^{\text{inflex}}(s,t) \right) \tag{5.2}$$

This quantity depends on the specific scenario, while the purchased power in Equation (5.1) is scenario-independent. This is because there is only one possible choice for purchasing power on the market, which is optimized across the set of scenarios. In each scenario, the allocation of purchased power to flexible loads is optimized according to the capacity constraints in the given scenario. A resulting net power imbalance, $P^{\text{net}} \neq 0$, incurs an additional balancing cost proportional to the imbalance, where a constant proportionality factor was assumed for simplicity.[10]

[10] In reality, balancing costs depend on the total imbalance in the control area and are differentiated between positive and negative imbalances. If a balancing responsible party's imbalance helps resolve the control area imbalance, balancing prices can even be negative [35]. However, publicly available data at ENTSO-E show a positive price for both imbalances and an equal price for negative and positive imbalance in the vast majority of time steps. This suggests that, on average, imbalances will incur a cost. Furthermore, energy suppliers do not know the exact price of imbalances when purchasing energy. Therefore, we find the assumption of a constant average balancing price sufficient to assess the impact of balancing requirements between the different mechanisms comparatively.

Thus, the optimization objective can be stated as:

$$\min_{P^{\text{pur}}(t),\,P^{\text{flex}}(u,s,t)} \sum_{t\in\mathcal{T},\,s\in\mathcal{S}} \Big(\pi^{\text{DA}}(t)\cdot P^{\text{pur}}(t) + \Big(\pi^{\text{DA}}(t)+c^{\text{Bal}}\Big)\cdot\theta(P^{\text{net}}(s,t))\cdot P^{\text{net}}(s,t) + \Big(\pi^{\text{DA}}(t)-c^{\text{Bal}}\Big)\cdot\theta(-P^{\text{net}}(s,t))\cdot P^{\text{net}}(s,t)\Big) \tag{5.3}$$

where $\pi^{\text{DA}}(t)$ is the day-ahead price at time t and $\theta(x)$ is the Heaviside theta function that is 0 when $x \le 0$ and 1 when $x > 0$. We assume that positive imbalance, i.e., requiring more power than purchased on the day-ahead market, has to be procured at a price higher than the day-ahead price with a constant offset for the balancing cost c^{Bal}. Negative imbalance, i.e., excess purchased power, is sold at a symmetrically lower price. What we describe as "balancing costs" here can be seen as a mix of re-trading on the intraday market and remaining portfolio imbalances balanced by the TSO at the applicable balancing prices at each hour. This stylized assumption allows us to include the anticipation of balancing costs for imbalances in a simple way.

5

The objective expression can be rewritten as indicated in Section 5.6. Furthermore, it is possible to leave part of the required EV demand unsatisfied due to tight network constraints or high prices. EV demand is likely not as cost-inelastic as traditional demand, though this depends on user preferences. Assuming that it is possible to have a certain q^{EVUD} (EV Unsatisfied Demand) at discomfort cost c^{EVUD} per kWh, we can add a term to the objective function that reflects this. Together with the aforementioned transformation, the objective then becomes:

$$\min_{P^{\text{pur}}(t),\,P^{\text{flex}}(u,s,t)} \sum_{s\in\mathcal{S}} \Big(\sum_{t\in\mathcal{T}} \Big(\pi^{\text{DA}}(t)\cdot P^{\text{disp}}(s,t) + c^{\text{Bal}}\cdot|P^{\text{net}}(s,t)|\Big) + c^{\text{EVUD}}\cdot q^{\text{EVUD}}_{\text{total}}(s)\Big) \tag{5.4}$$

The unsatisfied EV demand is not dependent on time, as it is expressed as an energy difference between the desired battery charge and the actual battery charge at the departure times of the EVs. The treatment of the absolute value in the objective function of Equation (5.4) is explained in Section 5.6.

The charge constraint for each EV at its departure time is then:

$$q_{i,s,t_u^{\text{dep}}} \geq q_u^{\text{target}} - q_u^{\text{EVUD}}(s) \tag{5.5}$$

And $q_{\text{total}}^{\text{EVUD}}$ is the sum of all individual unsatisfied demands. Assigning individual discomfort costs for each user based on their preferences in a real-world implementation would also be possible.

Additionally, there are the following constraints: The rate of charge of an EV is bound by the maximal throughput of the charger, which is what we call the "technical capacity" of the device connection in Section 5.2:

$$l_{i,t}^{\text{ev}} \leq P_u^{\text{EV,max}} \tag{5.6}$$

The size of the battery binds the charge of the EV battery:

$$\underline{q_u} \leq q_{i,t} \leq \overline{q_u} \tag{5.7}$$

EVs can only charge when they are parked at home, from arrival time to departure time:

$$l_{i,t}^{\text{ev}} = 0, \text{ if } t \notin [t_u^{\text{arr}}, t_u^{\text{dep}}] \tag{5.8}$$

The battery charge of an EV is initialized to the starting charge at $t = 0$. Afterward, it is updated based on how much was charged in the previous period, taking into account the charging efficiency of the EV. Before the EV arrives at home, its charge is reduced by the daily driving demand.[11]

$$q_{i,t} = \begin{cases} q_u^{\text{start}}, & \text{if } t = 0 \\ q_{i,t-1} + \eta_u^{\text{eff}} \cdot l_{u,t-1}^{\text{ev}} \cdot \Delta t, & \text{if } t \in [t_u^{\text{arr}}, t_u^{\text{dep}}] \\ q_{i,t_u^{\text{dep}}} - q_u^{\text{daily}} & \text{if } t = t_u^{\text{arr}} - 1 \end{cases} \tag{5.9}$$

In addition to these constraints, a further tightening of the available network capacity may occur due to the congestion management method. In static capacity subscriptions, the charging power of an EV is limited to the subscribed capacity of the customer minus the inflexible load that this customer has at a given time (or to

[11] We assume that arrival and departure times are the same time of day each day for simplicity. They are different for different users though.

zero, in case the inflexible load already exceeds the subscription):

$$l^{\text{ev}}_{u,s,t} \leq \max\left(P^{\text{subscribed}}_{u} - P^{\text{inflex}}_{u}(s,t), 0\right) \tag{5.10}$$

This is typically not a hard constraint. As discussed in Section 5.2.3, the user may be able to exceed the subscribed capacity in exchange for a higher volumetric charge. But for the modeling, we assume that this higher charge is always higher than wholesale price differences, so users would not intentionally choose to exceed their subscribed capacity. Note that the inflexible load of the user at time t is not known to the energy supplier when making the day-ahead purchasing decision, Equation (5.4). This is why we introduced different load scenarios, s, over which the energy supplier optimizes jointly. For assigning static subscriptions, we use the cost assumptions presented in Table 4.2. We compute the best-subscribed capacity for each household based on their inflexible loads over a year. Additionally, for EV owners, we add a capacity of 0.5 kW per each 2.5 kWh of daily demand to reflect the higher capacity needs of these users.[12]

For modeling the day-ahead CLC, we assigned each user a variable subscribed capacity of 11.5 kW. This is sufficient to charge an EV at the full charger capacity of 11 kW during the night. [13] In analogy to Equation (5.10), the limitation becomes:

$$l^{\text{ev}}_{u,s,t} \leq \lambda^{\text{activation}}(t) \cdot P^{\text{sub.variable}}_{u} \tag{5.11}$$

where $\lambda^{\text{activation}}(t)$ is a time-dependent activation factor of the variable subscription level. On the day ahead, the DSO announces the activation factors for the next day. When it expects no congestion, this factor is equal to 1. When it does expect congestion, this factor is set to below 1. We use only a single activation level to better compare the interruptible connection strategy, which sets the available capacity to 5 kW, the same value used for interruptible connections.

In interruptible connections as proposed by the BNA (Section 5.2.1), the network capacity can be limited specifically for the flexible device to a pre-defined value

[12]This simple heuristic is typically not too far off from the optimal result. We do this because, in real situations, customers will likely not know their exact daily demand, and it also varies over time, so finding an optimal solution here seems overly ambitious. We have also studied the impact of varying the assigned subscription to the next higher or lower level (+/- 0.5 kW), and it did not change results significantly.

[13]Note that this is somewhat different than the setup currently envisioned by ACM in Section 5.2.2, where participants bid for the lowest price reduction for a variable capacity. This is because the latter concept is envisioned mostly for industrial customers. In our setup, it would be difficult to model a bidding process for every EV, as it requires a lot of assumptions on the individual valuations of the network capacity of the users.

p^{limited}, e.g. 4.2 kW, during times of congestion:

$$l_{i,t}^{\text{ev}} \leq p^{\text{limited}} \quad \forall\, t \in \mathcal{T}^{\text{cong}}(c),\, u \in \mathcal{U}^{\text{curt}}(c,t), \tag{5.12}$$

where $\mathcal{T}^{\text{cong}}$ is the set of all time intervals with congestion and $\mathcal{U}^{\text{curt}}(t)$ is the set of users selected for curtailment. Alternatively, the constraint can be applied at the connection level, in which case a higher p^{limited}, e.g. 5 kW is used:

$$l_{i,t}^{\text{ev}} + P_u^{\text{inflex}}(t) \leq p^{\text{limited}} \quad \forall\, t \in \mathcal{T}^{\text{cong}}(c),\, u \in \mathcal{U}^{\text{curt}}(c,t), \tag{5.13}$$

We implemented this version in the case study to better compare with the day-ahead variable limitation.

This constraint is difficult because neither the congested times nor the set of curtailed users is known to the energy supplier when making the day-ahead purchasing decision, Equation (5.4). Thus, we introduce an additional set of curtailment scenarios c in this method, which describes the degree of congestion at each time. For ease of modeling, the energy supplier assumes only three different curtailment scenarios for each time step: 1. no curtailment, 2. 50% of devices curtailed, and 3. 100% of devices curtailed. Each scenario occurs with a certain time-dependent probability. The curtailment probability will typically be higher when the network is highly loaded. In residential areas, the traditional peak hours are during the evenings when many people come home from work. However, we assume that most users use smart EV charging, which uses low wholesale prices. In such a case, the network peak may be moved to the times of lowest wholesale prices [32]. Thus, we assume that the energy supplier assumes there is a chance of curtailment during the two lowest-wholesale-price hours each night. The objective function Equation (5.4) can then be amended to include this curtailment assumption:

$$\begin{aligned} \min_{P^{\text{pur}}(t),\, P^{\text{flex}}(u,s,c,t)} \quad & \frac{1}{\#\mathcal{S}} \sum_{s \in \mathcal{S}} \Bigg(\sum_{t \in \mathcal{T}} \sum_{c \in [0,50,100]} \rho(t,c) \cdot \Big(\pi^{\text{DA}}(t) \cdot P^{\text{disp}}(s,c,t) + c^{\text{Bal}} \cdot |P^{\text{net}}(s,c,t)| \Big) \\ & + c^{\text{EVUD}} \cdot q_{\text{total}}^{\text{EVUD}}(s) \Bigg) \end{aligned} \tag{5.14}$$

where $\rho(t,c)$ is the probability of c% of curtailment at time t. It is usually 0% curtailment with probability 1 and 0 otherwise. We assume a non-zero probability of curtailment events only for the two lowest wholesale-price hours.

In addition to day-ahead planning, there are two more phases (see Figure 5.1): 1.: updates on the intraday market and 2.: the dispatch stage or delivery phase. The intraday stage is largely analogous to the day-ahead trading stage. In it, energy suppliers can adjust their planning and use price spreads between different intra-day time steps and between the power purchased on the day-ahead market and the intraday. However, this only results in adjusting the day-ahead schedule; thus, we do not model this stage explicitly. Thus, for modeling simplicity, we fuse the intraday and dispatch stages into a single modeling stage.

In this intraday balancing and dispatch stage, the energy suppliers' main objective is to minimize imbalance costs, given a fee for portfolio imbalances and the option to re-trade energy in the intraday market. Here, the inflexible loads of users and the activation of curtailment of interruptible connections are known. I.e., all the previously unknown capacity limitation constraints have now been revealed. Thus, the objective can be stated as:

$$\min_{P^{\text{flex}}(u,t,s^*)} \sum_{t \in \mathcal{T}} \pi^{\text{DA}}(t) \cdot P^{\text{net}}(t,s^*) + c^{\text{Bal}} \cdot |P^{\text{net}}(t,s^*)| + c^{\text{EVUD}} \cdot q^{\text{EVUD}}_{\text{total}} \tag{5.15}$$

where s^* denotes the scenario of inflexible load and curtailment decisions that is realized in real-time (which is in general different from any of the projected scenarios $s \in \mathcal{S}$ of the day-ahead problem), and we use the same cost assumptions as in Equation (5.4) to be consistent with the day-ahead stage.

The energy supplier can adjust the dispatch of flexible demand $P^{\text{flex}}(u,t)$. For example, if some users are curtailed in the interruptible proposal but others aren't, it can redirect power flows from the curtailed users to the non-curtailed ones. Moreover, it can re-trade power in the market at a price correlated to the day-ahead price (we assume perfect correlation here for simplicity), but again with a penalty c^{Bal}. Lastly, we add a term that reflects the possibility of leaving EV demand unsatisfied for a specific discomfort cost.

We use a rolling time horizon of 48 hours for the day-ahead optimization problem to capture saving opportunities that result from pre-/postponing charging due to expected higher/lower prices on the next day. We assume that the day-ahead planning is done at noon for the times starting from 12 p.m. The dispatch stage is done simultaneously for all 24 hours starting at midnight, to simplify fulfilling the intertemporal constraints of EV charging.[14] At this stage, we assume that all relevant

[14]Note that in reality, this optimization would have to be performed on a rolling basis as more information becomes available with an updated set of scenarios for expected future inflexible demand in the following hours, as in the day-ahead objective. However, we reduced this problem by integrating all 24 dispatch decisions into one optimization problem for modeling simplicity. In this balancing stage, purchasing

Parameter	Values
General	
Number of households	50
Number of EVs	25
Time step	60 minutes
Imbalance cost assumption	20 ct/kWh
Unsatisfied EV load value	40 ct/kWh
Static capacity subscription	
Cost of the subscribed cap.	80 Eur/kW
Cost below subscribed cap.	3 ct/kWh
Cost above subscribed cap.	30 ct/kWh
Day-ahead CL and interruptible connection	
Capacity during congestion	5 kW
Scenario generation method	
Number of scenarios	10
Relative std. deviation	2 %
Decay parameter	0.9
Simulation dates	02/01/2021 - 16/01/2021

Table 5.2: Parameter values for simulation case study.

parameters of the capacity constraint are known for the next 24 hours, while for the following 24 hours after that, we use the same projection as in the day-ahead model (again to capture the intertemporal constraints over multiple days).

The relevant parameters of the model are summarized in Table 5.2. We use power prices from EPEX-NL[15] for January 2021 and household load profiles generated with the Load Profile Generator[16] by [36]. The electric vehicle charging profiles are taken from [37].

day-ahead electricity (at a lower cost) is no longer possible, and the problem is only about how to dispatch the already purchased load among the different EVs. Thus, the resulting differences do not change the results significantly.

[15] https://www.epexspot.com/en/market-data, complete historical data was generously made available by EPEX for academic usage

[16] https://www.loadprofilegenerator.de/

5.4.3. RESULTS

We begin by discussing the purchased power of the energy supplier for all flexible and inflexible loads in the different strategies in Figure 5.2. For the interruptible connection proposal, we distinguish between a naive and an anticipating implementation: in the naive version, the energy supplier does not account for the possibility of curtailment in its day-ahead planning. Thus, this implementation leads to the highest spikes of flexible loads in the planning, as the energy supplier assumes that the full technical capacity will always be available. In the anticipating mode, the energy supplier considers the possibility of curtailment in their day-ahead purchasing decision. Thus, they already reduce the highest load peaks for the next day to reduce the risk of curtailment.

Similarly, in the day-ahead variable CLC, during the periods with the highest expected loads (i.e., the times with the lowest prices), the available capacities for variable contracts are reduced by the network operator. This has a similar effect as the downward adjustment of purchased loads in the anticipating version of the

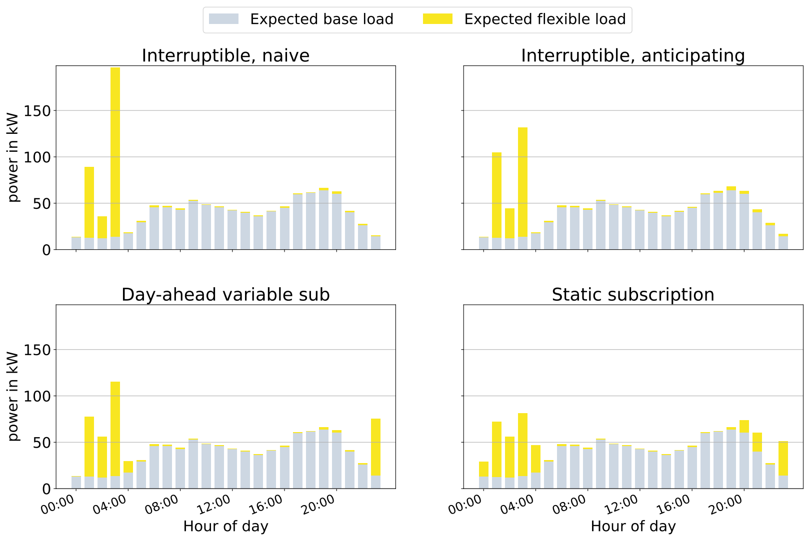

Figure 5.2: Purchase decisions for flexible loads day-ahead under different congestion management methods on an exemplary day during the optimization time period.

interruptible connection implementation and spreads out flexible loads over a longer time. Lastly, in the static capacity subscription version, the spikes in flexible loads are reduced even more and spread out over an even longer time. This is due to the higher capacity restrictions (see Figure 5.6), which limits EV charging (or other flexible loads) to the subscribed capacity at all times. In summary, all three proposals reduce peaks of flexible loads.[17]

We now review some results of individual users to understand how the different proposals work. For this, we distinguish between light and heavy EV users, as it is interesting to see how the mechanism affects different user groups differentially. Heavy users are defined as those with a daily demand of 11kWh or more, medium users with a demand of 6 to 11kWh, and light users below 6kWh daily. In Figures 5.3, 5.4 and 5.5 we show the three mechanisms for a randomly chosen light and heavy user for the same example day as Figure 5.2 (with the same users in each graph). In the interruptible connection on this day, Figure 5.3, the network operator implemented curtailment at 3:00 am. We can see how the heavy EV user can use the total network capacity without congestion.

This contrasts with the day-ahead variable capacity limitation implementation, Figure 5.4. Here, in the chosen example day, the network operator has announced a reduction of available capacity for all hours from 1:00 to 3:00 am, as congestion was anticipated to be likely during these hours. Thus, the network capacity is considerably reduced for the heavy EV user, compared to the interruptible connection. On the other hand, since the reduction was announced on the day ahead already, it gave more planning certainty to the energy supplier, which will become apparent when we look at balancing requirements (Table 5.3).

In the static capacity subscription, Figure 5.5, the available capacity for flexible devices is determined solely based on the subscribed capacity and the inflexible load of a user at each time. The light EV user here has a 1.5kW subscription while the heavy user has 6.5kW subscription. They use their total subscribed capacity for multiple hours to fulfill their charging needs. As we can see from this and from Figure 5.2, the static subscription spreads out flexible loads more than the other strategies and prevents users from using the total technical capacity of their devices and the entire available network capacity during all times.

Now, we focus on the impacts on the energy supplier in terms of total costs and

[17] In the naive implementation of the interruptible proposal, the large peaks are curtailed in real-time, which incurs large balancing costs. Thus, the energy supplier presumably would start anticipating curtailment to reduce costs.

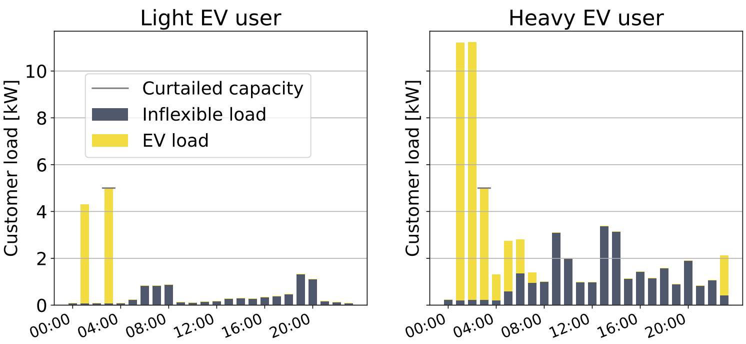

Figure 5.3: Interruptible connection in example day. Same users as in Figures 5.4 and 5.5.

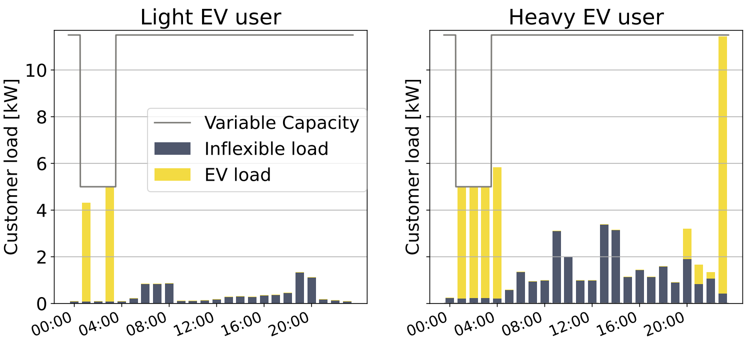

Figure 5.4: Day-ahead variable capacity limitation for flexible load in example day.

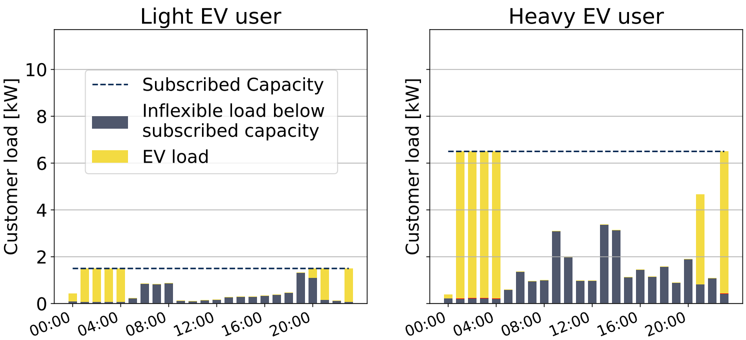

Figure 5.5: Static capacity subscription in example day.

Table 5.3: Day-ahead purchasing costs and balancing energy requirements in different congestion management methods

	Interruptible, naive	**Interruptible, anticipating**	**Day-ahead CLC**	**Static cap. subscription**
Total day-ahead market costs [Euro]	922	920	931	933
EV charging day-ahead market costs [Euro]	97.3	95.1	105	108
Pos. imbalance [kWh]	280	260	108	118
Neg. imbalance [kWh]	2.5	0	0	2.1
Imbalance costs [Euro]	56.4	51.8	21.6	23.7

required balancing. Table 5.3 shows the total day-ahead wholesale price cost and balancing energy requirements in the different strategies. It is noticeable that the differences in wholesale electricity costs for charging the whole EV fleet are not that large: in our data set, it is at most 9.2 Euros over the chosen 2-week time span. This is because the price differences between the cheapest and 2nd, 3rd, and 4th-cheapest times are not that large. We would also expect this effect to continue when there will be many more flexible loads: these will usually bid up the prices at the cheapest hours to the level of the next cheapest hours.

Concerning the required balancing energy, we find significant differences. We distinguish between a positive balancing requirement, which occurs when too much power has been procured, and a negative balancing requirement, which results from too little power procurement. Negative balancing occurs when the charge requirements of EVs cannot be fulfilled due to previous curtailment or due to the realization of a different load scenario, and power has to be procured at the balancing market as a last resort.

The naive implementation of an interruptible connection that ignores the possibility of being curtailed leads to large balancing requirements when curtailment occurs. Furthermore, it sometimes requires the additional procurement of energy due to negative imbalances. The anticipating implementation reduces the required curtailment somewhat and avoids the need to procure additional energy for negative imbalances. This could be improved even further if the network operator would update the energy suppliers with more information about expected congestion, such that they could improve their purchasing decisions. Day ahead variable capacity limitations and static capacity subscriptions incur much lower balancing requirements. The reason for this is that in these cases the only source of uncertainty on the day-ahead is the inflexible load of customers, which determines how much capacity is available for the EV charging. For static capacity subscriptions we find that sometimes the uncertainty on the inflexible load can also lead to a requirement for additional energy due to negative imbalances.

Note: With current cost assumptions, none of the strategies incur unsatisfied EV demand. We can push the model towards that situation when we set the cost of unsatisfied EV demand close to the balancing cost. In reality, balancing prices vary over time, and when they are very high the model would choose to leave EV demand unsatisfied instead.

Lastly, we discuss the impacts of the different strategies on the capacity that users have available for charging their EVs. Figure 5.6 shows the distribution of available capacities over all simulated time steps separated by user types.[18] Note that the violin plot appears to be a continuous distribution, even though the underlying data is discrete. [19]

In the static capacity subscription, the available capacity for EVs is given by the subscribed capacity minus whatever inflexible loads the user uses. Thus, the distribution spreads across the range of possible capacities from 0 to the subscribed capacity of the respective EVs. We assume that heavy users tend to sign up for higher subscribed capacities, so the maximal available capacities tend to get bigger for heavier users. In the day-ahead variable subscription, the distribution mirrors our input assumptions. As explained above Equation (5.11), users sign up for a variable subscription of 11.5 kW here. Thus, most of the time they have almost the

[18] We consider only time steps where the vehicle is parked at home and available for charging for these calculations.

[19] E.g., in the interruptible connection, the upper value is always fixed to the full charging capacity of 11 kW, even though it appears from the plot as though there are capacities just below 11 kW, which is not true. This is a shortcoming of this type of plot, but we nevertheless found it more intuitive to grasp than other types of plots.

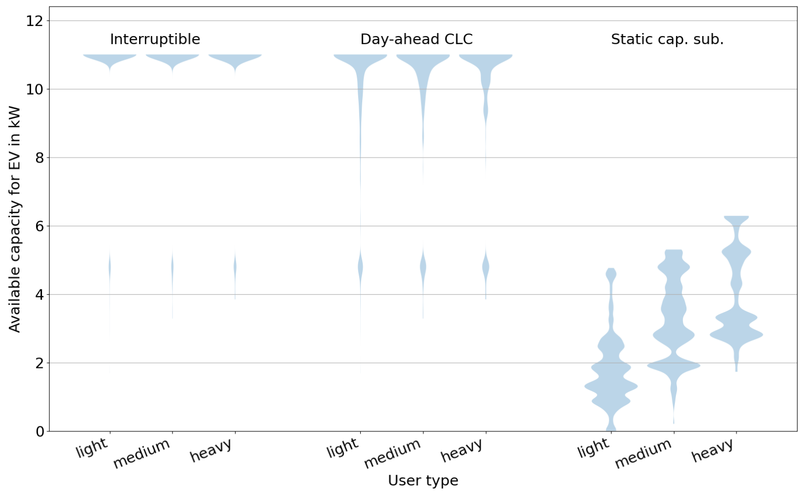

Figure 5.6: Available capacity for EVs with different congestion management methods

full technical capacity of 11 kW available for charging. The times when capacity is limited on the day ahead are visible as a smaller cluster around 5 kW, the available capacity when limitations are announced. In the interruptible connection proposal, the limitation occurs more rarely than the day-ahead limitation. This is because the network operator can wait and see until near real-time to observe whether congestion is actually happening, while the day-ahead activations are based purely on anticipation and therefore have to occur more frequently.

5.5. Discussion

As shown in Section 5.4, each of the presented congestion management mechanisms can reliably resolve congestion. However, they each come with particular benefits and drawbacks. In this section, we discuss the performance of the mechanisms based on both qualitative evaluation and our case study results.

5.5.1. BNA PROPOSAL AND INTERRUPTIBLE CONNECTIONS IN GENERAL

The main strength of interruptible connections is that it does not restrict network access when there is no congestion, as can also be seen from Figure 5.6. This means that users of flexible loads can use the full technical capacities of their devices most of the time and consequently use low wholesale prices (Table 5.3), as well as charge EVs or heat their homes with heat pumps quickly when desired. This allows for efficient network loading during these times.

However, users run the risk of being curtailed in near real-time. Our case study shows this leads to higher balancing costs in this approach (Table 5.3). This may result in risks for aggregators who manage multiple connections: a near real-time curtailment may lead to an energy imbalance in their portfolio. If they cannot spread this energy imbalance over other flexible loads, they are liable for the resulting imbalance costs and re-procurement of electricity (see Section 5.3.1). This typically leads to balancing costs, and the electricity that could not be delivered needs to be re-procured at market prices. This also suggests that this proposal may not be viable for individual critical loads such as large industrial consumers for whom an unforeseen outage of equipment due to reduced capacity would incur prohibitively high losses in production lines.

Furthermore, interruptible connections may be better suited for situations with low frequency and congestion depth, where curtailment remains an exception. When congestion occurs very frequently and at high levels, the activation of curtailment may become so frequent that a strategy with more security (like static capacity subscriptions) may become preferable.

Another drawback of this mechanism is that in its current form, it is not cost-reflective, as the tariff reduction doesn't depend on usage. For example, a user with a heat pump with a technical capacity of 4kW who rarely uses this total technical capacity and is rarely curtailed receives the same lump-sum rebate as a user with an 11 kW EV charger in a congested area who may be curtailed often. Furthermore, the mechanism is somewhat discriminating: users in congested areas are curtailed more often than those in non-congested areas, even though they get the same rebate. However, this is a general feature of dynamic congestion management mechanisms, as network congestion is spread unevenly throughout the network [32]. Lastly, implementing this mechanism requires the installation of load-limiting devices that the network operator can control, a cost factor that we did not consider in our case study.

5.5.2. ACM proposal and day-ahead variable capacity in general

In principle, a limitation of variable capacity announced before the day-ahead market closes could efficiently resolve congestion. It does not limit network capacity when congestion can be ruled out with certainty. Also, it gives users (or aggregators) more planning certainty for scheduling flexible loads, as they can include the network capacity constraint in their trading decisions on the day-ahead and intraday markets. Moreover, regarding cost-reflectiveness, this class of proposals is a step ahead of the BNA proposal: users pay (or get a rebate, depending on the mechanism design) explicitly based on how much of their capacity is variable.

Our simulation results show that the day-ahead announcement significantly reduced the balancing requirements for the energy-supplying party Table 5.3. Moreover, the required restriction of network capacity is far below that of the static capacity subscription (Figure 5.6). However, at the same time, the restriction is also significantly more frequent than in interruptible connections. This is also reflected in slightly higher charging costs for EVs (Table 5.3). These costs affect heavy EV users more than light EV users, for whom even the reduced capacity is still sufficient to mostly charge their EV at the lowest wholesale prices (Figure 5.4).

It is also important to note that this mechanism still requires a fallback option like redispatch or curtailing connections when unforeseen congestion occurs, which we did not explicitly model here. If congestion occurs that was not anticipated on the day ahead, e.g., due to wrong estimations by the network operator or exploitation of spreads on the intraday market by aggregators and other large customers, it is the network operator's responsibility to become active and remove this congestion, e.g., through re-dispatch markets[20]. This may pose a risk, as re-dispatch markets can be costly and are known to be vulnerable to strategic behavior (inc-dec gaming), as market participants may artificially create problems to be paid by the network operator to remove them again [38, 39]. In the residential sector, an alternative to market-based redispatch could be the curtailment of connections like in the BNA proposal as a fallback.

Depending on the fallback mechanism, risks are distributed differently: redispatch places a financial risk on the network operator and may not be suitable for LV feeders due to strategic behavior. Furthermore, because of the added costs in case the network operator underestimates congestion, they may tend to overestimate it to protect against these costs. This would reduce the mechanism's efficiency

[20] In the Netherlands, for example, the GOPACS platform is intended to be used for this purpose.

as the capacity limitation would become activated more frequently, even when unnecessary. On the other hand, curtailing connections again leads to a residual risk of curtailment for users (albeit likely lower than in a mechanism based solely on interruptible connections). Curtailment may thus not be suitable for many industrial customers.

Lastly, the current ACM proposal envisions selling capacity limitations on a market where customers bid for the lowest required price per kW reduction to contracted capacity. This may work well in a liquid market with a large pool of bidders where strategic behavior and collusion can be ruled out. However, it might not work well for small feeders, where a single aggregator could control a large part of the flexible loads and charge exaggerated prices.

5.5.3. STATIC CAPACITY SUBSCRIPTION

The most significant benefit of the static capacity subscription is the (near-)absolute planning certainty, as it guarantees the available capacity long-term. After the finalization of the contracts, users know exactly how much capacity they have for the contract phase (notwithstanding unforeseen power outages). This also means that this mechanism requires no additional tasks from the network operator, in contrast to the other two approaches (see Figure 5.1)[21]. Moreover, this mechanism performs well regarding cost-reflectiveness [25], and it lets users decide their capacity level considering their utility, e.g., from high-capacity EV charging, rather than an externally imposed restriction like in the BNA proposal. Lastly, further benefits are that this mechanism introduces no spatial discrimination based on congestion and is relatively simple, without the need to communicate available capacity or install load-limiting devices.

The main problem with this mechanism is that it restricts users to their subscribed capacity, even though their devices can draw much more power. For example, EV chargers are often available at 11 or 22 kW and heat pump power consumption is

[21] However, this only holds if sufficiently many customers are induced to stay below the subscribed capacity, as otherwise, a violation of network bounds may still occur. In this respect, one potential shortcoming of the mechanism is that it triggers no additional demand response once the load exceeds the subscribed level. Customers are not incentivized to spread out an exceedance of the subscribed level over multiple timesteps rather than having it all in a single time step. This may be resolved already by the relatively low likelihood of many customers coincidentally exceeding their subscribed load at high levels. Still additionally, it should be ensured that all customers have automated management of their flexible device, which prevents exceedance of subscribed load as much as possible. Furthermore, the cost of exceedance could also be designed in an escalating way, such that exceeding the subscribed level by higher margins becomes more expensive. [40]

similarly in the order of $1-10\,\text{kW}$ [41]. Thus, users of these devices can either spend more money on procuring a higher capacity (or paying the higher charge for exceeding capacity) or use their devices more often at a power consumption rate much lower than what would be technically possible.

As our results indicate (Table 5.3), the impact may be small regarding the costs required to charge a typical daily demand of most EV users, as most users do not require large amounts of energy on most nights. However, the user discomfort may be relatively high, as it may be frustrating to have only the low subscribed capacity available for their devices (at low per kWh-prices) when the technical capacity of these devices is much higher, see also Figure 5.6. This becomes important when users require a higher capacity, e.g., to charge a vehicle quickly or heat a home faster.

5.5.4. Limitations of the case study

Due to resource and data availability constraints, our case study provides only a limited proof-of-concept of the proposed mechanisms rather than a real network simulation. The most consequential limitations are:

- The neighborhood is small, with only 50 households and up to 25 EVs.
- We did not consider distributed generation (DG) like solar PV panels, which brings additional uncertainty for inflexible loads and may sometimes be used to reduce load at the network connection point to below the capacity limitation required by the mechanism.
- We considered only smart charging, not vehicle-to-grid/vehicle-to-home or the operation of batteries, which can further aid in respecting the required capacity limitations.
- We neglected power flow constraints and only modeled a single network constraint at the LV transformer, ignoring reactive power and voltage concerns.
- We assumed all flexible loads in the area are managed by the same supplier. In reality, multiple suppliers will be active in a given region and compete with each other.
- We also assume the supplier is only active in a single neighborhood. In reality, they will be active in multiple neighborhoods. This could make it easier to avoid balancing costs by shifting energy flows from congested to non-congested areas.

- We use a 60-minute time step in our modeling. On the day-ahead market, it is already possible to trade in 15-minute time steps. Therefore, overloads may occur at this resolution[22] Therefore, in an improved simulation or implementation in reality, the settlement time step for the capacity limitation should perhaps align with the smallest trading time steps of the electricity market in a given location.

However, we believe the main conclusions drawn in the preceding chapters are valid, as they are based on the general properties of the proposed mechanisms not affected by any of these limitations.

5.6. CONCLUSION AND POLICY IMPLICATIONS

We investigated network congestion management mechanisms based on network capacity limitations for flexible loads, currently discussed in the Netherlands and Germany. The mechanisms we have analyzed can be sorted by the lead time at which reductions of available network capacity are announced: near real-time interruptible connections, day-ahead variable capacity limitation contracts, or long-term static capacity subscriptions.

In principle, all these solutions can help resolve network congestion, but each proposal has some drawbacks in its current form. The interruptible connection of the BNA proposal allows users to make full use of their capacity when there is no congestion but can introduce unexpected balancing requirements. The day-ahead capacity limitation removes congestion efficiently and with planning certainty when it is anticipated correctly by the network operator. However, if the congestion forecast is wrong, it can lead to excessive restrictions or a need for an emergency fallback mechanism. Long-term capacity subscription provides complete planning certainty but always restricts users to the subscribed capacity, even when network conditions do not require this. In the following paragraphs, we advise on possible improvements based on our analysis.

The BNA proposal and interruptible connections in general

[22] If the price spread of several 15-minute time steps within the same hour is large enough on the intraday market, it would make sense for an energy supplier to buy a lot of power in one-time step and very little or none in another, such that their average load over the whole hour is below the subscribed capacity for their users, but that at 15-min level overloads occur which may damage the network infrastructure.

The cost-reflectiveness of this proposal can be improved. As discussed in Section 5.2.1, currently, a network tariff reduction is given to any user with a device with a power capacity higher than 4.2 kW, independent of the usage of this device and of whether there is congestion in the area (in case of multiple devices for the same user, the network operator has to decide on whether the mechanism is applied on a per-device basis or for the connection as a whole with a higher minimum capacity). In line with tariff-setting regulatory principles and previous research [25], we recommend making the proposal more cost-reflective by charging heavier users more than light users while accounting for the expected depth and duration of interruptions. This might require changes to how financial remuneration for this proposal is implemented. Rather than giving a discount for making the connection interruptible, a charge could be associated with installing a flexible device above 4.2 kW. This charge should be higher, the more capacity is desired for the device, and the fewer interruptions are tolerated. Note that this requires the network operator to be informed about all the high-power devices installed in their network. This means that there needs to be a binding obligation for users to register these devices, and possibly also a penalty for failure to do so.

Furthermore, the network operator should strive to limit unplanned interruptions as much as possible to reduce balancing requirements. As we showed in Table 5.3, balancing requirements can be reduced when the energy supplier anticipates possible curtailments. To aid this process, the network operator could send information on the day ahead on expected congestion, with updates during the intraday timeframe. Information on the frequency and location of curtailment events per area should be made available by the network operator.

The ACM proposal on day-ahead capacity limitation contracts

As discussed in Section 5.5, a potential problem is that the network operator does not anticipate congestion sufficiently and requires a fallback option when additional congestion occurs unexpectedly. To limit the requirement for this emergency fallback as much as possible, it could be helpful to require customers to send their intended schedules after the day-ahead market closes to confirm that congestion based on day-ahead schedules does not occur. In cases where customers intend to make large upward modifications of their day-ahead schedules in intraday markets, they might be required to check with the network operator whether this is still possible.[23]

Furthermore, the proposal envisions end-users to bid for reductions in network price that they require to make their capacity flexible. As dominant players like aggregators who control a large share of flexible loads on residential feeders could abuse this bidding process, making the contracts only with individual end users might be better and, additionally, to turn around the buy/sell positions: the users could pay the network operator a higher price for fixed capacity and a low price for network capacity that can be reduced. This reduces the financial risks for the network operator.

Static capacity subscription

The main problem of the capacity subscription is the permanent incentive to restrict consumption to the subscribed capacity, even when there is no congestion. Several strategies could alleviate this. Firstly, one possibility is to activate the capacity reduction incentive only when there *is* network congestion. This would require setting up additional communication channels to communicate to users when this is the case. Secondly, it could be an option to implement a two-part subscription. This is explained further under the following recommendation.

Recommended solution: two-part subscription for flexible and variable capacity

Based on our analysis, we propose a new mechanism combining the static subscription's advantages with the more dynamic solutions: a two-part capacity subscription. One part is a base capacity subscription for network capacity guaranteed to be available as in the normal capacity subscription. The part has a relatively high price per kw of subscribed capacity. In addition, customers can choose to add a variable subscription. The variable subscription is significantly cheaper per network capacity per kW. In return, the network operator can reduce it on the day ahead or close to real-time, depending on the congestion situation in the network. This approach would combine the cost-reflectiveness and planning certainty of a capacity subscription with the ability of an interruptible connection to

[23] Note that this might give an incentive to aggregators to exaggerate their day-ahead schedules, as that gives them more flexibility to adjust upwards on the intraday. One solution could be requiring them to prove their intended schedules by showing the corresponding trade receipts of the day-ahead market. These should sum up to all of their intended local schedules.

make the best use of available capacity. It would also avoid the potential for market power abuses when users are asked to bid for a required reduction in network prices. Due to the limited scope of this chapter, which was focused on investigating current proposals, we did not explicitly simulate this proposal in our case study. However, we recommend it to be studied in depth in future work.

Appendices

APPENDIX A: SCENARIO GENERATION

We use a simple auto-regressive model of the first order, i.e., an AR(1) model for generating scenarios of inflexible loads and prices for Equation (5.4). The scenario generation is based on a given set of input data for inflexible loads and day-ahead prices. We assume that the day-ahead planning process is done at noon of the preceding day, as this is the gate closure time of the day-ahead market in the Netherlands. We further assume that the network operator can observe the aggregate load at the transformer level and share this information with the energy supplier to make forecasts for purchasing decisions. Though this is not always the case, we expect measuring devices at LV transformers to become more common.

Based on the last observed load time step at noon, we forecast an ensemble of scenarios centered around the supplied input data set. In the simple AR(1) model, we draw the errors for each time step independently from a Gaussian distribution centered at 0 with an inferred standard deviation based on the variability observed in the input data set:

$$\xi(t) = \phi \cdot \xi(t-1) + \epsilon(t) \tag{5.16}$$

where $\xi(t)$ are the errors relative to the input data set, ϕ is called the *decay parameter* and $\epsilon \sim \mathcal{N}(0, \sigma^2)$ is random white noise. We sample a number n_S of scenarios that the supplier and network operator use to solve their stochastic optimization problem. By the same process, we generate a scenario for the realized values of inflexible load in the intra-day problem Equation (5.15). This guarantees that the scenarios used for planning have the same statistical properties as the finally realized scenarios and that sometimes extreme scenarios are also realized. If we simply took the given input data to be the actually realized values, this would not be true.

APPENDIX B: OPTIMIZATION OBJECTIVE TRANSFORMATION

The first part of the optimization objective Equation (5.3) involving the theta functions can be transformed as follows:

$$
\begin{aligned}
&\pi^{\mathrm{DA}}(t)\cdot P^{\mathrm{pur}}(t)\\
&+\left(\pi^{\mathrm{DA}}(t)+c^{\mathrm{Bal}}\right)\cdot\theta(P^{\mathrm{net}}(s,t))\cdot P^{\mathrm{net}}(s,t)\\
&+\left(\pi^{\mathrm{DA}}(t)-c^{\mathrm{Bal}}\right)\cdot\theta(-P^{\mathrm{net}}(s,t))\cdot P^{\mathrm{net}}(s,t)\\
&=\pi^{\mathrm{DA}}(t)\cdot P^{\mathrm{pur}}(t)+\left(2\cdot c^{\mathrm{Bal}}\cdot\theta(P^{\mathrm{net}}(s,t))+\pi^{\mathrm{DA}}(t)-c^{\mathrm{Bal}}\right)\cdot P^{\mathrm{net}}(s,t)\\
&=\pi^{\mathrm{DA}}(t)\cdot P^{\mathrm{disp}}(s,t)+c^{\mathrm{Bal}}\cdot|P^{\mathrm{net}}(s,t)|
\end{aligned}
$$

where we used $\theta(-x)=1-\theta(x)$ in the first equation and $2\cdot\theta(x)-1=\mathrm{sign}(x)$, as well as the definition of net power, $P^{\mathrm{net}}=P^{\mathrm{disp}}-P^{\mathrm{pur}}$.

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Appendix C: Absolute value variable transformation

To transform the absolute value function in the day-ahead optimization objective, Equation (5.4), we express this value as the difference of its positive and negative parts:

$$P^{\mathrm{net}}(s,t)=P^{\mathrm{net},+}(s,t)-P^{\mathrm{net},-}(s,t) \tag{5.17}$$

Where we require both of these quantities to be non-negative:

$$P^{\mathrm{net},+}(s,t),\,P^{\mathrm{net},-}(s,t)\geq 0\quad\forall\, s,t \tag{5.18}$$

The absolute value can then be expressed as the sum of these two linear parts:

$$|P^{\mathrm{net}}(s,t)|=P^{\mathrm{net},+}(s,t)+P^{\mathrm{net},-}(s,t) \tag{5.19}$$

Theoretically, we also require that only one of the parts in Equation (5.17) can be non-zero, as the net power can be either positive or negative (or zero), but not both at the same time. In practice however, this isn't necessary. The optimization objective Equation (5.4) is minimal when only one of them is non-zero, otherwise we could always remove the non-zero common part to achieve a lower value. Thus, the solver will always set one of them to zero.

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6

Investments and Dispatch in Residential Energy Usage Under Different Electricity Rates and Network Tariffs

The previous chapters of this dissertation focused on how best to manage congestion from flexible end-use devices in residential areas and how to assess the performance of network tariffs. However, network tariffs and congestion management mechanisms are only part of a consumer's final energy bill. In this chapter, we take a wider lens and investigate how network tariffs interact with the price of the electricity-generation-related component. Furthermore, we expand the analysis to include investments in addition to the dispatch of flexible loads and deeper decarbonization targets.

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6.1. INTRODUCTION

Residential energy demand is changing significantly due to the energy transition to renewable sources. It is increasingly electrified, e.g., by switching from Internal Combustion Vehicles (ICVs) to Electric Vehicles (EVs) and switching from gas-based space heating, water heating, and cooking to electric technologies such as heat pumps and electric stoves. This adds a significant amount of electricity demand. Moreover, a substantial share of this demand is flexible: EV charging typically only needs to fulfill a certain amount of battery charge, and heat pumps can pre-heat homes or storage tanks, especially when well insulated.

Simultaneously, the electricity supply from the energy system is increasingly based on intermittent renewable sources. This may lead to lower average generation prices, as these sources have no fuel and low levelized electricity costs, which are expected to decline further in the future [1]. However, fluctuations in the price of electricity in the market are expected to increase because of the intermittent availability of these sources. There may be high price spikes when renewable energy is unavailable due to a lack of wind and solar radiation, as more expensive backup power plants or demand response/curtailment must fill in then.

Lower average prices of generation should eventually be passed on to the end-users by electricity retailers, which has a beneficial impact on the electrification of end-uses. However, residential electricity rates have usually been designed as simple flat rates per kWh. These do not pass on the price fluctuations of the electricity market price signal to the consumer. This means that customers have no incentive to react to these price fluctuations and use the flexibility of their loads to adjust their electricity consumption.

Furthermore, consumers' final electricity rate includes not just the electricity generation price but also other components. The most significant of these components is often the distribution network tariff: the price customers pay for using the electric distribution network ([2]). Currently, distribution network tariffs are often either fixed payments (per year or month) or added to the per kWh price that users pay for the electricity generation component and other components, such as taxes, retailer margins, and transmission fees. When network tariffs are fixed or based on per kWh prices, they do not give incentives to users to reduce their peak consumption [3] and, therefore, they may not prevent network overload that happens due to significant simultaneous peaks of, e.g., of EV charging or heat pump usage.

Thus, with higher shares of flexible demand and intermittent renewable generation sources, electricity rate design and network tariffs need to be updated to better use the flexibility of demand to move electricity usage along with the availability of intermittent renewable sources within network constraints. Flat per-kWh electricity rates may prevent the efficient alignment of flexible demand with intermittent supply. Fixed or flat per kWh network tariffs may lead to high network peaks due to not incentivizing flexible loads to flatten peaks.

This chapter aims to study the impacts of different rate designs and network tariff choices on residential household energy consumption patterns. We combine different choices for the electricity generation-related component and the network tariff to four final rate designs: a flat per kWh rate for both generation and network tariff, a Time-of-Use kWh rate for both with higher prices during the day on weekdays, a real-time market price for generation with a fixed network tariff and a real-time market price with a network capacity based network tariff. We investigate the impact of these rate design choices on investments in electrification, dispatch of the chosen technologies, costs, network load, and resource usage. Furthermore, we investigate model runs with tighter carbon constraints to investigate increasingly higher levels of electrification.

We use the open-source energy system model Calliope[1] to build a 25-household neighborhood modeled according to a typical Dutch population that is connected to the distribution network through an LV transformer. We map investment options for decarbonizing residential energy demand, retail rates, and network tariffs onto input assumptions for Calliope. We employ a first-order approximation where we use an instance of the Calliope model for the whole European energy system in 2030, including the stated capacity targets of the Netherlands [4] and an assumption on flexible demand this year. We do not explicitly model the feedback of electrifying residential energy demand on the national level power prices. Based on electricity prices from this model, we compute the optimal investment and dispatch decisions on the residential level.[2]

The chapter is organized as follows: Section 6.2 discusses the current literature around decarbonizing residential energy demand, Section 6.3 presents the study design and the methodology used. Section 6.4 shows the results and discusses their

[1] https://www.callio.pe/

[2] Technically, these decisions have feedback on the national level electricity prices, but we consider this to be a second-order effect ignored in the current study. In a future study, we aim to tackle the integrated problem, including the feedback loop.

implications. Finally, Section 6.5 concludes.

6.2. LITERATURE REVIEW

Mittelviefhuis et al. [5] consider the decarbonization of an 83-building neighborhood in St. Gallen, Switzerland, in a multi-energy system with mobility. They use Gurobi for joint optimization of all energy carriers based on either costs or CO2 emissions. Their main conclusion is that more than half of emissions could be reduced by switching to electric vehicles and hub technologies for electricity and heating and that this switch is less costly than the status quo in the long run. However, it comes at the expense of much higher upfront costs.

The same authors extend their analysis to investigate centralized and decentralized electricity supply options [6]. They find that considering limitations to supply has a strong impact on the resulting costs of different decarbonization scenarios. They also explicitly include grid limitations, though they do not consider the tariffs paid for these and the retail rates customers pay for electricity as part of their analysis.

Rinaldi et al. [7] consider residential heating and hot water in conjunction with storage options and building retrofitting. This and the preceding analysis are based on central techno-economic optimization without considering the impact of retail rates and tariffs. They find that significant interactions exist between different flexibility options. In particular, they conclude that combining flexible load and storage types significantly increases PV self-consumption and absorbs energy that would have otherwise been curtailed or fed back to the grid.

Aniello and Bartsch [8] investigate regulatory choices in a single-household model. As in our analysis, they consider different network tariffs as well as electricity price structures, which combine into a superposition of fixed (per year), flat and dynamic volumetric (per kWh), and capacity-based (per kW) charges. The dynamic electricity price in their analysis is based on the carbon content of electricity in the grid; it internalizes the costs of CO2 emissions. They show that combining capacity charges with dynamic electricity prices can lead to a cost-efficient decarbonization of the residential sector while respecting network constraints. Their literature review further adds many interesting points from previous analyses.

Saumweber et al. [9] review electricity rate structures and the principles behind their design. They propose a new rate-setting method based on multi-criteria optimization, incorporating economic efficiency, cost-reflectivity, equity and environmental considerations. They investigate the proposed rate in a simulation model with 19 prosumers and a utility. However, in their modeling, they use 19 different scenarios in which they consider only the investment decisions of one prosumer at a time while keeping the others fixed, which ignores interaction effects at the system level, such as on network peaks. They find that traditional rate designs based on static consumer loads are not well-suited for situations when customers become prosumers because of the feedback of customer investment choices in DG on utility costs. They advocate reducing the design space of retail rates to only those that are Pareto-optimal, considering the multi-objective optimization.

Manso-Burgos et al. [10] investigate the impact of different electricity tariffs for the specific case of local energy communities in Spain. They use a linear optimization model for a community of 20 households with an additional PV installation of up to 100kW and compare different tariffs and sharing models for self-consumption of the PV generation. They find that it is beneficial for the community to allow variable sharing of PV generation as opposed to static sharing and that a new tariff with a higher price during midday also increases the profitability of the community. However, their analysis does not include storage options and no explicit modeling of network effects.

6.3. Modeling setup

We use Calliope [11] to optimize the investments and dispatch decisions of 25 households based on a given rate design for electricity and network prices, as well as optional constraints on the total emissions of the neighborhood. Calliope has previously been used to model large-scale energy systems. We chose to use this model due to its modular and streamlined nature of adding and combining technologies and demand, which allows for a natural representation of household energy systems and because it is free and open-source. This section presents the implemented setup of the model.[3]

6.3.1. General setup

Each household is represented by a node with five different types of final energy demand: electricity, space heat, transport, cooking, and hot water. Each demand can

[3] The complete model is available at: https://gitlab.tudelft.nl/rhenning/calliope-local/-/tags/Model_version_for_paper

be satisfied with different technologies. Calliope distinguishes between conversion technologies, which convert an input carrier into a final energy demand (or into an intermediate carrier which can then be further converted into final demand), and storage technologies, which can store an energy carrier and release it at a later point for satisfying final energy demand. Each technology has associated technological parameters: lifetime, capacity investment cost, operational cost, O&M costs, and conversion efficiency for conversion technologies or maximal charge rate, leakage, and charge/discharge efficiency for storage technologies. Our parameter choices are presented in Section 6.5.

We base our case study on a stylized neighborhood of the Netherlands, presented in [12] (Figure 6.1). The initial situation is based on the assumption that a certain stock of technologies already exists (a so-called brown-field approach). In the model, this is implemented as a zero cost of capacity for these technologies. In this initial situation, we assume that all transport demand are fulfilled by diesel cars, space and water heating demand by gas boilers, and cooking demand by gas stoves. This aims to approximate the current situation where 90% of households rely on gas systems for cooking, space, and water heating [13] and only 5.8 % of cars were Electric Vehicles at the end of 2022 [14].

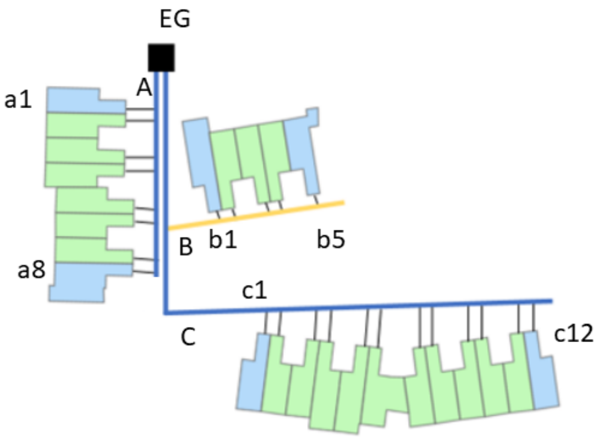

Figure 6.1: Schematic representation of the neighborhood.

The neighborhood is connected to the national electric grid by a node representing the area's low-voltage transformer station (labeled "EG" in Figure 6.1). It can be used both for electricity import for consumption and export of excess solar PV production, in case PV panels or household batteries are installed. Each household has an unlimited connection to gas and diesel supply.

6.3.2. Technologies and energy carriers

The available technologies for investment are air-source (air-to-air) heat pumps (ASHP), ground-source heat pumps (GSHPs), electric resistance heaters, solar PV panels, solar thermal vacuum tubes, battery energy storage systems based on lithium-ion, improved building envelope thermal insulation, enhanced thermal insulation, induction cooking stoves, electric boilers, electric vehicles, and thermal storage tanks. The investment costs are given in Table 6.2. All investment costs are annualized in the model.

For energy dispatch, we assume the final demand to be fixed, but flexibility can be exploited with storage technologies for final demand or intermediate energy carriers: household batteries for electricity demand, EV batteries for transport demand, the thermal mass of the building for final space heat demand and a hot water storage tank for hot water demand. Cooking does not feature explicit storage, but for electric stoves, the electricity used for cooking can be stored in batteries.

Figure 6.2 shows the system's energy flow for electricity and transport technologies. Grid electricity is associated with a monetary cost that depends on the chosen rate design and time and with a CO2 emission factor that also varies by time based on the generation mix in the grid. We assume the household's network connection converts grid electricity to household electricity. This is necessary to represent the impact of a limited network capacity due to capacity-based tariffs (Section 6.3.4). Household electricity can also be generated by solar PV panels, stored in batteries, and used to fulfill electricity demands. We include the possibility of load shedding, which comes at a high cost of 60 € per kWh[4]. The maximal size of PV panels is limited by the available rooftop space, and the availability of solar energy is modeled as a time-dependent capacity factor that depends on the weather, see Section 6.3.5.

We include transport in this diagram as an example of a final energy demand. For Internal Combustion Engine Vehicles (ICEVs), the energy flow is straightforward: Diesel is converted by the ICEV engine directly into transport demand. The Diesel supply carrier is associated with a monetary cost (2 € per liter, equating to 0.2 €

[4] Based on the Value-of-Lost-Load (VoLL) determined by the Dutch regulator ACM, https://www.acm.nl/system/files/documents/vaststelling-value-of-lost-load.pdf

per kWh) and a CO2 emission factor (0.264 kG/kWh). For EVs, we introduced another intermediate energy carrier, EV electricity, to represent different charging technologies and electricity storage in the EV battery. Home charging can be done at the normal household electricity prices and is limited to 7.6 kW. Public charging is done at a flat rate of 0.5 € per kWh at a maximum of 100 kW. Both charging technologies have additional household-specific constraints that prevent them from being used simultaneously as transport demand occurs, as the vehicle cannot simultaneously charge and drive. This treatment of EV charging follows the investigation in [15]. We did not implement vehicle-to-grid or vehicle-to-home charging here, but it could be added by allowing the home charging technology to convert EV electricity back to household electricity.

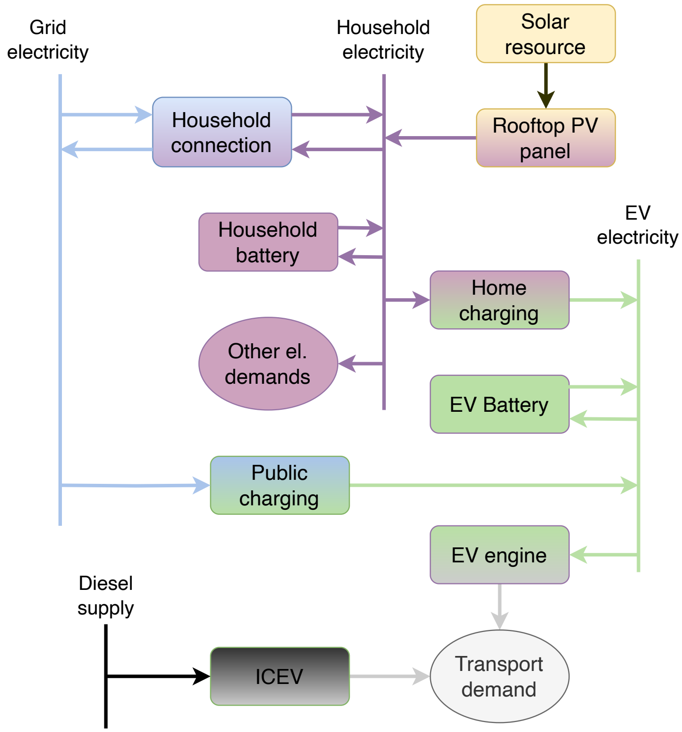

Figure 6.2: Energy flow diagram for electricity and transport technologies

Figure 6.3 shows the energy flows in the model for space heating. This energy demand is more complicated than the others since we included the possibility of building renovations in the model. Based on the investigation in [16], we added

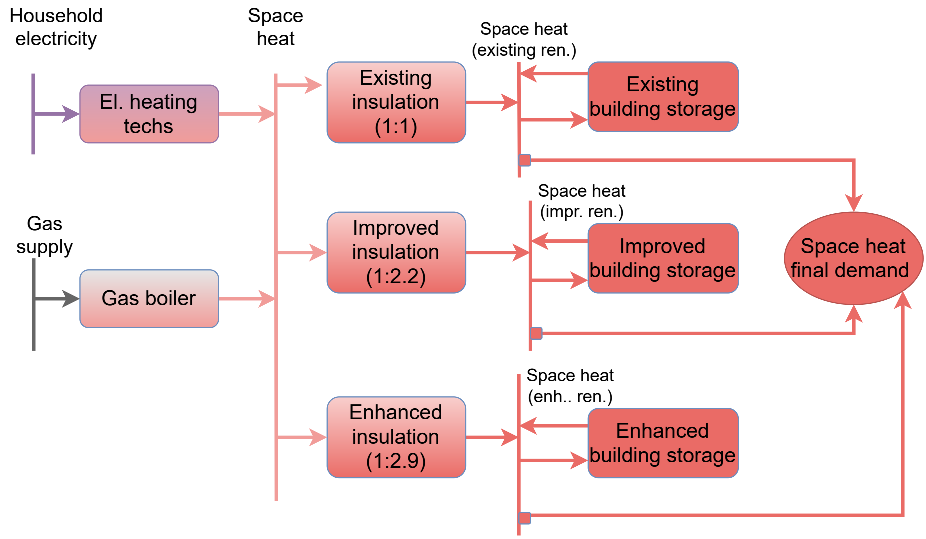

Figure 6.3: Energy flow diagram for heating technologies and final heat demand

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different building envelope types to implement renovation. Furthermore, we added an intermediate energy carrier for space heating. In the first step, an input energy carrier (household electricity or gas) is converted into this intermediate space heat energy carrier by a heating technology (ASHP, GSHP, electric resistance heater or gas boiler). This intermediate space heat carrier is converted into another intermediate space heat carrier that is specific for each renovation type: space heat existing (insulation), space heat improved (insulation) and space heat enhanced (insulation). Dummy technologies with a 1-to-1 conversion are used to convert each of the three different insulation space heat carriers into final space heat demand. This is necessary to keep the different renovation types from interacting in the model.

These conversions allow us to model the impact of building renovation: a better-insulated building requires less heat energy to reach the same temperature as a worse-insulated building. With existing insulation levels, the envelope is just a dummy technology that has no capacity costs and converts space heat 1-to-1 into final space heat demand.[5] But with better insulation, less input energy is required. Thus, we assume that the conversion to the improved and enhanced insulation space

[5]For the existing insulation level, we actually assume an efficiency slightly less than 1, see Table 6.2. This is because our assumption for the initial state is slightly worse insulation than the one used in the input data set for heating [17].

heat can have efficiencies higher than one since the initially assumed demand can now be satisfied with less input energy. One drawback of this renovation treatment is that it does not prevent the model from installing only a partial renovation, i.e., it uses improved or enhanced insulation for part of the final space heat demand and existing insulation for the remaining part.

On top of a more efficient conversion, we also assume that better thermal insulation allows the thermal energy to remain in the building longer. This is implemented by adding a thermal storage reservoir for each insulation-specific space heat carrier, which represents the thermal mass of the building. For each insulation level, there is a corresponding thermal storage that has a lower leakage parameter the better the insulation, see Table 6.3. This storage does not have a capacity cost, but its size is limited by the corresponding envelope insulation. This leads the model to always implement these two technologies together since paying the capacity cost for envelope insulation would not be efficient without using the corresponding storage at zero cost.

In addition to transportation and final space heat demand, we also mentioned three other demands. Electricity demand is fulfilled by household electricity, which can be obtained from the grid or supplied by PV panels or household batteries. Hot water demand is fulfilled by a gas boiler, which can convert gas into both space heat and hot water or by an electric boiler, which converts household electricity into hot water. Cooking demand is fulfilled by a gas stove, which converts gas into cooking demand, or by an electric stove, which converts household electricity into cooking demand.

6.3.3. AVOIDING BINARY CONSTRAINTS IN CALLIOPE

Calliope's preferred operation mode is as a purely linear model without mixed integer constraints. In our case study, we face a number of investment choices, which are of a binary nature: a particular technology, like PV panels or improved home insulation, is either invested in or not. We attempted to run Calliope with mixed integer constraints but found that it does not handle large amounts of binary constraints well. Therefore, we changed our strategy and ran the model as a purely linear optimization model, which massively sped up computation time and improved the stability of results.

To do this, we had to make a number of compromises in modeling: we did not impose a minimum on the installed capacity of any technology, and we also did not consider a fixed installation cost but rather included installation costs in the per-kW costs of installed technologies. This means that in some cases, we get very low results for the invested capacities, such as 50 W solar PV panels or 0.5 kW ground source heat pumps. These results may be seen as unrealistic, but they can still provide indicative qualitative insights into differences between tariffs and decarbonization targets. Furthermore, for some technologies, very low capacities are actually available. E.g. for solar panels, some companies are starting to sell kits with PV capacities as low as 100Wp[6]. For ground-source heat pumps, we can imagine that rather than having a 0.5 kW heat pump for a single household that multiple households in one building share a larger size heat pump.

For technologies that supply the same final end-use demand, Calliope offers an option that helps avoid binary constraints: the demand share per timestep decision.[7] Activating this option turns the relative shares of conversion technologies, which provide the same final demand, into a decision variable for the model. This means that a mix of conversion technologies can provide the same final demand, e.g., EVs and ICEVs can provide transport demand, but they have to do so *at the same ratio in each time step*. The ratio at which these technologies are used is a new (linear) decision variable. This often leads the model to choose only one of these technologies. This is because if it is cheaper to supply a part of the demand (e.g., 50%) by investing in a new technology, then it is usually also cheaper to supply the remaining demand by investing more in this technology. This is the behavior that we observe for switching cooking from gas stoves to electric stoves, heating from gas boilers to air source heat pumps, and driving from ICEVs to EVs (the latter only when it is forced by a carbon constraint though, see Section 6.4).

However, this rule has notable exceptions: when we add a constraint on carbon emissions, the model installs partial insulation upgrades for many households (see Section 6.4.2). This is likely to reduce emissions from grid electricity for electric heating technologies by just as much as necessary to reduce emissions below the given cap. This might be seen as unrealistic, but again, the results can be seen as indicative: building insulation upgrades help reduce grid-related emissions. In reality, they may not occur as partial insulation upgrades per household but as a certain percentage of households using full insulation upgrades.

Furthermore, the demand share per timestep decision is only available for

[6] https://www.eco-worthy.com/collections/the-cabin-solar-power-systems

[7] https://calliope.readthedocs.io/en/stable/user/advanced_constraints.html#demand-share-per-timestep-decision

technologies that supply a final demand in Calliope. It is not implemented for technologies that supply intermediate carriers, like space heat in our implementation (Figure 6.3). Thus, we could not activate this option for heating technologies, which means that the results for space heating often include a mix of technologies, mostly air-source heat pumps, and ground-source heat pumps. While this clearly represents a drawback of the model, we found the gains in computational speed and stability of results to be worth making this concession.

6.3.4. IMPLEMENTATION OF ELECTRICITY RATES AND NETWORK TARIFFS

As described in Section 6.1, final electricity rates are composed of the price for generation, a distribution network tariff, and additional charges for transmission, taxes, and possibly subsidy schemes. This study focuses on the generation-related components and the network tariff. We consider four rate design options: a flat per kWh rate for both generation and network tariff, a Time-of-Use kWh rate for both with higher prices during the day on weekdays, a real-time market price for generation with a fixed network tariff and a real-time market price with a tariff for network capacity per kW.

Thus, these rate designs are characterized by three components: fixed charges, volumetric (per kWh) charges, and capacity (per kW) charges. Fixed charges are included in ex-post calculations, as they do not change the investment and dispatch decisions made by the model but only total costs. Volumetric components are included as an input variable for the cost of electricity supplied from the grid. Capacity components are calculated as the price of the capacity of the household connection, see Figure 6.2. Flexible operation of batteries and pre-heating can reduce the peak and, therefore, the need to contract capacity. The network capacity limitation is applied to both consumption from the grid and feed-in of excess solar PV generation.

6.3.5. CASE STUDY DATA

ELECTRICITY GENERATION PRICES AND CARBON CONTENT

To simulate a 2030 energy system, we performed a run with the Calliope Europe model [18] with the stated capacity targets of the Netherlands from 2030 the Climate and Energy Plan of the Netherlands and the II3050 scenarios [4, 19]. We use the 2018 capacity factors for variable renewable sources to keep a consistent weather year choice. From this run, we obtain hourly prices for electricity as the marginal cost of generation and the carbon content of electricity at each time step.

These hourly prices are used as the basis for our assumption of real-time electricity prices. However, as real household electricity prices do not just include the cost of generation but also taxes, transmission fees, supplier mark-up and possibly other costs, we use four times the value of the hourly prices as our assumption for the Real-Time Prices (RTP) π_t^{RT}) for the energy component of the Electricity Rate.[8] For exporting electricity from solar PV panels back to the grid, we use the hourly marginal prices themselves as our assumption for the export price. This is only half as much as households pay for electricity because the taxes and grid fees do not accrue to the households but to the transmission system operator and the state.[9]

In rate designs with fixed and capacity-based network tariffs, we pass this RTP directly to the consumers as the cost for energy. These designs cover network charges separately (see Section 6.3.4). In contrast, we add the energy component to the network component in the rate designs with network tariffs based on volumetric charges.

6

To compute the flat and Time-of-Use (ToU) rates for the energy component, we compute the total Energy component Cost (EC) of all households in the base run without investments, based on their electricity demands $D^e_{t,hh}$:

$$EC^{RT} = \sum_{hh}\sum_{t} D^e_{t,hh} \cdot \pi_t^{RT}, \tag{6.1}$$

where hh indicates households and t time steps. The simulation time horizon is one year (2018) in hourly time steps.

In this initial situation, we calibrate the flat and ToU energy component charges to yield the same total electricity payments for all households. The flat rate for energy equals the weighted average cost of electricity over the year. We acknowledge that this is a favorable assumption for consumers as fixed-price energy component (π^F)

[8] This is motivated by the compilation of final household electricity prices in Figure 1.3. In 2018 the energy-related component was, on average, around 35% of the final price in European countries, but we expect this to shrink as more affordable renewable energy becomes available, as in our input scenario with the Dutch 2030 energy system.

[9] Other export prices, such as fixed feed-in tariffs (FITs), would also be possible, but we assume that feed-in prices will move more towards RT market prices in the future to avoid excessive wealth transfers to solar PV owners.

contracts tend to have a premium to cover the hedging of consumers.

$$GT^{V} = \frac{EC}{\sum_t \sum_{hh} D^e_{t,hh}} = 0.106\,€/\mathrm{kWh} \tag{6.2}$$

The ToU rate is designed with two price levels, where the higher price time is twice as high as the low price period. The higher price times of use cover from 8 am to 8 pm on weekdays, while the rest of the times and weekends are low-price periods. This time-of-use price for the energy component (π_t^{ToU}) is also designed to equal the total energy costs with RTP:

$$EC = \sum_t \sum_{hh} \pi_L^{ToU} \cdot D^e_{t-L,hh} + \sum_t \sum_{hh} \pi_H^{ToU} \cdot D^e_{t-H,hh} \tag{6.3}$$

which leads to rates of

$$\pi_L^{ToU} = \frac{1}{2} \pi_H^{ToU} = 0.0712\,€/\mathrm{kWh} \tag{6.4}$$

For the low π_L^{ToU} and high π_H^{ToU} rate respectively.

6

NETWORK TARIFFS

As for the case of the energy component, network tariffs are also designed such that the expected costs in the no-investment run are equal in all cases. We use as a baseline the current fixed tariff (NT^{fixed}) of a standard residential network connection in the Netherlands [20], which amounts to 250 € per household per year. Thus, total network costs (NC) for this neighborhood of 25 households are

$$NC = NT^{\text{fixed}} \cdot N_{hh} = 6250€ \tag{6.5}$$

To convert these costs into a flat volumetric network price, we compute the average of these costs per kWh as in Equation (6.2):

$$NT^{\text{flat}} = \frac{NC}{\sum_t \sum_{hh} D^e_{t,hh}} = 0.089€/\mathrm{kWh} \tag{6.6}$$

The conversion to the ToU rate happens in analogy to Equation (6.3) and yields

$$NT_L^{\text{ToU}} = \frac{1}{2} \pi_H^{ToU} = 0.060\,€/\mathrm{kWh} \tag{6.7}$$

We also model a capacity-based network charge, where we add a yearly per-kW price on the capacity of the household connection in the model (Figure 6.2). This connection capacity applies to both withdrawals from the grid and feed-in of PV generation units or batteries. The Capacity charge is computed as the total grid cost over the sum of the maximum hourly electricity demanded capacity per household:

$$NT^{\text{capacity}} = \frac{NC}{\sum_{hh} max_t(D^e_{t,hh})} \approx 65€/\text{kW}/year \tag{6.8}$$

Demand and weather data

We use the LoadProfileGenerator [21] to simulate the electricity demands of 25 households. We did not include heating technologies or generation from PV panels in the generator, as we wanted Calliope to decide on the investment and dispatch choices for these technologies. We also removed the cooking demand from these electricity profiles. We converted it into a corresponding demand for gas stoves to mimic an initial situation in which cooking is satisfied by gas stoves. Transport demand is based on the RAMP-mobility project [22][10].

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We use the Dutch hourly residential heating profile from single-family houses heating demand from When2Heat [17]. We scale these profiles by the average gas consumption in Zoetermeer (South Holland) in 2018 and their yearly electricity demand for accounting for household-to-household variations. We assume that each household will follow this trend, but to represent variability, we scale the consumption by randomizing the hourly household consumption between 75% and 125 %. We used data from the Calliope Europe model based on Renewables Ninja for the solar irradiation profile.[11] All weather-dependent data is used with the same weather year (2018) to account for the correlation between vRES production, heating needs, and electricity prices.

6.4. Results and discussion

This section presents the results from our modeling runs and discusses their implications.

[10] See also https://github.com/RAMP-project/RAMP-mobility.
[11] https://www.renewables.ninja/

6.4.1. MODEL RUNS DEFINITION AND CARBON EMISSIONS

To have a basis of comparison, we first performed a baseline run where no investments are possible (called “No inv.”). Households are not renovated; their cooking, space heating, and water heating demands are supplied by gas, and their transport demand is supplied by diesel. In this case, the choice of rate design does not matter for the results, as no flexible assets that could change dispatch decisions can be installed. Thus, there are no differences between rates for both investments (as these are impossible) and dispatch.

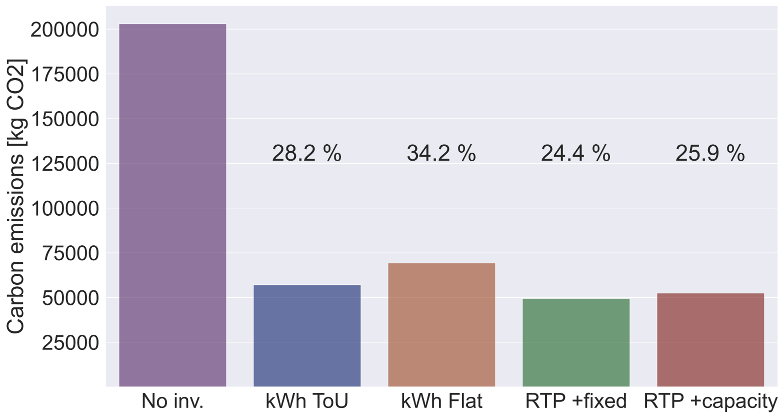

Figure 6.4: Total emissions of model runs without carbon constraint and percentage of emissions of unconstrained runs relative to no-investment case

Next, we performed additional model runs to assess the investment and dispatch decisions based on the electricity rate design faced by households and different degrees of decarbonization targets. As previously mentioned, we use the following rate design choices:

1. **“kWh ToU’:** A ToU per kWh price that includes both the energy component and the grid tariff with the rates as computed in Equation (6.3).
2. **“kWh Flat”:** A flat per kWh price that includes both the energy component and the grid tariff with the rate as computed in Equation (6.2)
3. **“RTP +fixed”:** A fixed network tariff of 250 Euro with real-time prices of the 2030 energy system modeled with the planned capacity expansions of the

Netherlands.

4. **"RTP +capacity":** A capacity-based network tariff of 65€ per kW of network capacity with real-time prices of the 2030 energy system modeled with the planned capacity expansions of the Netherlands. The capacity component is as computed in Equation (6.8)

Figure 6.4 shows the total emissions in each of these runs. The base case without investments leads to around 203 metric tons of CO_2 emissions. Interestingly, allowing for investments immediately decreased carbon emissions by around 70% with each of the chosen rate designs, even when no carbon budget is enforced. However, this result is highly sensitive to input price assumptions. It is mainly driven by the low electricity prices from our simulated 2030 Dutch energy system and the relatively low investment price of air-source heat pumps. We can see that there are also strong variations between different rate designs, which we will discuss further in the following chapters. Flat kWh pricing leads to significantly higher emissions than all other scenarios.

Furthermore, we also investigate further decarbonization by tightening the carbon budget. These were defined relative to the no-investment run. As the unconstrained runs already lower emissions to 24-34% of the no-investment case, we only considered carbon budgets tighter than this. We focus the presentation of results on carbon budgets of 10 and 2% of the no-investment case.

6

6.4.2. Technical configurations

This subsection focuses on the runs where investments were allowed and investigates which technologies were installed with different rate designs. As mentioned in Section 6.3, we use Calliope as a purely linear optimization model without mixed integer constraints. This can lead to results that are unrealistic, such as installing very small capacities of heat pumps and batteries, or using only partial renovations.

Figure 6.5 shows the installed capacities for technologies related to space heating, the largest energy end-use in households. Air-source heat pumps (ASHPs) are installed in all rate designs, even without a carbon constraint. This is due to their relatively low investment costs and because the 2030 electricity system with the Dutch RES capacity targets leads to low electricity prices, which makes it cost-efficient to use ASHPs to replace gas space heating. This also explains the significant drop in emissions of the no-constraint runs relative to the no-investment

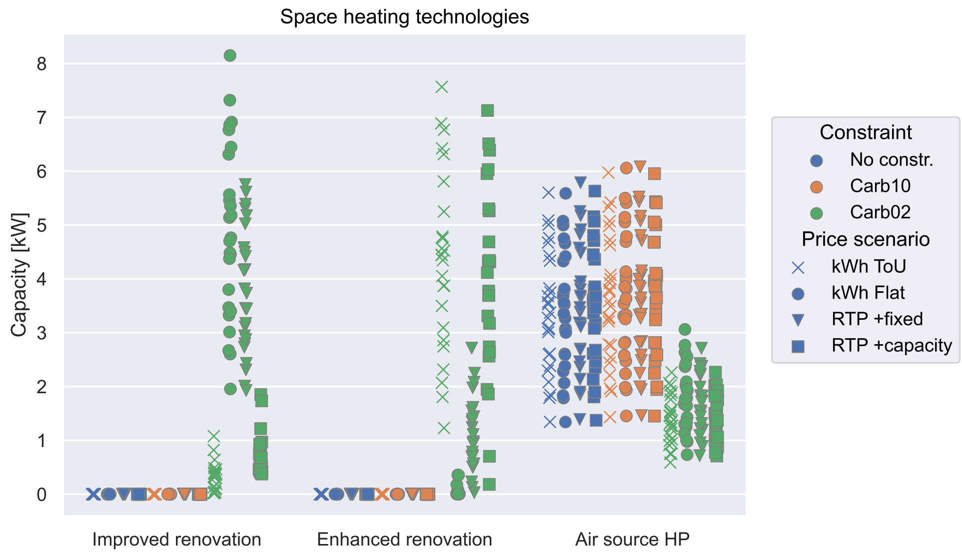

Figure 6.5: Deployment of space-heating-related technologies of all households across scenarios

case in Section 6.4.1. GSHPs are not installed in any rate design or carbon budget, as their marginal efficiency improvements in electricity usage do not outweigh the increased investment costs, compared to ASHPs, with the cost assumptions we used (see Section 6.5).

The significant drop in heat pump capacity for very low carbon budgets of 2% can be explained by the corresponding increase in renovation. Renovation strongly increases the efficiency of using electricity through lower energy requirements and better storage in the thermal mass of the building. This leads to corresponding reductions in electricity-related CO2 emissions. We see some variation regarding the tariff here: the flat rate and the real-time electricity rate with a fixed network tariff lead to higher usage of the “improved renovation” category. In comparison, the ToU rate and the real-time electricity price with capacity-based network tariff lead to stronger usage of the “enhanced renovation” category, which is more expensive but more efficient. The reason for this is mainly the bettor storage parameters of the thermal mass of the building with enhanced renovation. In ToU tariffs, this helps pre-heating the house during low-price hours, while in capacity tariffs, it helps to lower peak consumption and keep the required network capacity low.

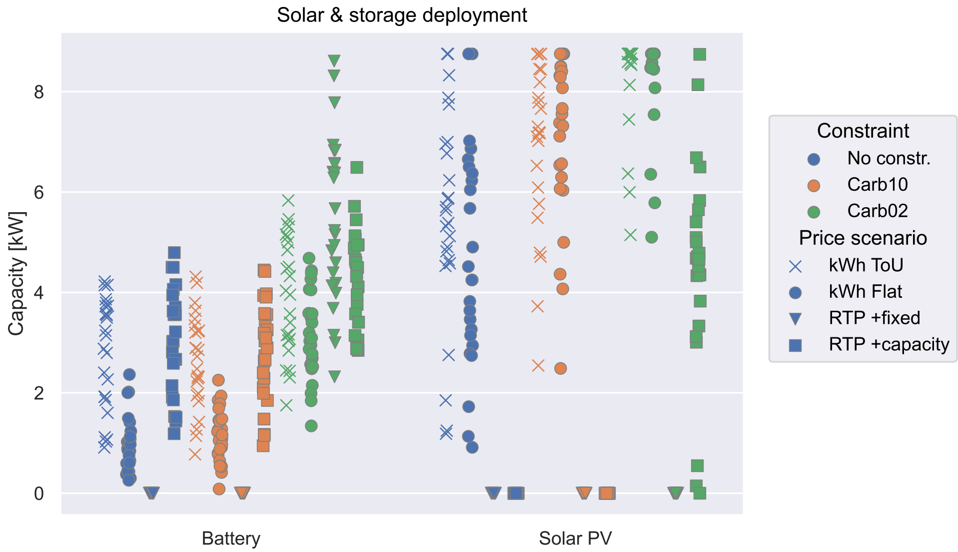

Figure 6.6: Deployment of solar PV and batteries

We see some similarities in the installation pattern for batteries in Figure 6.6, also a storage technology. However, this is a more complex case due to the interplay of batteries with solar PV, which offers a free alternative to grid electricity when the sun is shining.

When the carbon constraint is loose, only the per-kWh network tariffs incentivize installing solar panels. In the ToU rate design with higher prices during the day, the price incentive for installing solar PV is stronger, which is why the installed capacities are highest in this rate when no carbon constraint is applied. With the 2% carbon constraint, solar PV is also installed in the real-time rate with a capacity-based network tariff to reduce grid-related CO2 emissions. In contrast, no solar PV is installed at a real-time rate with fixed network tariffs; instead, batteries with very high capacities are installed. This allows to draw a lot of electricity during low CO2-content hours (which coincidentally are usually also the low-price hours) and use it when the grid-electricity CO2 content is high, or feed it back into the grid at higher prices (see also Figure 6.12 and Figure 6.13). The real-time rate with capacity-based tariffs strikes a middle ground: it has low solar capacities than the volumetric tariffs and, on average, lower battery capacities than the fixed network tariff with real-time rates. This allows to keep both the peak grid load and the excess solar production (which can only be fed back into the grid up to the subscribed capacity) low (see Figure 6.12 and Figure 6.13).

It is striking that installing solar PV is inefficient with real-time prices and fixed or capacity-based network tariffs, even at carbon budgets of 10% (and even 2%, in the case of fixed network tariffs). This is because electricity can be procured at relatively low market prices in the assumed 2030 generation scenario for the Netherlands. However, this 2030 generation scenario also assumes a large share of solar generation, which creates a modeling dilemma as we only look at an isolated local neighborhood and not the whole energy system here. It suggests that adding more rooftop solar PV may not be worth it when a large amount of solar generation is installed elsewhere. However, for this to be true, a large amount of solar generation must be installed, which may be at least partially assumed to be on rooftops. On the other hand, if this generation share is driven predominantly by large open-field plants, then it may be that individual rooftop solar PV installations are not cost-competitive due to a lack of economies of scale.

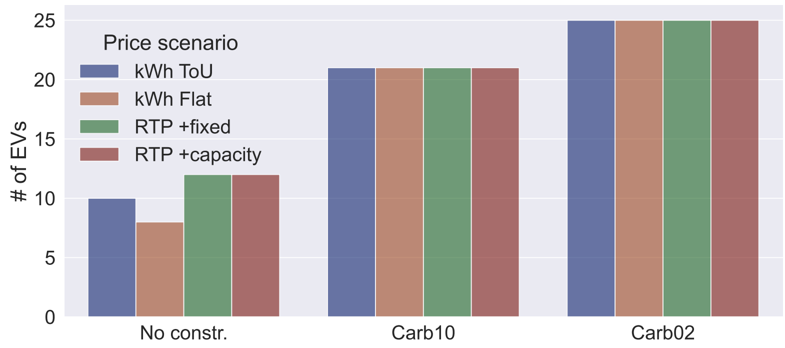

Figure 6.7: Deployment of EVs

Figure 6.7 shows the deployment of EV numbers. Even without a carbon constraint, investing in EVs is cost-efficient for heavy car users who benefit from the lower fuel and operational costs. We can also see that real-time and ToU prices are more likely to induce this shift, as these allow vehicle charging during lower-price hours. This also explains the relatively higher emissions of the flat tariff design in Figure 6.4. With more substantial carbon constraints, more cars are electrified to reduce emissions further.

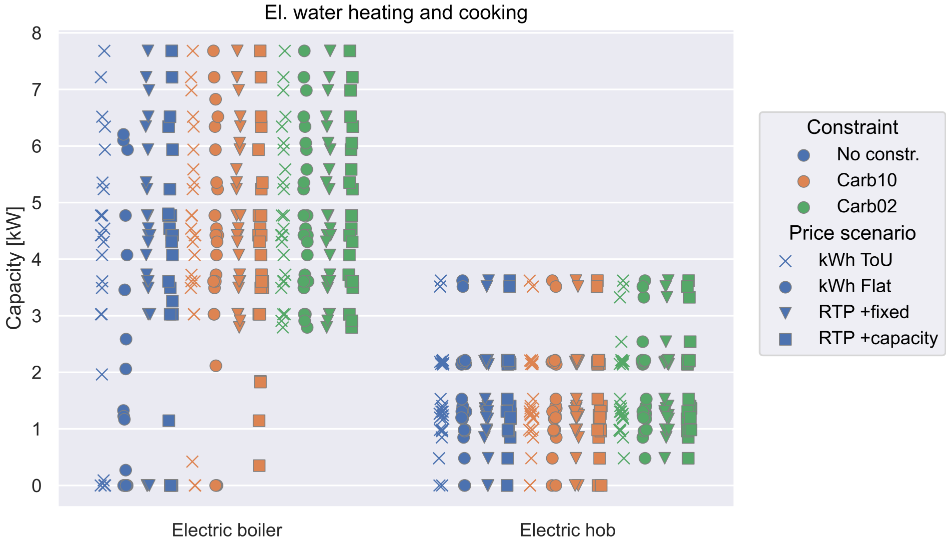

Figure 6.8: Deployment electric water boilers and hobs

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Regarding water heating in Figure 6.8, we see many users installed electric boilers even without a carbon constraint. This is because for heavy users there are operational savings of using electricity compared to gas, which justifies the investment cost in electric boilers. All users switch completely to electric water heating at the tightest carbon constraints.

For cooking, the switch to electric hobs happens without carbon constraint already for most users, similar to water heating. However, capacity-based tariffs still induce two households in our data set to use gas stoves. Upon investigating the hourly dispatch of these technologies, we found that this behavior is driven by very large cooking demands in individual hours on December 24$^{\text{th}}$ and 25$^{\text{th}}$. These would require increased subscribed capacity, which would be too expensive to justify the investment in electric hobs for these houses. This demonstrates that capacity-based tariffs should be designed carefully and that isolated exceedances of the subscribed capacity should perhaps be tolerated for an increased per-kWh price [3]. In reality, users may also be able to balance demand better, e.g., by turning down the heat pump or EV charger when they require a lot of electricity for cooking. A smart energy management system may automate this.

6.4.3. COSTS

Figure 6.9: Total user costs of different rate designs and carbon constraints

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Figure 6.9 shows the total costs of each rate design for different constraints. We can see that costs in the unconstrained runs are significantly lower (about a quarter) than in the forced no-investment run. Tightening the carbon budget further slightly increases costs, but even a very low carbon budget of 2% still results in lower total costs than the no-investment case. These results are mainly driven by the input assumptions on the Dutch electricity system's electricity price and CO2 content with the stated 2030 capacity targets. We can see that the flat price structure leads to the highest user costs, while real-time prices lead to the lowest costs, allowing users to use the flexibility of their electrified end-use devices and avoid high-priced hours.

Figure 6.10 shows the investment costs and Figure 6.11 the variable costs in each run. Investment costs are annualized for all assets. Variable costs include fuels, electricity, O&M costs, and, in the case of capacity-based network tariffs, the cost of network capacity. We can see that investment costs increase steeply with tighter carbon constraints. At the same time, variable costs decrease steadily.

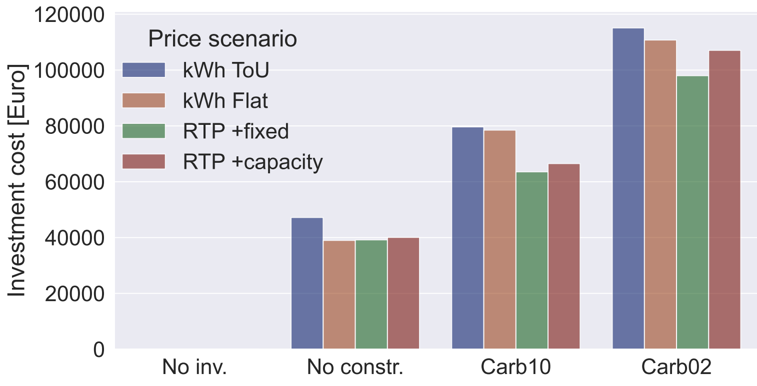

Figure 6.10: User investment costs of different rate designs and carbon constraints

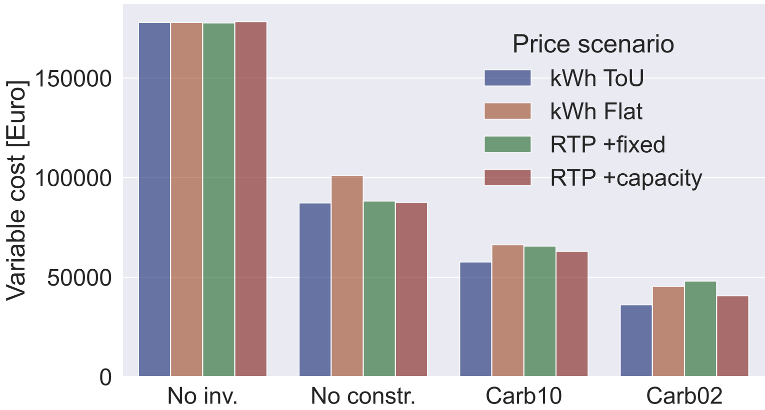

Figure 6.11: Variable costs of different rate designs and carbon constraints

Considering the relative differences between rate designs, we calibrated the price parameters of each design to lead to roughly the same total costs in the no-investment run. In the unconstrained runs, the fixed per kWh rate designs lead to higher user prices, especially with flat prices. This is because the flat design offers no benefit for shifting the load of flexible devices, other than for better self-consumption of PV generation. The ToU design offers some benefits and the real-time price design offers the most significant benefit for using the flexibility of devices. Focusing on the real-time designs, the investment costs are higher in the capacity-based network tariff, which is mostly offset by lower variable costs than the fixed network tariff.

6.4.4. EFFECTS ON NETWORKS

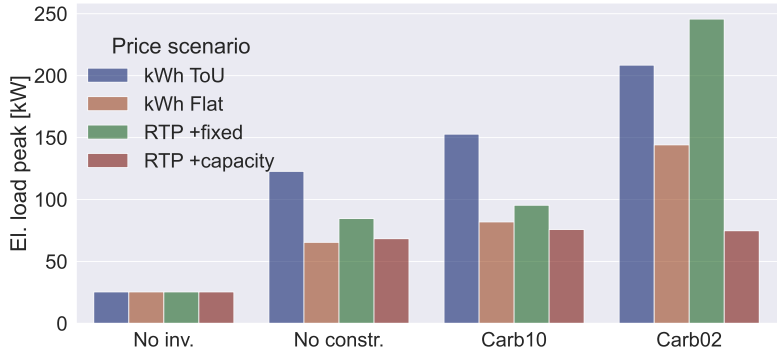

Figure 6.12: Electric peak load of different rate designs and carbon constraints

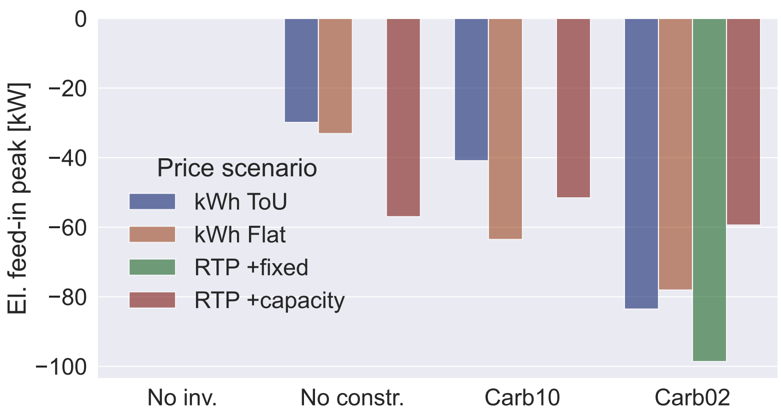

Figure 6.13: Electric feed-in peak of different rate designs and carbon constraints

Electrification has a profound impact on networks. Figure 6.12 and Figure 6.14 show the peak electricity load and feed-in from solar PV and batteries in each model run.

Peaks increase massively when investments are allowed and households electrify their energy end-uses with significant differences between tariffs. In the real-time rate with fixed network tariffs, the network peak increases almost 9-fold in the 2% carbon budget relative to the no-investment case. The capacity-based tariff limits this increase to only about 3-fold, the lowest of all studied designs. Interestingly, the load peak in capacity-based tariffs also does not increase significantly compared to the no-constraint case. In conjunction with the discussion on costs in Section 6.4.3, this shows that once many loads are electrified, the inherent flexibility of EVs, batteries, and space heating can provide network-serving load shifting at very low additional costs.

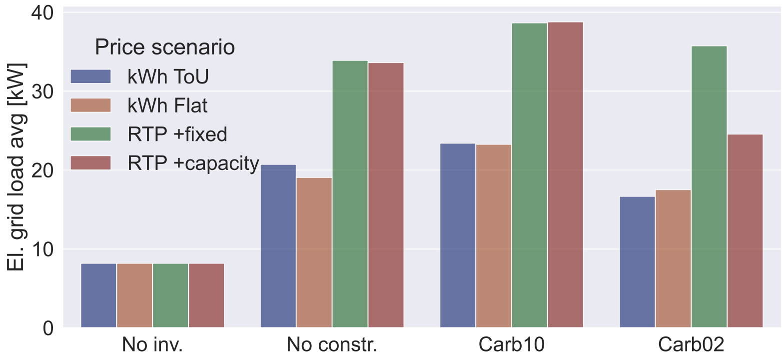

Figure 6.14: Average electric load of different rate designs and carbon constraints

Figure 6.14 shows the average electric load in each scenario. Interestingly, at higher decarbonization rates, average electricity usage declines again. This can be explained by the technological configurations discussed previously: at very tight carbon budgets, households are induced to renovate (Figure 6.5) and install more batteries and solar PV (Figure 6.6). This leads to efficiency gains and increased self-consumption, which more than offsets the additional electricity usage from the additional EVs (Figure 6.7), boilers, and hobs (Figure 6.8).

Capacity-based network tariffs give a strong incentive for peak reduction, but not for reduction of average load. Especially at loose carbon budgets, they only tend to spread out the load more. At the 2% carbon budget, they lead to lower average loads than the fixed network tariffs, mainly due to solar PV installation (Figure 6.6), which is not triggered under fixed network tariffs.

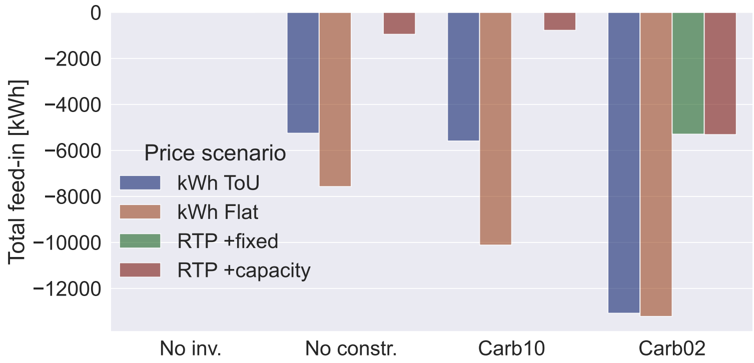

Figure 6.15: Total feed-in of different rate designs and carbon constraints

Figure 6.15 shows the total feed-in from solar PV and batteries. The fixed per kWh rate designs lead to much higher feed-ins, due to their increased incentivization of solar PV. At tighter carbon budgets, the real-time rate designs also lead to significant feed-in. In these designs, this is mainly driven by batteries, which are used for energy arbitrage, especially in the summer months, when there are steep price differences during day and night on the market.

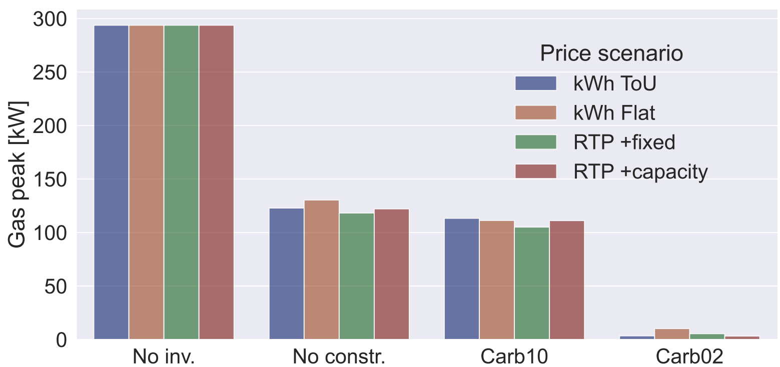

Figure 6.16: Gas peak load of different rate designs and carbon constraints

Figure 6.16 and Figure 6.17 show the analogous graphs for gas consumption. We can see that both peak- and average gas consumption decline strongly in all rate

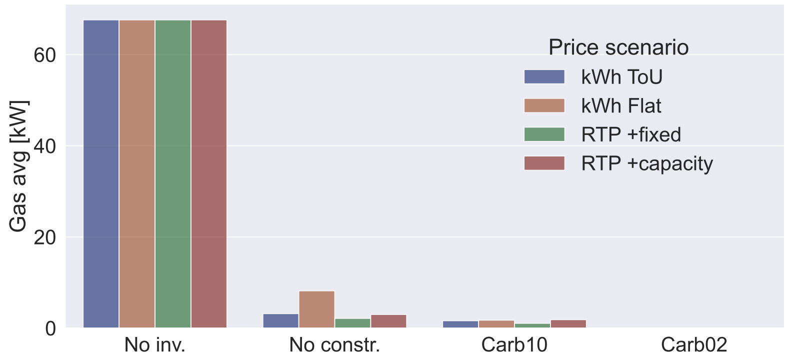

Figure 6.17: Average gas load of different rate designs and carbon constraints

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designs. While peaks remain at about a third of the no-investment peak in the unconstrained and 10% carbon budget scenarios, average consumption immediately drops to 2-10% of the no-investment value when investments are allowed. This shows that gas-consuming technologies are only kept around for a few isolated incidences with very high heat demand and high power prices in these scenarios. At these low levels, it may be questionable whether running a gas network is still worth the cost or should it be dismantled. The remaining demand for gas could also be electrified or switched to heat networks. We cannot answer this question with our model as we do not consider a gas network model, but it is an interesting line for future research. We can see that the flat per kWh rate design still uses a higher amount of gas in the unconstrained scenario, another driver of the higher emissions in this scenario in Figure 6.4. This is because with this rate design, it is impossible to use lower-electricity prices at any time, so there is no point in pre-heating the home for strong peaks in heating demands. Thus, for the heating demand peaks, the model uses a combination of ASHPs and gas boilers here. At the 2% carbon budget, gas consumption virtually vanishes in all rate designs.

6.4.5. Resource demands

Electrification also has a strong impact on the final energy consumption. Figure 6.18 shows the total consumption of Diesel, electricity, and gas (in kWh) for the no-investment, no-constraint, and decarbonization runs. We averaged across rate designs to create this graph to emphasize the general trend.

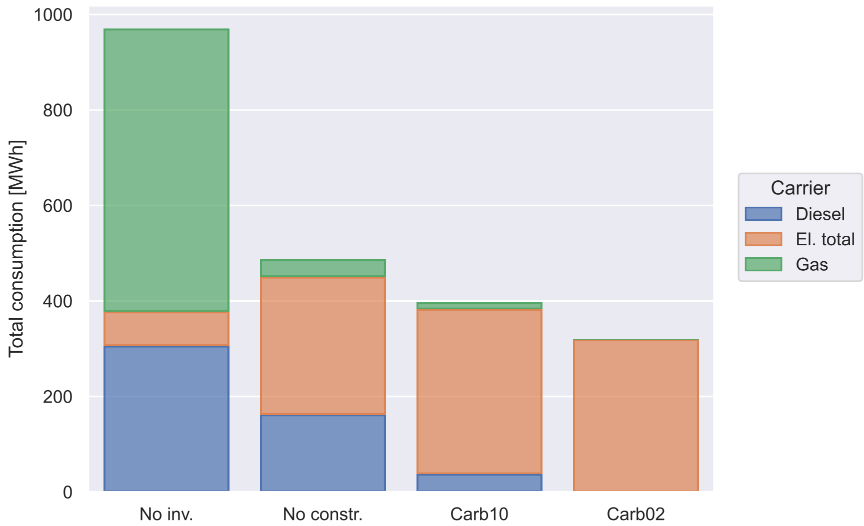

Figure 6.18: Total consumption of energy carriers in different carbon constraints

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As we already saw from the network load (Section 6.4.4), electricity consumption increases strongly when we allow investments due to the electrification of space heating and cooking. However, the increase in electricity consumption is more than offset by a decrease in gas and diesel consumption. This is due to a corresponding increase in the energy efficiency of heat pumps, EVs, electric boilers and hobs over their fossil-fuel-based counterparts.

At higher decarbonization levels, gas and diesel are completely eliminated from the energy carrier mix. Furthermore, electricity consumption is also declining moderately due to efficiency improvements.

6.4.6. LIMITATIONS

In addition to the limitations that come with using a purely linear model for modeling investments (as described in Section 6.3), our approach has several modeling limitations. We assume that customers are completely rational and optimize their energy consumption. Furthermore, we assume perfect foresight. In further work, we aim to optimize investments over a number of data years and simulate dispatch under unknown conditions. We also assume that customers are able to afford the upfront investment costs implied in the optimal choice, which may not generally be the case in reality.

6.5. Summary and conclusions

In this chapter, we investigated different electricity rate designs and focused on the choice of the generation-related component and the network tariff. Based on our input assumptions for a 2030 Dutch energy system with the stated generation capacity targets of the Dutch government, we found that the network tariff may become the dominant component of electricity rates in the future as prices for generation are expected to decline. This means that the choice of network tariff may be more influential than the choice of the generation-related component.

We investigated four different rate designs: a flat and a ToU volumetric rate for generation and network tariff and real-time prices for generation with either a fixed or a capacity-based network tariff. We found that volumetric network tariff designs lead to higher total user costs and emissions, particularly for flat rates. Higher electricity costs mainly drive this cost increase, as users cannot use low electricity generation prices when the network tariff is added to the per kWh price of electricity. Due to the higher cost of electricity, the volumetric tariffs also incentivize the deployment of rooftop solar PV, even when this may not be economically efficient at the system level. ToU rate designs help to reduce both user costs and emissions somewhat, but rate designs with real-time prices for the generation-related components are found to be the most effective both with regards to user cost, as well as emission reductions.

Electric network load and feed-in peaks increase significantly under all rate designs due to the increasing electrification of end-uses that are expected with lower electricity prices. The capacity-based network tariff strongly dampens the increase in peaks. It does this mainly by incentivizing the installation of home batteries, which allows households to reduce their peak consumption from the grid. However, at the whole-system level, it might be less costly to upgrade the network instead or install communal batteries behind congested assets, but we have not included these strategies in our modeling yet. We intend to investigate them in future work.

At tighter decarbonization levels, we observe additional end-use electrification and efficiency improvements: ICEVs are increasingly switched to EVs, space and water heating is completely electrified, building insulation is improved, and more PV panels and batteries are installed. However, there are notable differences between rate designs. A fixed ToU rate for network and energy and a real-time rate for energy with a capacity-based network tariff both stimulate higher efficiency improvements in renovation. In the ToU-rate design, this is due to the possibility of pre-heating the home during low-price hours with more efficient heat storage in the building. With the capacity-based network tariff, it is due to the incentive to limit maximal electricity consumption and spread out the load more, for which better insulation also helps. All rate designs stimulate the usage of batteries at tight carbon budgets, where the real-time rate with fixed network tariffs gives the strongest incentives. It allows the most usage of energy arbitrage between high and low prices on the market, without the capacity-based tariff's additional costs of network connection capacity. On the other hand, the real-time rate with a fixed network tariff is also the only one that does not incentivize solar PV at all, even at the tightest carbon budget, it relies purely on batteries to reduce grid-related emissions.

The peak and average load of the gas network drops strongly under all rate designs. In the unconstrained model runs, we see that a fixed flat rate for both the energy and network components still leads to a higher reliance on gas than the other studied rate designs. This is because peaks in heating demands are fulfilled by a combination of heating from heat pumps and gas boilers in this design, while in the other designs, there is typically some spreading out of the electric load to lower-price hours. At tighter decarbonization levels, both peak and average load of the gas network drop to very low levels in all rate designs, which raises the question of whether having and operating a gas network is still worth the cost at these high levels of electrification. Since we did not include a cost model of the gas network, we cannot answer this question, but it is an interesting topic for further research.

We emphasize that the model used considerable simplifications to enable the treatment of the problem as a purely linear model. We did not include binary investment constraints but modeled them as linear choices with a purely capacity-based investment price per technology. Furthermore, we assumed that end-users are rational and optimize their investment and dispatch choices on the given prices with perfect foresight. An improvement of the modeling strategy to include mixed integer constraints as well as an optimization over different scenarios and with limited foresight is envisioned for future work.

Appendix: Technology parameters

Table 6.1: Supply carrier parameters. Diesel/gas emission factors based on [23].

Supply carrier	Availability	Price [Euro/kWh]	CO2 emissions [kG/kWh]
Grid elelectricity	infinite	0.053 (avg)[a]	0.05 (avg)[a]
Diesel	infinite	0.2[b]	0.264
Gas	infinite	0.135	0.204
Solar resource	weather-based	0	0

[a] Grid electricity prices and CO2 content vary hourly and are based on a Euro-Calliope run with the 2030 Dutch capacity targets.
[b] corresponds to around 2 Euro/l

Table 6.2: Conversion technology parameters. Space and water heat parameters based on [24]. Space heat final parameters based on [16]. Solar PV and solar thermal based on [25]. Transport and cooking parameters based on commercially available models.

Output carrier	Conv. Tech.	Input carrier	Lifetime [years]	Energy Efficiency	Maximal capacity [kW]	Capacity cost [Euro/kW]	O&M cost [Euro/kW]	Production cost [Euro/kWh]
Space heat	Gas boiler	Gas	25	0.6	20	0	20	0
	ASHP	Home el.	12	Varying[a]	20	424	40	0
	GSHP	Home el.	20	Varying[a]	20	1740	40	0
	El. Heater	Home el.	30	0.99	20	853	8	0
Sp. heat final	Exist. env.	Space heat	30	0.914	20	0	0	0
	Impr. env.	Space heat	30	2.2	20	2623	0	0
	Enh. env.	Space heat	30	2.98	20	3423	0	0
Home el.	Net. con.	Grid el.	1	1	17.3	0 (65)[b]	0	0
	Solar PV	Solar res.	25	0.85	8.7[c]	840	20	0
	Load shed.	None	inf.	1	inf.	0	0	60
Transport	ICEV	Diesel	15	0.25	300	0	0	0.348[d]
	EV	EV el.	15	0.75	300	~ 2000[e]	0	0.205[d]
EV el.	Home charg.	Home el.	15	0.98	7.6	130	15	0
	Pub. charg.	None	inf.	0.98	100	0	0	0.5
Water heat	Gas boiler	Gas	25	0.6	20	0	20	0
	El. Boiler	Home el.	30	1	20	100	17	0
	Sol. thermal	Solar res.	25	0.9	5.9[c]	1200	20	0
Cooking	Gas hob	Gas	25	0.4	15	0	0	0
	El. hob	Home el.	25	0.85	15	100	5	0

Footnotes of Table 6.2:

[a] The efficiency of heat pumps is pre-computed for every hour based on the outside temperature.
[b] Connection capacity costs are only applied in the capacity-based network tariff.
[c] Solar PV panels and thermal vacuum tubes are limited by the size of the available rooftop area, which we assume to be 40 square meters for all households.
[d] For electric vehicles, O&M costs are implemented on a per-km basis. This translates to a production cost per-kWh of output energy of the engine in the model.
[e] EV cost is standardized to 30,000 Euro for an EV with a 75 kWh battery. To force this in the model without binary constraints, we used a different capacity cost for each household, which was obtained by dividing 30,000 by the maximal driving demand of each household.

Table 6.3: Storage technology parameters. Envelope Thermal Storage (TS) based on [16]. Water tank based on [24]. Household battery based on available commercial models.

Carrier	Storage Tech.	Life-time	Energy eff.	Leak. [1/h]	Max. [kW]	C-rate [kW/kWh]	Cost [Euro/kWh]
Sp. heat final	Exist. env. TS	30	1[a]	0.4	15	0.5	0[b]
	Impr. env. TS	30	1[a]	0.3	15	0.5	0[b]
	Enh. env. TS	30	1[a]	0.2	15	0.5	0[b]
EV el.	EV battery	15	1[c]	0	100	1.33	0[d]
Home el.	Battery	15	0.95	0	50	0.5	330
Water heat	Water tank	30	1	0.01	50	0.5	50

[a] Thermal conversion efficiency is included in the corresponding envelope.
[b] Cost for building thermal storage is included in the envelope upgrade. The capacity of each storage is tied to the capacity of the corresponding envelope by additional constraints in the model (see Table 6.2).
[c] EV charging efficiency is included in the charging technology.
[d] Cost for EV battery is included in the EV (see Table 6.2).

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Discussion

7.1. Answers to research questions

The overarching research question for this thesis is stated as “How can congestion in electric distribution grids be avoided by controlling flexibility of new end-use devices?” in Section 1.4.

To answer it, we first performed a literature review of articles about congestion management methods in Chapter 2 to answer the question “Which options for managing congestion of electrical loads have been proposed, how do they relate to each other, and which risks are present in each?”

We found that there are various methods for dealing with congestion, which may be used in combinations. Some are based on the network tariff, which network operators collect from users for network access to pay for building and maintaining the network. Others are applied in addition to and often independently of the network tariff. Tariff-based methods can have static or dynamic access prices. Local Flexibility (or redispatch) Markets (LFMs) can be applied in addition to tariffs. Direct-control-based methods can be applied in addition to tariffs or be included in the tariff conditions.

Each method has different strengths and weaknesses, summarized in Table 2.3. An important difference is the type of risks associated with each method and whom it affects. The risks that can be present are network price risk for either the user or the network operator, risk of curtailment for the user, and residual risk of network overload for the network operator. In general, market-based methods tend to have a higher price risk for the network operator (at least in the surveyed literature), dynamic tariffs and capacity auctions have a price risk for the user, and direct control schemes have a curtailment risk. Static tariffs result in the highest residual risk of network overload. In contrast, mechanisms that operate further ahead of real-time (e.g., day-ahead) have a lower risk, and near real-time mechanisms have the lowest risk of the surveyed mechanisms because the most recently available information is used in them.

We further demonstrated in Chapter 3 that LFMs may have an exceptionally high price risk for the network operator due to the potential problems of gaming such markets. Thus, we recommend avoiding these approaches for small congestion areas (e.g., single low-voltage feeders at the neighborhood scale) and carefully considering alternatives to a market or providing strong regulatory oversight in case a market is still the desired solution.

Tariffs emerged as a promising solution to reduce the scope of congestion. However, the literature did not provide a clear framework for objectively evaluating the performance of new tariffs, which is important when considering a new tariff system. Thus, we next answered the question "How can the performance of new network tariff proposals be analyzed objectively?" in Chapter 4. To this end, we proposed a methodological framework of performance indicators for network tariffs and a cost-accounting model for networks within which these indicators can be assessed. We demonstrated the use of this framework in a simple case study for a residential neighborhood. Suggestions for possible indicators are given in Table 4.1.

As a result of this case study, we found that network capacity-based tariffs perform particularly well in situations with many high-power flexible loads, as they give an incentive for these loads to reduce their peak consumption. Other congestion management methods based on limiting network capacity for flexible devices have also recently been proposed by Bundesnetzagentur in Germany and the Duch regulator ACM. In the German proposal, the capacity of specific devices can be limited to 4.2 kW by the network operator in near real-time in case of congestion. In one of the Dutch proposals, the network operator announces the capacity limitation on the day ahead, before the closing of the day-ahead market. As all of these proposals are based on limiting network capacity, we next turned to the question "How do different capacity-based congestion management approaches compare, and how can their performance be improved?" To answer this question, we again performed a simulation case study where we applied three different capacity-based mechanisms to a residential neighborhood with a high penetration of EVs.

The main insights from this study were that in terms of performance for managing congestion, all of these proposals perform well in theory. Capacity subscriptions are more restrictive as they are based on long-term contracts that limit capacity to the subscribed value, even when there is no congestion. It turned out that this did not lead to significant increases in prices for EV charging with the given wholesale market prices (from 2021). However, it may reduce user comfort as fast charging is impossible or more expensive. Most of the time, this fast charging is unnecessary as users commute for only 10-50km on a normal day, and charging the EV at a low speed is sufficient to add the required charge overnight. Still, this may pose a nuisance when filling the whole battery in one night is desired, e.g., because users want to prepare for travel or when they charge their EV only every couple of days.

In contrast, in near real-time capacity limitations as proposed by the German regulator BNA, users have the full capacity of their chargers available most of the time. Still, they may be unexpectedly curtailed in near real-time when congestion occurs. This creates a risk for energy providers, as they may incur portfolio imbalances due to curtailment. They will likely start to anticipate potential congestion due to this effect and already lower their energy purchases in case congestion is expected. However, these forecasts are never without errors, and remaining portfolio imbalances will likely occur.

The network operator could mitigate this risk to a degree by publishing expectations of congestion. In this way, near real-time limitations would become more similar to the day-ahead announcement of limitations proposed by the Dutch regulator ACM, where energy companies can already consider the limitations when making energy purchases. However, in day-ahead limitations, the risk shifts to the network operators: if they underestimate congestion, they must have a fallback option for additional curtailment closer to real-time. Thus, network operators are incentivized to be conservative in their congestion estimates and limit available capacity somewhat more than necessary.

In summary, going from long-term lead times of the announcement of capacity limitation to shorter times increases the mechanism's efficiency and creates bigger risks. This risk lies with the network operator in the day-ahead announcement of limitations, and with the energy supplier in the near real-time limitation.

To give users more freedom of choice and improve the cost-reflectiveness of the mechanism, we recommended establishing a 2-part capacity subscription: one part of the subscription is for firm network capacity, which is guaranteed to be available, notwithstanding network outages. This is meant to cover all base-load and inflexible loads of network users. A basic service floor of around 2kW should be available for a low price for equity reasons, and an increase beyond this floor should be relatively expensive, as firm capacity is more difficult to guarantee in times of strongly increasing peak loads. The second part of the subscription is for non-firm capacity, which is offered at lower prices but can be curtailed (fully or partially, depending on the contract) by the network operator during congestion. This allows users of flexible loads to use their full technical capacity when there is no congestion and minimizes the required restrictions. In addition, the network operator should send out congestion expectation estimates so that energy companies can factor these into their planning.

We can now answer the main research question posed above: flexibility of end-use devices can be controlled to avoid congestion using capacity-based mechanisms, both long and short-term. The preferred model emerging from this thesis is a combination of capacity subscriptions for both firm and non-firm network capacity.

After answering this question, we returned to this thesis's motivating question: "How can a cost-efficient transition to renewable and carbon-free energy sources be enabled in residential contexts?" For this to happen, users must electrify their end-use devices, and the resulting network congestion problems must be managed. The electricity prices and network tariffs that users pay may influence their investment and dispatch decisions and the size of the resulting network peaks. Thus, we next turned to the question: "How do electricity retail rates and network tariffs influence investments and dispatch in residential energy usage?"

We answered this question by using the Calliope modeling framework. We implemented a residential neighborhood of 25 households based on typical Dutch consumption and weather patterns. The electricity market price and carbon content were modeled with a European instance of the Calliope model that used the stated Dutch generation capacity targets of 2030. We investigated four different rate designs: a flat and a ToU volumetric rate for both generation and network tariff and real-time prices for generation with either a fixed or a capacity-based network tariff. The main insights from this study were:

- We found that volumetric network tariff designs lead to higher total user costs and emissions. Higher variable electricity costs mainly drive this, as users cannot use low electricity generation prices when the network tariff is added to the per kWh price of electricity. Due to the higher cost of electricity, the volumetric tariffs also incentivize the deployment of rooftop solar PV, even when this may not be economically efficient at the system level.
- The additional loads due to electrification may strongly increase the requirements on electricity networks: in our case study, the peak at the electricity connection grows by a factor of 3-5 when electrification is enabled, relative to the base case with no investments (when no carbon constraint is applied).

- The capacity-based network tariff strongly dampens the increase in peaks. It does this mainly by incentivizing the installation of home batteries, which allows households to reduce their peak consumption from the grid.
- The peak and average load of the gas network drops strongly under all rate designs. In the unconstrained model runs, we see that a fixed flat rate for both the energy and network components leads to a higher reliance on gas than the other studied rate designs.
- At higher decarbonization levels, both peak and average load of the gas network drop to very low levels in all rate designs, which raises the question of whether having and operating a gas network is still worth the cost at these high levels of electrification. Furthermore network peaks increase even more, especially in the scenarios with ToU and real-time pricing. The capacity-based network tariff keeps the increase in network peaks to around 3-fold, even in the tightest decarbonization scenario.

Thus, to answer the motivating question above, a transition to renewable and carbon-free energy in residential contexts can be enabled to a large degree by providing affordable electricity with very high shares of renewable energy at the national scale. Ideally, market prices for electricity generation should be passed directly to household consumers as real-time prices. Network tariffs should be capacity-based to avoid adding additional costs to the market price for generation and to incentivize the smart use of flexibility.

The actual technology deployment and dispatch decisions depend strongly on the specificities of the surveyed neighborhood, such as the state of insulation of homes and the size and age of the existing network equipment. Furthermore, many areas have the potential for other solutions, such as geothermal heating and heat networks that we did not model in this study.

Further progress could be made by developing tailored strategies for different neighborhoods and housing types. In some areas, upgrading the network sooner and incentivizing stronger electrification, e.g., using air-source heat pumps, may be more efficient societally. In others, it may be better to incentivize better home insulation and ground-source heat pumps more strongly to avoid the necessity for network upgrades if possible. Larger infrastructure questions, such as the decommissioning of the gas grid and the new build of heat grids, also factor into these decisions but are outside the scope of this thesis.

7.2. ADDITIONAL INSIGHTS GAINED

In addition to the insights on the research questions that were made explicit above, there were also realizations during the thesis that perhaps did not warrant a scientific publication in their own right but are nevertheless interesting to mention.

Many proposals for highly elaborate solutions for network congestion exist, e.g., through auctions of network capacity [1–3]. These are theoretically appealing and may be a promising solution for future energy systems with a high degree of energy management systems that can communicate their owners' preferences autonomously. However, currently, this degree of automation may not be possible and due to the increasing degree of congestion already occurring in networks, simpler solutions are likely required during a transition time. For this, capacity-based tariffs and curtailment mechanisms seem more promising. They likely already achieve most benefits of more elaborate solutions with much lower implementation costs.

Considering the decarbonization of residential energy demand, we noted that hydrogen had been considered as potentially a significant energy carrier for residential applications when work on this thesis began. However, it seems that the current consensus is that hydrogen will be too expensive, at least in the near future [4, 5], for this role and will only be applied in industrial applications at first. It could also be used for large-scale urban CHPs[1], but apart from demonstration projects, it will likely not be distributed in a grid akin to the gas grid in residential areas within the next decade.

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7.3. RECENT REGULATORY DEVELOPMENTS

This section briefly surveys recent developments in regulatory practice concerning network tariffs and congestion in a few European countries. The general trend seems towards capacity-based methods, which we also recommend here.

Flanders implemented a measured peak power tariff (based on the measured peak of network load of users) for around 80% of the users' network charges in January 2023[2]. A study by the University of Ghent and the Flemish Energy- and Climate-agency concluded that this tariff structure does indeed lead to reduced stress on the distribution grid [6].

In the Netherlands, regulators and network operators are actively discussing a new network tariff structure [7, 8]. A capacity subscription ("Bandbreedtemodel" in Dutch)

[1] https://www.microgridknowledge.com/infrastructure/chp/article/11429242/fit-for-the-future-hamburgs-hydrogen-fueled-combined-heat-and-power-plant

[2] https://lumiworld.luminus.be/up-to-date/wat-is-het-nieuwe-capaciteitstarief/

seems promising for residential tariffs, but no final consensus has yet been reached. Network operators may be worried as they do not know how their revenue will change when transitioning to the new tariff system. Furthermore, they find it difficult to suggest a certain value for their subscribed capacity to customers, as it may lead to customer resentment in case of increased charges, especially when a sub-ideal subscription value has been suggested to them. On congestion management, it was decided to rely on a mixture of methods: a market for voluntary capacity limitations, non-firm connection agreements for new parties, market-based redispatch, and Use-It-Or-Loose-It (UIOLI) for network capacity of parties with existing contracts for firm capacity.

In Norway, a capacity subscription tariff was discussed for several years. It seemed to be the preferred model of the national regulator, but it faced steep resistance from network operators and the general public. However, from 2024 on, 50% of the network tariff will have to be allocated to measured peak power consumption, similarly to Flanders (the remaining 50% are allocated to energy consumption). Additionally, some DSOs offer a night-time discount on the energy-dependent part [9].

In Germany, the regulator is going ahead with the interruptible connection proposal described above and in Chapter 5 from 2024 on [10]. The minimal available capacity during curtailment events has been increased from 3.7kW to 4.2kW in response to concerns about excessive restrictions from stakeholder consultations.

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8

CONCLUSIONS

This chapter summarizes the main findings, synthesizes the policy advice from the entire thesis, and suggests further research directions.

8.1. SUMMARY OF FINDINGS

Design of congestion management methods

Congestion in distribution networks can be addressed through network tariffs and specialized mechanisms that are applied in addition to tariffs (Chapter 2). We divided the possible methods into four categories (Section 2.5): static tariffs, dynamic tariffs, local flexibility market-based (LFM) methods, and direct-control-based methods (which can be part of the tariff or be applied in addition to it). This categorization is based on the following design choices:

- DSO position: offer or buy-back of access rights. Static and dynamic tariffs are offer-based, LFMs buy-back-based and direct-control can be either.
- load/feed-in controlling party: DSO or user. Direct-control methods are based on DSO control, and the others are based on user control (this includes handing control over to intermediaries like aggregators).
- timing of determination of access conditions: long-term, day-ahead, or near real-time. Static tariffs are long-term, dynamic tariffs are day-ahead or near real-time, LFMs can be any of the three, and direct control methods are typically

near real-time (the conditions are set long-term, but whether control actions occur is typically only known closer to real-time).

Additional important design choices (Section 2.4) are:

- which loads the mechanism applies to: all or only flexible with dedicated control infrastructure.
- price formation method: regulated or different kinds of auctions
- spatial variation: single feeder level, neighborhood-level, larger sub-zone-level, whole network
- firmness of network access: firm or non-firm
- contract commodity: physical connection, network capacity, delivered energy
- pricing structure: linear increase in commodity or tiered pricing (e.g., increasing/decreasing block pricing)

These design choices influence the performance and risks of the mechanism (Section 2.6).

- Methods based on dynamic access prices may create a price risk for the end-user, while market-based buy-back methods create a price risk for the DSO. Direct-control-based mechanisms create a curtailment risk for the end-user.
- Static access-price-based methods are helpful for creating rough signals for structural congestion. They are not discriminating but inefficient as they cannot be adapted to specific congestion situations.
- Dynamic access-price-based methods are more adaptable and efficient but may also introduce price discrimination, and some users may have difficulty reacting to the dynamic price signal.
- Local markets can theoretically be efficient but risk being gamed, especially when applied at a high spatial resolution where single parties can acquire market power. Thus, they are more suited for larger network zones where a liquid market can be guaranteed. Even then, they should be monitored, and baseline-based methods should be avoided as much as possible due to the potential misrepresentation of baseline problems. Direct-load-control-based methods can be effective for all congestion problems but create new implementation requirements (installation of a load-controlling device) and can lead to portfolio imbalances of load-serving entities when applied widely.

These insights are also summarized in Table 2.3 and Section 2.6.1.

Tariff assessment

The performance of network tariffs with respect to their regulatory objectives should be assessed with quantitative indicators (Chapter 4). This can be done with the help of a cost framework for networks that relate the customers' usage parameters, i.e., their load and feed-in to the network cost factors: losses, voltage issues, network upgrades, and fixed costs (Section 4.2). In addition, indicators need to be defined for each desired objective (Section 4.3). For example, one can use the correlation between users' tariff charges and the costs they incur for cost-reflectiveness. For non-discrimination, one can use the average and maximal difference in tariff charges of a given load curve in different locations in the network. One can use the load factor or relative size of peaks at critical assets for cost efficiency. Further suggestions for indicators are given in Section 4.3. Additional indicators can be proposed for other concerns. For example, there may be cross-subsidies among customer categories, such as between active consumers who install flexible devices (EVs and heat pumps) or solar PV and passive consumers who don't. This could be expressed in the per-kWh difference of tariffs between these groups and may be used as in indicator for equity (or lack thereof).

A preliminary case study for tariff performance assessment showed that capacity-based tariffs are much better suited to fulfill cost-reflectiveness and efficiency objectives in a future with significant amounts of flexible loads in distribution networks.

Congestion management methods based on capacity limitations

Alongside capacity-based network tariffs like a capacity subscription, day-ahead, and near real-time capacity limitations are also effective in handling congestion. Each method's main advantages and downsides are summarized in Table 8.1 and discussed in Chapter 5.

The preferred mechanism for congestion management emerging from this thesis is a two-part capacity subscription tariff: one part for firm network capacity, which quickly increases in price for additional capacity beyond a basic service floor for normal household needs, and an additional part for variable network capacity, which is cheaper but may be partially reduced during times of congestion in the network.

Investments and dispatch in residential energy usage under different electricity prices and network tariffs

Table 8.1: Advantages and downsides of capacity-limitation mechanisms

Mechanism	**Advantages**	**Downsides**
Static capacity based tariff	• Planning certainty for energy suppliers • Ease of implementation	• Overly restrictive when there is no congestion
Day-ahead capacity limitation	• Planning certainty for day-ahead market purchases • Restricts capacity only when congestion is expected	• Network operator may over- or underestimate congestion, resulting in unnecessary restrictions of network capacity • Need for an emergency fallback option to resolve remaining congestion
Interruptible connection	• Allows full use of available network capacity when no congestion occurs • Network operator has a high degree of control to avoid network overload	• Unexpected curtailment of network capacity may lead to portfolio imbalances for energy suppliers • Not cost-reflective when based on an equal lump-sum rebate for all participating flexible devices

We found that implementing the Dutch targets for renewable capacity in 2030 may significantly lower electricity prices due to the higher availability of renewable energy for low marginal generation costs. Passing these lower prices to residential end-users should incentivize substantial electrification of residential energy end-uses, such as replacing gas stoves with electric stoves and gas-based heating with heat pumps or heat grids. However, this increasing electrification may lead to strong network peaks, necessitating costly network upgrades when not managed properly. We found that capacity-based tariffs help strongly limit the network peaks, reducing the need for network upgrades.

However, they do this by incentivizing the installation of individual household batteries. Societally, this may be less cost-efficient than upgrading the network or installing communal batteries. We did not implement these strategies in our modeling but plan to include them in future work.

We further found that adding the network tariff as a per kWh to the electricity price leads to higher household costs and emissions than fixed or capacity-based network tariffs. These higher electricity costs also further incentivize PV panel installation, even when this may no longer be cost-efficient at the system level. This provides another justification for not adding network tariffs to the volumetric rate, but rather as a capacity-based tariff.

Lastly, usage of the gas network will drop significantly due to electrification. This raises the question at which point it may no longer be cost-efficient to run a gas network and rather rely on complete electrification, or supplying heat with heat grids.

8.2. POLICY ADVICE

Congestion management and new network tariffs: The preferred model for managing congestion in distribution grids emerging from this thesis is a capacity-based tariff that combines firm and non-firm network capacity.

Electricity rates: The market price signal for electricity generation should ideally be passed to consumers. However, care should be taken in situations with high price volatility that may lead to excessively high prices. Consumer contracts should include hedging options for these risks, e.g., a price ceiling. The network tariff should not be added as per kWh rate to the electricity price, as this has distorting effects. An alternative could be time-varying network-cost-reflective energy charges, or firm and non-firm capacity pricing as proposed above.

Governance of the transition process: Tariff revisions are politically contentious, as transitioning to a new system creates winners and losers. The political discussions in NL, Noway, Belgium, Germany, and other countries show that the regulator has a role in moderating these discussions and finally reaching a conclusion that parties can accept. Discussions about new tariffs should be underpinned by an objective evaluation of their performance, which can be done with a framework of performance indicators as presented in Chapter 4. Independent entities can use this framework to assess proposed and current tariffs.

Clarification of terms and concepts: Many different variants of seemingly similar concepts are used in the literature. For example, understanding the differences between “non-firm network capacity”, “alternative transport rights”, and “capacity limitations” can be challenging in the Dutch context. Ideally, regulatory and advisory bodies should compile a glossary of terms.

8.3. DIRECTIONS FOR FURTHER RESEARCH

Generalizability of findings: The modeling in this thesis focused on residential end-users and EVs as flexible loads. Expanding the tariff and congestion modeling analysis to different customer groups, such as industrial, agricultural, or commercial end-users, and different residential loads, such as heat pumps and shiftable wet appliances, could provide an interesting addition.

Different flexibility characteristics, such as different time scales for shifting loads, could be reflected in tariff conditions. For example, heating loads should only be curtailed for a limited amount during a given period to ensure that temperatures do not drop below minimal acceptable values. On the other hand, when some industrial processes are curtailed on a given hour, they may also be curtailed at low additional costs in the following hours while the process has been interrupted anyway, rather than holding off curtailment in the following hours but then curtailing again several hours or days later when the process has been started up again.

The “Big-picture” network management, considering options at all time scales and the trade-offs between them: short-term congestion management, medium-term tariffs, and contracts, and long-term network and infrastructure planning (see Figure 1.1). In this thesis, we focused mostly on tariffs and congestion management with existing infrastructure. We neglected the long-term options for network upgrades/expansion planning and matching demand centers close to supply. However, short and long-term solutions are intertwined. In some areas, it may be beneficial to upgrade the network earlier because even with congestion management, the social welfare gains of a bigger network outweigh its costs. In other areas, it may be the opposite. It would be an interesting project to consider a larger network and find recommendations or prescriptions for prioritizing areas for upgrades and demand matching vs. areas where tariffs or other methods should manage congestion. In addition to tariffs and contractual forms of congestion management, this could include network reconfiguration options to relieve congestion, as discussed in [1, 2] for example.

Behavioral aspects: For charging EVs, we assumed customers either optimize or use charge on arrival, but they may not be so predictable. Price signals alone are no guarantee that customers will act in network-serving ways. How to best nudge customers to behave in network- or energy-system-serving ways is an interesting field for further research. Ideally, this should include intermediaries like aggregators, smart energy management systems, or energy suppliers who make it easy for customers to comply with new mechanisms and create savings based on price-based mechanisms.

Stochastic modeling of flexible loads: We chose to model each EV individually with an arrival and departure time and daily demand. However, it would be more efficient to model a large pool of vehicles by a few aggregate parameters, like aggregate demand in a given area over a specified time horizon. An aggregator could ask customers for their parameters and aggregate them and learn customer behavior over time.

Simplification of temporal resolution and investment decisions in local energy system modeling: We detailedly modeled the neighborhood at an hourly time scale and solved individual investment and dispatch decisions in a MILP optimization problem. However, the hourly resolution could be transformed into a sequence of representative days and time slices by chronological clustering algorithms [3] to save computation time. Moreover, the individual investment decisions complicate the optimization problem, as their natural representation in optimization adds binary constraints (invest or no invest), which makes the problem hard to solve. It could be interesting to transform these problems into well-known forms of discrete optimization problems for which powerful algorithms exist, like knapsack problems [4, 5].

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Curriculum Vitæ

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List of Publications

The following is a list of published papers on which this thesis was built.

- R. Hennig, M. Jonker, S. Tindemans, and L. De Vries. "Capacity Subscription Tariffs for Electricity Distribution Networks: Design Choices and Congestion Management". In: *International Conference on the European Energy Market, EEM*. vol. 2020-September. IEEE Computer Society, 2020. ISBN: 9781728169194. DOI: 10.1109/EEM49802.2020.9221994
- R. Hennig, S. H. Tindemans, and L. De Vries. "Market Failures in Local Flexibility Market Proposals for Distribution Network Congestion Management". In: *International Conference on the European Energy Market, EEM* 2022-September (2022). ISSN: 21654093. DOI: 10.1109/EEM54602.2022.9920980
- R. J. Hennig, D. Ribó-Pérez, L. J. de Vries, and S. H. Tindemans. "What is a good distribution network tariff?—Developing indicators for performance assessment". In: *Applied Energy* 318 (2022), p. 119186. ISSN: 0306-2619. DOI: 10.1016/J.APENERGY.2022.119186. URL: https://linkinghub.elsevier.com/retrieve/pii/S0306261922005554
- R. J. Hennig, L. J. de Vries, and S. H. Tindemans. "Congestion management in electricity distribution networks: Smart tariffs, local markets and direct control". In: *Utilities Policy* 85 (Dec. 2023), p. 101660. ISSN: 0957-1787. DOI: 10.1016/J.JUP.2023.101660
- R. J. Hennig, L. J. de Vries, and S. H. Tindemans. "Risk vs. restriction—An investigation of capacity-limitation based congestion management in electric distribution grids". In: *Energy Policy* 186 (Mar. 2024), p. 113976. ISSN: 0301-4215. DOI: 10.1016/J.ENPOL.2023.113976