Distribution network tariff design and active consumers: a regulatory impact analysis

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Distribution network tariff design and active consumers: a regulatory impact analysis

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Tim Schittekatte

Composition du Jury :

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Thèse de doctorat

Acknowledgements

Sunday 20 January 2019 noon, Florence – It is rather cold and grey but anyhow, the view from the office is not too bad at all. I left writing the acknowledgements section to the last moment. I thought about what to write here already a couple of times, but it seems to be easier in thoughts than on paper.

First of all, I want to thank my director and co-supervisor Jean-Michel Glachant. He is the man who made this all possible. I never thought that a chance meeting on a train in Paris about three years ago would lead to where I am today. I want to thank him for following his gut, trust, wisdom and support. Further, I thank my supervisor Yannick Perez for helping me throughout this process and the academic and outside-academic advice. Most indispensable for the realisation of my research was definitely my shadow-supervisor and research leader at the Florence School of Regulation, Leonardo Meeus. He learned me, and the learning is still ongoing, how to convert a research idea into an academic paper that is rightly framed, answers relevant questions and is to the point. I want to thank him for never stopping to challenge me, his patience and enthusiasm. Many thanks also to Ilan Momber for introducing me to the world of complementarity modelling and all advice. Further, my professional life would have looked quite differently without Marcelo Saguan. He gave me my first job which somehow led to this adventure. Thank you all for guiding the way!

I would also like to thank the member of my jury to accept the invitation: Anna Creti, Michael Pollitt, Carine Staropoli and Margharita Comola. Your time and effort are highly appreciated.

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ÉCOLE DOCTORALE
Sciences de l'homme et de la société (SHS)

Université Paris-Saclay

Titre : Les structures tarifaires des opérateurs de distribution et des consommateurs actifs : une analyse de la régulation économique

Mots clés : tarifs d'accès des réseaux de distribution, économie de l'énergie, systèmes photovoltaïques, batteries, théorie des jeux

Résumé : La diffusion des panneaux solaires photovoltaïques à prix abordables nous amène à repenser à la manière avec laquelle les coûts des réseaux de distribution sont récupérés auprès des consommateurs. Historiquement, les consommateurs étaient facturés pour l'utilisation du réseau de distribution principalement sur la base de leur volume (net) d'électricité consommé. Avec tel type de tarif de réseau, les consommateurs qui installent des panneaux photovoltaïques contribuent beaucoup moins à la récupération du coût d'investissement réseau. Cependant, ces consommateurs (prosummeurs) dépendent autant du réseau qu'avant. La question examinée dans cette thèse est de savoir comment définir le tarif du réseau de distribution dans ce contexte changeant. Des différents modèles de théorie des jeux sont développés pour faire cette analyse. Dans ces modèles, en plus des investissements dans l'énergie solaire photovoltaïque, des investissements dans les batteries du côté des consommateurs sont aussi considérés. Ce rapport de thèse consiste en un bref aperçu suivi de quatre chapitres indépendants et d'une conclusion.

Title: Distribution network tariff design and active consumers: a regulatory impact analysis

Keywords: distribution network tariffs, energy economics, solar PV, batteries, game theory

Abstract: The uptake of affordable solar PV panels challenges the way in which costs of distribution networks are recuperated from consumers. Historically, consumers were charged for the use of the distribution network mainly according to their (net) volume of electricity consumed over a period of time. With such volumetric network charges, consumers installing PV panels contribute a lot less towards the recuperation of network costs. However, these consumers (prosumers) still rely on the network as much as they did before. The question investigated in this thesis is how to re-design the distribution network tariff in this changing context. Different game-theoretical models are developed to conduct this analysis. In the models, not only investments in solar PV but also investments in batteries at the consumer-side are considered. The thesis consists of a brief overview followed by four standalone chapters and a conclusion.

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OVERVIEW

This thesis centres around the design of electricity distribution network tariffs for residential consumers. Distribution network tariffs are paid by consumers to contribute to the recuperation of the distribution network. The distribution network is needed to deliver electricity locally. In most countries, distribution network tariffs were designed assuming consumers to be rather passive and fully reliant on the supply from the electricity network to satisfy their electricity needs.

However, due to strong cost reductions in the investment cost of Distributed Energy Resources (DER), consumers can now fulfil part of their electricity needs with their own generated electricity, better control their use of electricity and even inject electricity into the network when their onsite generation exceeds their demand. They become so-called active consumers. Consequently, the physical electricity flows in the distribution network are changing. A change in the physical flows also has an effect on the financial flows; in this context, the allocation of the distribution network costs among consumers. The distribution network tariff design which was historically in place is therefore challenged. How to re-design the distribution network tariff to deal with this new reality has elicited the interest of practitioners, policymakers and academics in the electricity sector and is the focus of this thesis. The thesis consists of this overview, four chapters and a conclusion. Each chapter represents a paper which stands on its own.

The **first chapter** is an introductory chapter. The chapter starts by introducing the importance of network charges in the final electricity bill and describes how distribution network tariffs are designed today. Then, the reader is reminded that the distribution network tariff is not the only way to recover grid costs: other ways are through connection charges, possibly distribution locational marginal pricing (DLMP) and general taxation. After, the main principles of distribution network tariff design are discussed, guiding the reader from the (theoretical) first-best distribution network design all the way to why current practices were chosen. Further, issues with current practices are discussed, and possible tools to overcome these challenges are briefly introduced. The chapter ends with a summary of the current state of the European debate on distribution network tariff design.

This first chapter is published as a chapter in:

- *T. Schittekatte & L. Meeus (2018), ''Introduction to network tariffs and network codes for consumers, prosumers and energy communities'', FSR Technical report. DOI: 10.2870/934379.*

This technical report served as a course text for an FSR online course the aim of which was to empower representatives of consumer organisations, energy communities and NGOs. The course took place from

12 to 26 April 2018. The course counted 88 participants from 22 different countries of which 45% were senior professionals. 58% of the course participants came from NGOs, 30% from consumer organisations and 12% from energy communities. The course was set up in collaboration with ENTSO-E, BEUC and RESCOOP.

The **second chapter** of the thesis illustrates how consumer adoption of solar PV and batteries affects the cost-efficiency of current distribution network tariff design and can have redistributional impacts. The distribution network tariff design problem is modelled as a mixed-complementarity problem (MCP), i.e. a non-cooperative game between consumers. In the game, the availability and costs of the two aforementioned technologies strategically interact with distribution network tariff structures. Four 'states of the world' for users' access to technologies are distinguished, and three tariff structures are evaluated. The assessed distribution network tariff structures are volumetric network charges with net-metering, bi-directional volumetric network charges for both injection and withdrawal, and capacity-based network charges. A key assumption in the second chapter is that all grid costs are sunk. This implies that changes in the electricity consumption patterns due to DER adoption by certain consumers have no impact on the total grid costs to be recovered. Under that assumption, the distribution network tariff design has mostly an allocative function, i.e. spread the network costs over the different consumers in an acceptable way while limiting the possible induced distortions.

This chapter is published as:

- *T. Schittekatte, I. Momber & L. Meeus (2018), ''Future-proof tariff design: recovering sunk grid costs in a world where consumers are pushing back'', Energy Economics 70, 484-498. https://doi.org/10.1016/j.eneco.2018.01.028.*

Further, this paper also won the 2nd prize for doctoral student papers at the French Association for Energy Economists (FAEE) in October 2017.

A policy brief based on the paper is published as:

- *Schittekatte, T., & Meeus, L. (2017), ''How future-proof is your distribution grid tariff design?'', FSR Policy brief 2017/03, DOI: 10.2870/27688*

This paper was also presented at:

- *5th International Conference of the Armand Peugeot Chair – Electromobility: Challenging Issues – Paris, December 2017*

In the **third chapter**, different grid cost scenarios or 'states of the grid' are considered, including the scenario for which many grid investments need to be done. These future grid investments are assumed to be driven by the peak consumption aggregated over all consumers. In that case, the network tariff design does not only have an allocative function but also the cost-reflectivity of the network tariff becomes important. In this chapter, the model introduced in the previous chapter is extended by turning it into a bi-level optimisation problem and is further reformulated as a mathematical model with equilibrium constraints (MPEC). The upper-level welfare maximising regulator can decide which distribution network tariff design to implement while anticipating the reaction of the lower-level consumers to the chosen design. The regulator can choose between the traditional distribution network tariff options: fixed charges, volumetric charges, capacity-based charges or any combination thereof. The modelling formulation is used to assess how to design a least-cost distribution tariff under two constraints that regulators typically face. The first constraint is related to difficulties regarding the implementation of cost-reflective tariffs. In practice, so-called cost-reflective tariffs are only a proxy for the actual cost driver(s) in distribution grids. The second constraint has to do with fairness. There is a fear that active consumers investing in DER might benefit at the expense of passive consumers.

This chapter is published as:

- *T. Schittekatte & L. Meeus (2018), ''Least-cost distribution network tariff design in theory and in practice'', FSR RSCAS Working Paper 2018/19.*

Currently, the manuscript is resubmitted to The Energy Journal after a ''Revise and resubmit'' decision in August 2018.

A policy brief based on the paper is published as:

- *Schittekatte, T., & Meeus, L. (2018), ''Limits of traditional distribution network tariff design and options to move beyond'', FSR Policy brief 2018/13, DOI: 10.2870/863622.*

This paper was also presented at:

- *World Congress for Energy and Resource Economists (WCERE) – Panellist of policy session – ''Smart grid for a carbon free energy future: the role of electricity pricing and distributed energy resources'' – Gothenburg, June 2018*
- *International Conference of the International Association of Energy Economists (IAEE) – Groningen, June 2018*

The topic of the **fourth and last chapter** is the interaction between distribution network tariff design and the business case of residential electricity storage. A new solution method is proposed for the MPEC introduced in the third chapter, based on the strong duality theorem. The model is used to analyse whether different distribution network tariff designs align the business case of storage with wider system benefits. Three distribution network tariff designs are evaluated: volumetric charges with net-purchase, bi-directional volumetric charges for both injection and withdrawal capacity-based charges. The outcomes under these distribution network tariff designs are compared to a first-best benchmark. The benchmark is a central planner who can decide unilaterally about the consumers' investment decisions in batteries. Besides the network tariff design, also time-varying energy prices are an important enabler for the business case of storage. Therefore, the impact of time-varying energy prices on the business case of storage and the interaction between different energy pricing schemes and the evaluated network tariff designs is described.

This chapter is written without co-authors and serves as a draft for a working paper. The additional finding regarding the interaction between different energy pricing schemes and the evaluated network tariff design might be omitted in the final version of the working paper. The reason for this is that this finding is expected to serve as a starting point for further research after the submission of the thesis. Earlier versions of this chapter were presented at:

- *Workshop storage taskforce SmartEN– Brussels, Belgium, 9 October, 2018*
- *DIW: SET-Nav Modeling Workshop - Two-stage decision making and modelling for energy markets– Berlin, 11 October 2018*
- *Conference on storage business models, organized by EASE and Vlerick Business School– Brussels, Belgium, 30 November 2018*
- *3rd AIEE Energy Symposium – Milan, Italy, December 10-12, 2018*

CHAPTER 1: DISTRIBUTION NETWORK TARIFF DESIGN: CONTEXT, MAIN PRINCIPLES AND CURRENT CHALLENGE

Abstract

This chapter starts by introducing the importance of network charges in the consumer bill and describing how distribution network tariffs are designed today. Then, the reader is reminded that the distribution network tariff is not the only way to recover grid costs, other ways are through connection charges, possibly distribution locational marginal pricing (DLMP) and general taxation. After, the main principles of distribution network tariff design are discussed, guiding the reader from the (theoretical) first-best distribution network design all the way to why current practices were chosen for. After, issues with current practices are discussed, and possible tools to overcome these challenges are briefly introduced. The chapter ends with a summary of the current state of the European debate around distribution network tariff design.

Keywords: Distribution Grid Cost Recovery, Distribution Network Tariff Design, Connection Charges, Harmonisation

This first chapter is published as a chapter in:

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This technical report served as a course text for an FSR online course the aim of which was to empower representatives of consumer organisations, energy communities and NGOs. The course took place from 12 to 26 April 2018. The course counted 88 participants from 22 different countries of which 45% were senior professionals. 58% of the course participants came from NGOs, 30% from consumer organisations and 12% from energy communities. The course was set up in collaboration with ENTSO-E, BEUC and RESCOOP.

1. The electricity bill: the components and who's responsible for what?

Figure 1 shows the breakdown of consumer electricity bill in capital cities across Europe. It can be seen that the electricity bill broadly consists of three components: energy costs, taxes and levies and network charges.

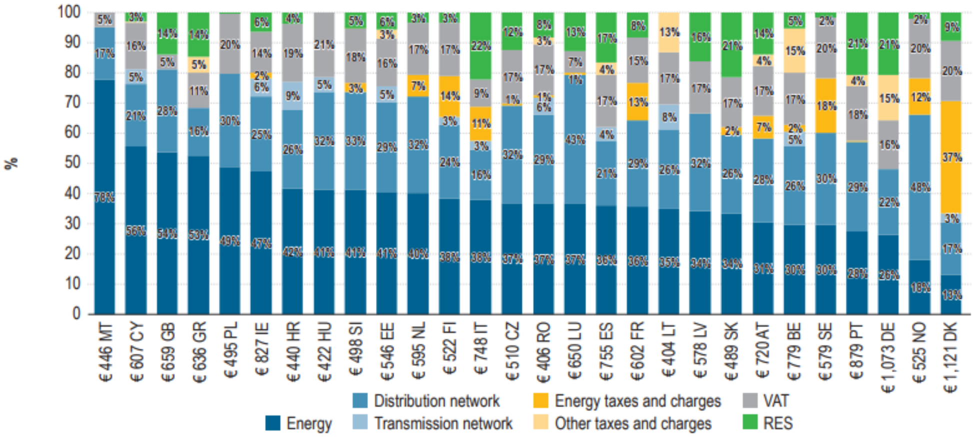


Figure 1: Breakdown of incumbents' standard offers for households in EU capital cities and total bill – November–December 2016 (ACER and CEER, 2017a)

Energy costs represented on average 35% of the final bill in 2016 but have declined (at least relatively) every year since 2012 as shown in Figure 2. Energy costs depend on the wholesale electricity market. In this market, electricity retailers buy electricity on behalf of their contracted customers. The final energy price a consumer sees will reflect the market conditions to a certain extent. Depending on the arrangement with the retailer, the final price for the consumer, expressed in euros per kWh, can be either time-varying or invariant to time.

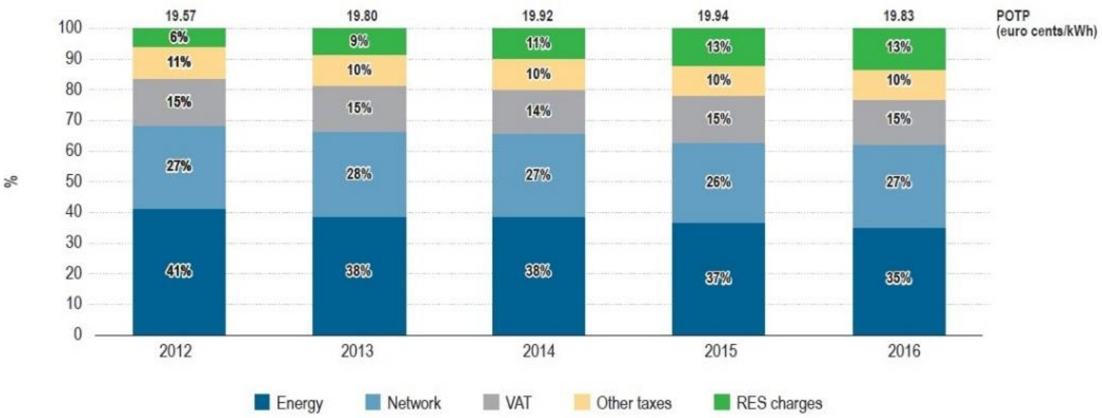


Figure 2: Weighted average of the electricity post-taxes total bill (POTP) and breakdown of incumbents' standard offers for households in EU capitals and Oslo – 2012–2016 (ACER and CEER, 2017a)

Taxes and levies represented on average 38% of the electricity bill in 2016. Value-Added Tax (VAT), averaging 15% in the EU, is added as a percentage of the final electricity bill. Levies in the electricity bill are increasing yearly as shown in Figure 2 and made up about 23% of the bill in 2016. Levies are recuperated through the consumer bill to pay for example for energy policy costs such as renewable subsidies or surcharges. Levies are paid, in most cases, in proportion to the electricity volume consumed, i.e. in euros per kWh or by a fixed charge per consumer. The high-cost burden of energy policy and how these costs are spread across different types of grid users has provoked intense public debate, see e.g. Bohringer et al. (2017) discussing the German case. The allocation of these costs and whether they should be recovered through the electricity bill at all is up to the government. This debate is not the focus of this thesis.

Probably even more discussed today is how to design the distribution network (access) tariff, which is currently the main method of recovering distribution network costs from consumers. In 2016, the proportion of total network charges in electricity bills averaged around 27% in the EU. The largest chunk of network charges in a consumer bill are the distribution network charges. Distribution network charges varied between 16 % and 48% of the bill, while for transmission network charges these percentages ranged between approximately 0% to 9%. For simplicity, throughout this thesis, when we refer to network charges, we mean distribution network charges. The reason that distribution network tariffs are discussed profoundly today is in most cases not because they are increasing strongly lately. Figure 2 shows that the proportion of network charges in the bill has been relatively stable over the last years. Instead, the discussion has more to do with their design. Figure 3 shows the way distribution network tariffs are designed for households in the EU in 2016.

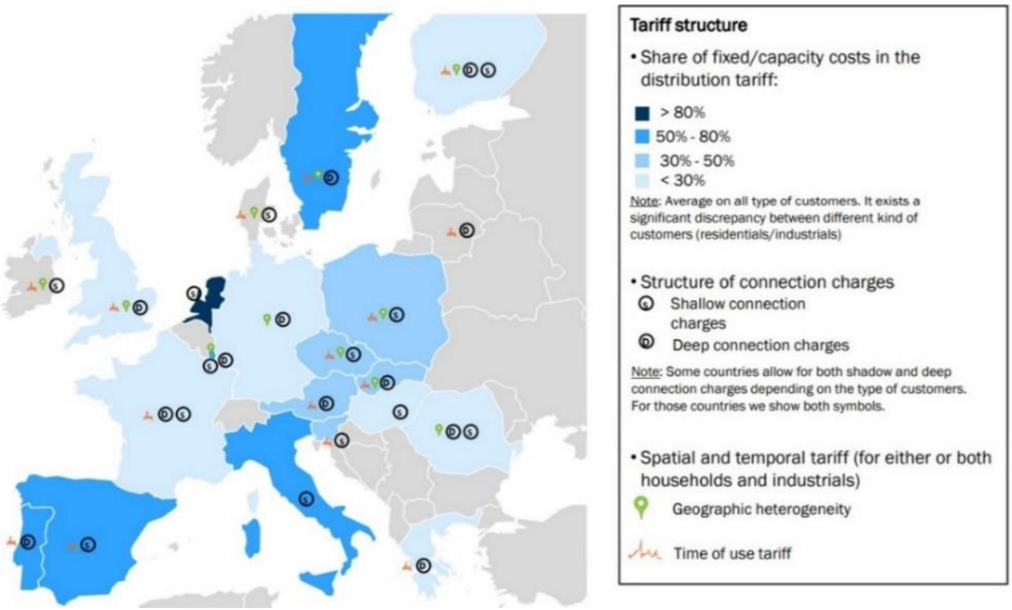


Figure 3: Distribution network cost recovery in Europe by Compass Lexecon (2016) based on European Commission (2015)

The first thing to notice in Figure 3 is that methods of grid costs recuperation and the structures of distribution tariffs are not harmonised across Europe. Similarly, as for transmission tariffs, the shares of volumetric/capacity component for distribution tariffs vary significantly across EU countries. A second important fact demonstrated in Figure 3 and also described in a report by the European Commission (EC) (2015), is that the majority of distribution grid tariffs mainly consist of volumetric charges. The EC report specifies that 69% of the revenue from households, 54% for small industrial consumers and 58% for large industrial consumers are recuperated through volumetric tariffs. The Netherlands is an exception as there is no volumetric component in the distribution network tariff for households.

As the network tariff is regulated, it is the National Regulatory Authority (NRA), not the market, that has the final say on the distribution network tariff design. In some EU countries, the NRA is solely responsible for the tariff design; in other EU countries NRAs and DSOs share the responsibility, e.g. the NRA decides on higher level principles, while the DSO proposes the tariff structure and level which need to be approved by the NRA (EC, 2015 and recital 36 of Directive 2009/72/EC).

2. **Other ways than access tariffs to recuperate distribution network costs**

In the debate about the recovery of distribution grid costs, the focus is mostly on the distribution network access tariff, i.e. the one you pay as part of your monthly or semestrial electricity bill. Besides the network access tariff, network connection charges and distribution locational marginal pricing (DLMP) are other ways to (partly) recuperate distribution grid costs. In practice, at least today, distribution grid costs will be recovered by a combination of the connection charges and the distribution network access tariff.

2.1 Connection charges

Connection charges, as the name indicates, are (in most cases) a one-time charge paid for the connection to the grid. In general, three types of connection charges can be distinguished: super-shallow, shallow and deep connection charges. The degree to which connection charges fully reflect the incremental cost of providing a user with a new or upgraded connection to the network depends on the type of connection charge.

With super-shallow connection charges basically no costs are charged for the connection. Shallow connection charges imply that grid users pay for the local infrastructure connection costs (the cable between a house and local feeder and other necessary equipment); these costs are easily attributed to a specific user. Deep connection charges consist of the shallow charges plus possibly incurred costs for wider network reinforcements needed to accommodate the connection request. Deep connection charges intend to fully reflect the incremental cost of providing a user with a new or increased connection to the network.

Shallow connection charges solely recover the connection from the user to the grid. Shallow connection charges generally do not 'steer' consumer behaviour, i.e. whether you connect your house or shop to a point in the distribution grid where there is very little or significant congestion, it does not affect your connection charge. On the other hand, deeper connection charges do send a signal to grid users. Namely, you will have to pay a different connection charge whether or not you connect to a point in the grid where there is already significant congestion. Deep connection charges will 'guide' grid users to connect to less congested points of the grid.[1] A main issue with deep connection charges is that new entrants will pay more than users already connected to the grid. Grid investment happens in practice in discrete ('lumpy') steps, a grid user connecting at the moment the grid is utilised near its maximum would have to pay the entire upgrade. Another difficulty with this type of charge is that the costs inflicted on the network by the user need to be estimated before actual grid usage.

Ofgem (2017a), the Great-Britain (GB) regulator, describes a practical implementation of distribution connection charges. They state that in GB the distribution connection charging regime is referred to as '*shallow-ish*'. Besides the full cost of assets that will be used solely by the connecting customer[2], connection charges can also recover a portion of the deeper reinforcement costs to the existing network needed to provide the user with firm access to the system. However, charges paid for the deeper reinforcement of the wider grid seem to be limited. Namely, in Ofgem (2014), it is reported that 95% of connections between 2011-2014 have not triggered any network reinforcement. Additionally, where a connection project triggered reinforcement, the connecting customer paid 59% of the associated costs. The other 41% of the costs were socialised through the network access tariff.

2.2 Distribution locational marginal pricing (DLMP)

Another way to recuperate grid costs is through DLMP, meaning that different locations (in the extreme case: nodes) in the network can reflect different energy prices at a certain point in time. The principle applied in DLMP is borrowed from transmission grid cost recovery and could, in theory, be

[1] An innovative tool in that regard are network capacity maps indicating the available hosting capacities at different points in the distribution network see e.g. http://www.westernpower.co.uk/connections/generation/network-capacity-map.aspx and https://www.capareseau.fr/

[2] Ofgem (2014) describes that the cost of the assets solely used by the connecting consumer will be based on the 'minimum scheme'. The minimum scheme is the solution designed solely to provide the capacity needed for the new connection at the lowest overall capital cost. A DSO may design an enhanced scheme (e.g. additional assets to accommodate a larger capacity or assets of a different specification) but the cost to the customer will not exceed that of the minimum scheme. The customer can also request works in excess of the minimum scheme, when it thinks this would be more beneficial.

also applied to distribution networks to recover part of the costs. In Figure 4 a simple example of locational pricing applied at nodal level is shown.

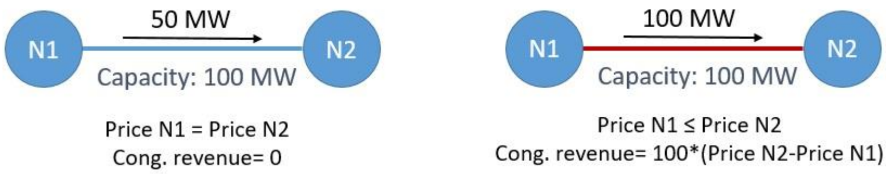
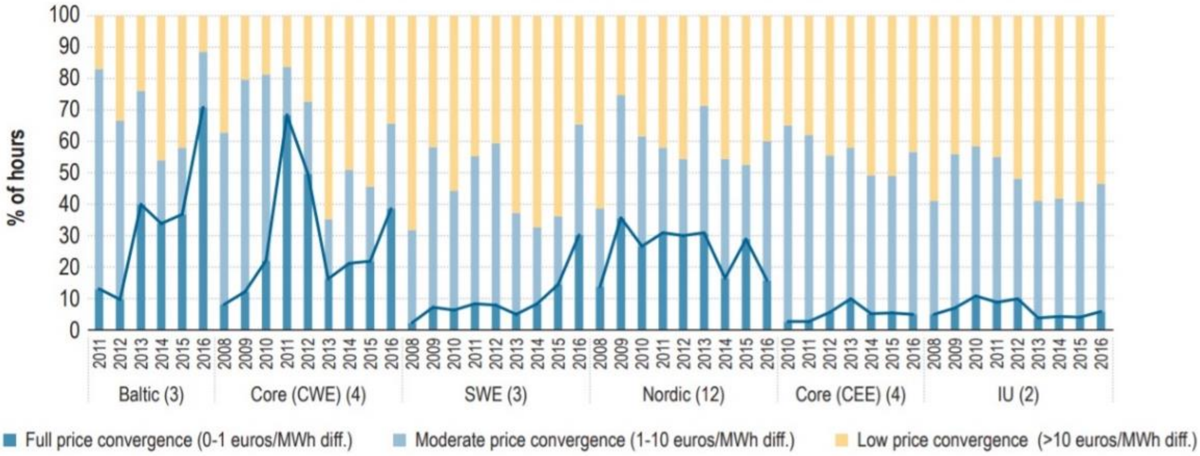


Figure 4: Simple example of locational marginal pricing. Left, no congestion. Right, congestion.

The left side of Figure 4 shows a situation without congestion (meaning the line is not utilized at its full capacity) between the two nodes N1 and N2. The price of the two nodes will be the same if we assume no energy losses. In this case, there is no congestion rent or income for the owner of the line. The right side of Figure 4 shows a situation where there is congestion between the two nodes. A price difference between the nodes occurs now. Electricity will always flow from the node with the lower price to the node with the higher price. The congestion rent, i.e. the income for the line owner, is calculated as the capacity of the line multiplied by the price difference between the nodes. Each market time unit (e.g. 1 hour or 15 minutes), the situation can change, i.e. congestion can occur or disappear depending on the electricity flows resulting from electricity trade. Thus, by applying distribution locational prices very short-term price signals are sent, informing grid users about the underlying network constraints.

The concept of locational marginal pricing is applied in European electricity markets at the transmission level. Namely, the European electricity market is organized as a set of bidding zones, which in most cases overlap with national borders. The network within these bidding zones is seen as a copper plate - no congestion is assumed- implying that within a bidding zone the electricity price is always uniform. However, the different bidding zones are connected through transmission lines ('cross-zonal interconnectors') for which the scarce capacity is taken into account by the market; a mechanism called implicit cross-zonal transmission capacity allocation. This means that if the interconnectors between two bidding zones are not congested at a certain point in time, the electricity price will be equal over the two bidding zones (so-called market coupling). If the interconnectors are congested, the electricity price in the two bidding zones will diverge (so-called market splitting).[3] Figure 5 illustrates price convergence between different bidding zones within certain regions in the EU. For example, the Baltics consist of three bidding zones representing respectively Lithuania, Latvia and Estonia. During 2016 the (day-ahead) electricity price between those three countries converged about 70% of the time.

[3] For more information, see e.g. Meeus and Schittekatte (2018), Section 2.2, in which the concept of bidding zones is explained more profoundly and Chapter 5, which describes the way cross-zonal capacity is allocated and calculated.



Source: ENTSO-E, Platts (2017) and ACER calculations.

Note: The numbers in brackets refer to the number of bidding zones included in the calculations per region.

Figure 5: Day-ahead price convergence in the EU by region as % of hours, 2011-2016 (ACER and CEER, 2017b)

This also means that 30% of the time at least one bidding zone had a different price as one or multiple interconnectors were congested. This implies that during those moments congestion rent was generated. This revenue is raised from the day-ahead auction in which the electricity prices in the different bidding zones is jointly determined as illustrated with an example in the box below.

Suppose that the day-ahead market auction for a certain hour results in a price in zone A of 50 €/MWh and a price in zone B of 60€/MWh. The satisfied demand in zone A is 100 MW, the satisfied demand in zone B is 150 MW and the interconnector capacity allocated for trade between the two zones was 50 MW. As there is a price differential between the two zones, it implies that the cross-zonal interconnector capacity is fully utilized, i.e. the total electricity flowing through the interconnector is 50 MW. Electricity flows from the low price zone (A) to the high price zone (B).

	Price	*Demand*	*Generation*	*Demand cost*	*Generation cost*
Zone A	50 €/MWh	100 MW	150 MW (demand zone A + interconnector)	€ 5,000	€ 7,500
Zone B	60 €/MWh	150 MW	100 MW (demand zone B - interconnector)	€ 9,000	€ 6,000
				€ 14,000	€ 13,500

The total amount collected by generation over the two zones is €13,500 while the total amount spent by demand equals €14,000. The difference between the two is the congestion rent of €500 equalling the price differential between the two zones (€10/MWh) multiplied by the capacity of the line (50 MW). This congestion rent is transferred to the TSO(s) owning the interconnector.

In Figure 6 the average annual congestion revenue and how it was spent per country over the period of 2011-2015 is shown.

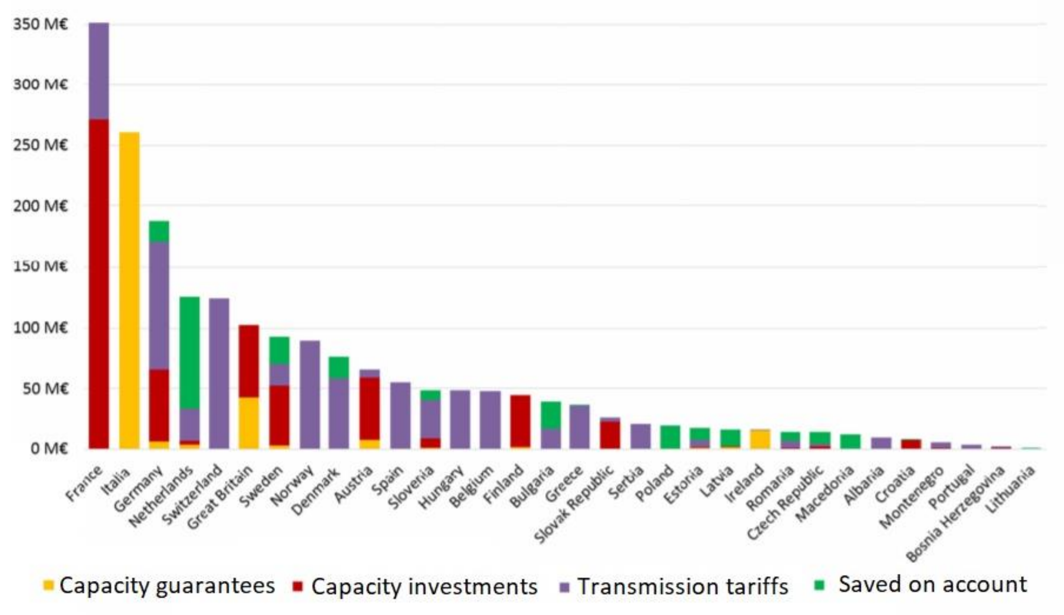


Figure 6: Average annual congestion rent and allocation of the rent per country for the period between 2011 and 2015 (ECN et al., 2017)

There are precise rules specifying how the obtained congestion revenues should be spent. More specifically, Art. 16 (6) of the Regulation (EC) No 714/2009 on conditions for access to the network for cross-border exchanges in electricity states that priority should be given to use this money to guarantee the actual availability of the allocated capacity or to maintain or increase cross-zonal interconnection capacity. However, if the revenues cannot be efficiently used for those purposes, they can be used to lower the (transmission) network tariffs up to a maximum amount decided upon by the relevant NRA. Remaining money should be saved to use for priority purposes when necessary in the future.

Obstacles would have to be overcome to apply the locational marginal prices (LMP) to distribution networks in order to recover part of the grid costs. There are two main issues: a public acceptance issue and a technical issue. First, if locational pricing is applied at the distribution level, it would mean that different areas of a distribution network would see different energy prices at certain points in time. This could be perceived unfair because this price difference is mainly created by the investment decisions in infrastructure by DSOs in the past and not by consumers who happen to live in an area which could see a rise in prices. The technical issue has to do with the fact that the number of lines and nodes at the distribution level is much higher than at the transmission level. Applying locational pricing at the transmission level is computationally already challenging, with the number of zones and the temporal granularity being the main parameters affecting the time to compute all prices. If a similar calculation would be done at the distribution level, innovations in algorithms and computational power will be needed. Also, real-time information about all flows in the lines as well as about the injection and withdrawal of electricity at all nodes is required. This is a very challenging task and will entail significant investments in IT necessary to turn the distribution grid into a 'smart grid'.

Abdelmotteleb et al. (2016) explain that the major difference between LMP used in transmission and distribution are the losses and congestion portions. In distribution networks, losses have a more relevant role than in transmission.[4] Moreover, congestion is rarer in DLMP calculations since distribution network topology is generally radial and feeds energy from one point. Abdelmotteleb et al. (2016) also add that even if DLMP would be implemented, complementary network charges are needed to recover the network costs fully and to send efficient long-term signals to network users.

3. **Principles and theory of distribution network tariff design**

After distilling relevant literature, three general principles for distribution network tariff design were distinguished. Namely, a tariff should be cost-reflective, allow the recovery of efficiently incurred grid costs and be fair.

3.1 Cost-reflectiveness

An important principle of distribution network tariff design is cost-reflectiveness. Cost-reflectiveness implies that the cost a consumer inflicts on the network should be reflected by the network tariff. In short, one should pay the price for her own actions. In theory, by having a cost-reflective tariff the consumer is informed to decide whether to use the network at a certain time (for which she will pay the inflicted cost) or whether to change her consumption behaviour for which she will have attributed a value or for which she has to invest in Distributed Energy Resources (DER).[5] If network charges are not cost-reflective, it means that consumers will not see the correct trade-off between utilizing the network or adjusting their consumption at a certain point in time. Two situations can occur:

[4] Losses in distribution can vary widely and are typically in the order of 4-10 % of the total energy offtake (see e.g. MIT Energy Initiative (2016a)). In transmission losses are around 1-2 % of the energy offtake (see e.g. Elia).

[5] In this section we assume the consumer to be the decision-maker, this is not always the case. An example can be a less affluent family renting a flat in the city with little to say on which investments to make in the building, including the heating system, let alone solar panel on a roof. Fairness and inflexible/passive consumers are further discussed in Subsection 3.3.

- First, the network tariff can be too low, meaning that the consumers' actions inflict more cost than the network charges they would have to pay. This means that we end up in a situation with an overly expensive grid as the consumers are not incentivized enough to adapt their actions, leading to a higher total system cost. An example would be that consumers who have an intelligent heating system driven by a heat pump command their house to be heated at moments when the electricity (including the grid) is priced cheaply even when the network is near congestion. If many people do so, it would eventually mean that the network needs to be expanded, while this would not have been the case if the network tariff was cost-reflective thus incentivizing the consumer to program their heating at times when the utilization of the grid was low. In the end, all consumers will have to pay back the cost of this (avoidable) network expansion through the tariff.

- Second, the network tariff can be too high, meaning that the consumers' actions inflict less cost than the network charges they have to pay. Using the same example, if network charges are too high, it could mean that consumers opt for gas heating instead of electric heating. Even though, if the network charges would be designed as cost-reflective, electric heating could have been a cheaper option as the electricity network could accommodate the extra load without problems, under the condition that the heating would be correctly programmed. This would mean that we end up in a situation with overpriced actions by the consumers and an underutilized grid, leading again to a higher total system cost for the final energy service than if the network tariff was designed properly.

In short, the idea is that a cost-reflective tariff will lead a cost-efficient outcome. What is meant with a cost-efficient outcome is that the cost-reflective tariff will lead to the overall lowest final cost for serving the electricity needs of all consumers.

When wanting to design a cost-reflective tariff, we need to know what cost to reflect, in other words, what drives the grid cost. Generally, it is agreed upon in the literature that the main cost driver of an electricity network, whether it is distribution or transmission, is the maximum peak demand aggregated over all consumers, also called the 'coincident peak demand'. A line or feeder is dimensioned to cope with the maximum power in kW or MW it is expected to carry at a certain point in time, not by the volume in kWh or MWh it is expected to transmit over a certain time period. This is very similar to highways or telecom lines. Other cost drivers could for example include losses or the penetration of solar PV which could induce bi-directional flows and thus requires investment in additional electronics (e.g. protection and voltage regulation) in the grid. For more information see also the Future of Solar Report by the MIT Energy Initiative (2015) and chapter 9 of IEA (2016).

So what does such a cost-reflective tariff look like in theory? For example, the Utility of the Future report by the MIT Energy Initiative (2016a) explains that a cost-reflective distribution network tariff consists of a forward-looking peak-coincident capacity charge. The capacity-based charge should be computed as the incremental cost of the network divided by expected load growth, the so-called long-run marginal cost (LRMC) of the network. However, there are constraints making the introduction of this tariff more difficult in reality; we divide them into two groups: implementation constraints (due to a lack of information and fairness concerns) and a cost-recovery issue.

First, implementation constraints, LRMC pricing is not so easy to implement in distribution grids. Gómez (2013) describes the distribution networks as follows: ''*A friend of mine who worked in a distribution company likened electric power generation and transmission to a bull and distribution to a beehive. Whereas generation and transmission comprise comparatively few and very large-scale facilities, distribution involves a much larger number and wider variety of equipment and components.*'' In other words, it is hard to get a complete picture of the distribution network. Plus, there is a lack of information about the network flows in real-time requiring significant investments in IT infrastructure in most countries. Without this information, it is almost impossible to truly reflect the grid costs in the tariff as it is not clear what is really going on in the network.

Even if all information would be known, such tariff should have a very fine locational and temporal granularity. In the extreme case, in order to apply it perfectly, it would almost be a user-by-user tariff. However, generally, a tariff per region or DSO area is applied in Europe (European Commission, 2015a). This is mostly done for reasons of simplicity and fairness.[6] Batlle et al. (2017) explain that in reality, such fine granularity is impossible and that some degree of consumer clustering is required. The authors continue that in the electricity sector, consumers have traditionally been grouped by voltage level, node location, consumption category (residential versus industrial), or even according to the occurrence of their peak load if a time-differentiation is applied. It is clear that each grouping

[6] Imagine you live in a district which did not see an update of grid infrastructure in the last decade and local demand is increasing. If a cost-reflective network tariff with finer locational granularity would be applied, it is possible that grid tariffs suddenly become substantially higher at certain times in your neighbourhood. This would happen to incentivise grid users to adjust their electricity withdrawal and injection patterns at times the grid is stressed in order to avoid or postpone costly grid reinforcements. Another district could have been upgraded just a couple of years before the implementation of such a tariff with finer locational granularity. This district could then see fairly low and constant grid tariffs as there is little need for reinforcements. The difference in grid tariffs would be caused mainly because of choices of the DSO in the past on which affected grid users had little influence. Very location specific tariffs could indeed increase cost-efficiency but they remove a certain 'socialisation' of grid costs.

alternative represents an (arbitrary) approximation of the LRMC and the timing of the peak, that may, to a greater or lesser degree, affect the overall cost-efficiency of the methodology.

In **Chapter 3 of this thesis,** it is demonstrated that if the regulator, setting the tariff, does not anticipate inaccuracy in the proxy of the network cost driver, self-interest pursuing active consumers can make sub-optimal decisions in terms of DER investment, possibly leading to consumer investing more in DER than the level of grid and energy costs that are avoided; thus a worse outcome in terms of overall welfare. If the regulator anticipates this inaccuracy, the welfare loss can be reduced.

In **Chapter 4 of this thesis,** it is demonstrated that if many future grid investments are expected and no truly cost-reflective network tariffs are implemented, consumers might possibly under-invest in batteries compared to what would be optimal from a system point of view. Also, batteries would be operated in a sub-optimal manner. Fewer grid costs are avoided that would be possible in a cost-efficient manner; thus potential welfare gains are missed out. More advanced network tariffs are needed, complemented with other mechanisms as implementation issues always remain to a certain extent.

Besides an implementation issue, there is a cost-recovery issue. It is well known (see e.g. Borenstein (2016); MIT Energy Initiative (2016) and Ofgem (2017a)) that purely cost-reflective charges do not guarantee full cost recovery of the efficiently incurred grid costs. Actually, what is done by cost-reflective network charges is to send a signal to the grid user to optimally make use of the network, leading to a cost-efficient outcome for all. However, cost-efficiency is decoupled from another objective, namely to recover all grid costs. In reality, there will always be residual part of the grid costs which are sunk, i.e. grid investments done in the past to meet future electricity demand and of which the total amount of costs is unaffected by the way the network is utilised. Therefore, a cost-reflective tariff, which is, in theory, the first-best solution from a cost-efficiency point of view, needs to be complemented with another charge to recuperate these sunk costs. This leads us to the second principle of distribution network tariff design, cost-recovery.

3.2 Cost-recovery

The idea behind the cost-recovery principle is that the Distribution System Operator (DSO), the company responsible for maintaining, developing and operating the distribution network, must be able to recuperate its ‘efficiently incurred grid costs’.[7] It should be reminded that the DSO is a natural monopoly, meaning that it is cheaper to have one company building and operating the distribution network than to have multiple companies, duplicating the necessary lines and competing for consumers to connect to their network. What this implies is that the tariff for using the network is not set by the DSO. Instead, it is the NRA who will assess how high the allowed revenue of a DSO should be and accordingly determine the network tariff. An exception is Spain where allowed revenues are set by the Government (European Commission, 2015a).

In general, incentive regulation should aim to guide DSOs to find an optimal balance between costs associated with investment, operation and maintenance, and energy losses on the one hand, and the quality of service provided on the other hand. Greater costs must be incurred to achieve higher quality and vice versa. However, the NRA can judge that some DSO expenditures were incurred inefficiently meaning that these costs cannot be recuperated through the tariff. For more information on incentive regulation of distribution grids see for example the chapter of Gómez in the Regulation of the Power Sector book by Pérez-Arriaga (2013). A recent detailed description of incentive regulation of electricity network companies can also be found in the first two chapters of the book by Meeus and Glachant (2018). In the first chapter, Rious and Rossetto (2018a) describe the history of incentive regulation in the British energy sector which was a front-runner in this respect. In the second chapter, Rious and Rossetto (2018b) discuss the implementation of monopoly regulation in Continental Europe. They explain that the choice of the best regulatory tools depends on the characteristics of the specific tasks of the regulated company and is constrained by the competency and resources of regulators.

The (simplified) cost-recovery process occurs as follows. First, it is the NRA that determines the allowed revenue for x amount of years, the regulatory period.[8] Then the tariffs are set by the NRA, possibly jointly with the DSO, anticipating future usage of the network and aiming to recover exactly the allowed revenue from the consumers. Imagine, for example, that the NRA decides that in the next years a DSO should be allowed to recover €1000 per year through access charges, the network tariffs are volumetric (€/kWh) and the expected electricity volume consumed by its connected consumer is 20,000 kWh per year. In that case, the network tariff for the next year should be set at 0.05 €/kWh. However, when checking the real consumption after the year has passed, it could be that the actual consumption was higher, meaning the DSO recuperated too much money, or lower, meaning the DSO

[7] The DSO can own the distribution network assets. Alternatively, these assets can also be owned by third parties (often municipalities) but managed by the DSO. In some jurisdictions the DSO is referred to as the Distribution Network Operator (DNO).
[8] Usually the duration of the regulatory period lies between 3 and 8 years.

did not recuperate enough money. In the former case, the DSO will have to give a rebate to its consumers the next time tariffs are set, in the latter case, the DSO will be allowed to set tariff slightly higher the next time in order to recuperate the missing money. This example suggests that the DSO is indifferent about the tariff setting as they cannot keep more money than the allowed revenue which is set independent of the tariffs. However, this is only true if the tariff recovers the investment costs of the past. To the extent that the tariffs also influence the need for grid investment in the future, the future allowed revenue cannot be completely decoupled from the tariff design.

So, how can the distribution network tariff be designed in the most cost-efficient way while making sure that all grid costs are recovered? In theory, the best way to design such minimal distortive charges is by applying Ramsey pricing. With this approach, the residual or sunk grid costs, the part of the grid costs not recuperated by purely cost-reflective charges, are assigned to consumers according to their elasticity to price. Inverse proportionality is followed; this means that a higher proportion of the residual network costs are allocated to those consumers who change their consumption behaviour the least in response to price changes. As such, the way the total grid costs are recuperated modifies as little as possible the optimal outcome compared to when consumer decisions are subjected solely to cost-reflective charges.

In **Chapter 2 of this thesis**, the relative performance of different tariff designs other than Ramsey pricing is shown in terms of cost-efficiency and distributional effects among consumers under the assumption that all grid costs are sunk. Four different states of the world differentiated by the investment cost of DER technology, in this case solar PV and batteries, are tested and find that the introduced distortions by the different tariff designs are very sensitive to the costs of DER technology.

Although cost-efficient, there is a critical issue with Ramsey pricing. Namely, it is often perceived as unfair as it discriminates users on the basis of their elasticity to prices (see e.g. Neuteleers et al. (2017)).[9] For example, network tariffs can be designed as such that two consumers who share the same load profile but have a different willingness to pay for electricity, pay a different share of the residual grid costs.[10] As mentioned above, the lower the elasticity, the higher the contribution to the residual grid costs. In the case of network tariffs, consumers with very low elasticity and thus bearing most of the residual costs could be passive consumers with little possibilities other than the grid to be supplied from electricity. Besides, to implement Ramsey pricing the price-elasticity of the different consumers needs to be estimated, something which is not easy to do. Therefore, strictly applying Ramsey pricing

[9] It must be added that unfair does not does imply unlawful.
[10] With the same load profile is meant that they consume the same amount of electricity at the same time.

is unattainable in practice, leading us to the third principle of distribution network tariff design: fairness.

3.3 Fairness

The main reason fairness is a principle of network pricing and not of, for example, the pricing of your sunglasses is the fact that network charges constitute a significant chunk of the cost of electricity which is considered a basic service to which everybody should have access. The notion of fairness is broad and needs more explanation, in this text fairness encompasses distributional issues (inflexibility, affordability and non-discrimination), transparency (simple and predictable) and last but not least, graduality.[11] In what follows, we describe the concepts one by one. Then we go over to the practical implication for network tariff design. Unavoidably, there will be a trade-off between fairness and cost-efficiency when designing tariffs. Distribution network tariffs are in that sense no different than all practical pricing systems for basic needs.

Regarding inflexibility, is using electricity at a certain time always a real choice? Not really, some electricity usage is rather inflexible. In that context, Bunzl (2010) uses the example of a hospital emergency room. It is not considered fair to charge higher network tariffs, even though cost-reflective, at times when consumers do not have a real choice whether to consume or not.

Besides some electricity usage being rather inflexible, there is also an issue with affordability. As mentioned, electricity is considered a basic need. Some household simply cannot afford to pay the 'real price' of their electricity usage. It would be deemed unacceptable to cut these consumers off. It could be argued that it is not unreasonable to include a 'usage tag' for different needs: basic needs such as heating versus luxury needs such as the charging of your electric car. Such pricing scheme is however not cost-efficient as different consumers would see a different price for a commodity with possibly the same cost. Also, such a system would be hard to implement. In some cases, it will be opted to supply vulnerable consumers with a cheaper tariff than the 'real price'. This will unavoidably lead to inefficiencies as described in the previous subsection. There are other methods to obtain a similar goal in a more efficient manner, e.g. by exposing consumers to the 'real price' but at the same time offer them a fixed sum as a rebate on the total electricity bill. As such the consumer incentives are not distorted while electricity remains affordable.

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[11] In this context, fairness is often used as a synonym of public acceptability or equity. These terms do not imply exactly the same; equity can be defined as a (moral/ethical) principle, fairness as a perception (of a process or a decision) and acceptance as an evaluation (outcome) that someone judges based on his/her subjective and selective assessment. These definitions were provided by Eva Schmid, a participant of the FSR online course on network tariff design and network codes for consumers, prosumers and energy communities.

Third, non-discriminatory. It is deemed fair that one is charged the same amount for using the same good or service, regardless of the purpose for which it is used or any characterizations of the consumers. At first sight, there seems to be a contradiction between the having non-discriminatory tariffs and affordability. Indeed, when certain consumer classes such as the vulnerable consumers have a cheaper network tariff for reasons of affordability, the tariff is indeed discriminatory. However, in some context, such practice can be regarded as fair.

Further, a network tariff should be simple as people have a limited amount of time. An overly complex tariff, even though cost-efficient, might take too much time for the consumer to understand it properly. Such practices lead to high transaction costs (in standard economics terminology) and frustration. When using a service or consuming a good, consumers want to know how much this action will end up costing them. Network tariff pricing should be predictable. Otherwise, a strong inconvenience for consumers can result.

Finally, this text talks about redesigning tariffs to deal with evolutions at the consumer and network side. Redesigning implies that we do not start from scratch: there is a tariff in place, and consumers can perceive changes in what they pay for the network (in the extreme case: 'bill shocks') unfair. In some cases, (passive) consumers can see their electricity bill increase strongly without changing their consumption; others could have invested in DER, e.g. a solar panel, basing their business case partly on that network tariff regime in place. Changing the tariff could render their investment, when already irreversible, loss-making. Neuteleers et al. (2017) describe that a price increase is acceptable if the underlying costs for that product have increased.[12] Contrarily, using excess demand (e.g. scarcity because of weather conditions) or an increase in monopoly power (e.g. single seller in a particular community) to raise prices is perceived strongly unfair.

In **Chapter 3 of this thesis**, it is demonstrated that with active consumers reacting to the way the grid is priced, taking fairness into account when redesigning the distribution network tariff can have a cost in terms of cost-efficiency. The proxy used for fairness in the paper is the increase in the network charges paid by passive consumers (e.g. consumers who do not have the financial means to invest in DER) due to actions of active consumers reacting to the way the network charges are designed; the larger the increase, the more unfair a network tariff is perceived. It is shown that results are sensitive to the grid cost structure, i.e. whether in a network most of the grid investments still have to be made

[12] Neuteleers et al. (2017) adds that at the same time, people deem it acceptable that the price stays the same if costs decrease. Both refer to the entitlements of the seller: changing costs should not decrease the firm's reference profits.

or whether most grid costs are sunk. If the proportion of sunk grid costs is high and the tariff design options are limited, it is an almost impossible task for the regulator to recover all grid costs in a cost-efficient way while limiting the distributional impact at the same time. More creative solutions might be needed to attain such goal; examples are differentiated fixed charges or specific low-income programmes. Another option could be to recover the sunk grid costs through general taxation instead of the electricity bill as also discussed in the MIT Energy Initiative (2016).

Recently, the academic literature and debate focused on fairness between active and passive domestic consumers. However, also other important debates concerning grid cost allocation are gaining momentum: the cost allocation between grid users (residential and smaller/larger industrial/commercial businesses) connected to different voltage levels of the transmission and the distribution network and, related, the cost allocation between consumption and production connected to the same network or even voltage level.

First, the cost allocation between voltage levels. Historically, electricity flowed from the high voltage levels all the way down. As a result, it was acceptable that transmission grid users did not pay for distribution while distribution grid users paid for transmission too. Also, within the distribution grid this cascading practice is applied with domestic grid users paying more than industrial clients connected to higher voltage distribution networks, see for example Brandstätt et al. (2015) explaining the German cascading principle. To the extent that the direction of the flows is changing, also this cascading principle could be challenged from a fairness (and a cost-efficiency) point of view. In some cases, for example in Germany in 2012-2013, certain large electricity users, often connected to higher voltage levels, were exempted from paying any network charges at all. Very recently the European Commission concluded that fully exempting certain large users from these charges was against EU State aid rules as it is an unfair advantage over firms in other countries and increases the financial burden on other electricity users (European Commission, 2018).

Second, the cost allocation between consumption and production units. In transmission, this discussion goes back far in time. Ruester et al. (2012) describe that many countries simply tend to socialize transmission costs among consumers and that this is in part due to historical reasons.[13] Only a few countries applied (non-significant) network charges to generation, a so-called G-component. For more recent data on the transmission network charges, please consult ENTSO-E (2017a) or the Sections

[13] Ruester et al. (2012) explain that in the past, when transmission was still part of national vertically integrated utilities, transmission costs were in general simply socialized over all consumers since under cost-of-service regulation and centralized planning it does not make sense to charge generators anything.

3.3 and 3.4 of the report by Glachant et al. (2017). In distribution networks, only since recently significant (mostly renewable) generation capacity is getting connected to the network where before the large majority of grid users were solely consuming electricity. Also, prosumers, grid users withdrawing electricity at times while injecting electricity at other times, and large storage facilities become more common distribution grid users. The advent of these new players further complicates cost allocation between consumption and production. In this regard the principle of 'symmetrical network charges' as brought forward by Pérez-Arriaga et al. (2017a) is relevant. What is meant with symmetrical tariffs is that an electricity injection in the network at a given time and place should be compensated at the same rate that is charged for withdrawal at the same time and place. This is an important guiding principle, and we expect this discussion to be an area of future research.

4. **The current challenge**

Until recently, consumers connected to the distribution network were not able to react strongly to price signals; therefore, there was not much gain to be made by cost-reflective tariffs. The fact that volumetric charges are only slightly cost-reflective was less of an issue. The distribution network tariff had a rather allocative objective, recuperating all the network costs in an acceptable way, instead of 'guiding' consumers to efficient grid behaviour. Also, volumetric distribution network charges were deemed fair as high-usage and thus higher network contributions correlated rather well with more affluent consumers. Further, such tariffs are predictable, simple and most meters were only capable of measuring the cumulated consumed volume thus making more advanced tariffs hard to implement.

However, times are changing, and technological evolutions at the consumer-side are challenging the use of volumetric network charges. Specifically, volumetric charges with net-metering, implying that a consumer will be charged for the net consumption from the grid over a certain period (e.g. month), are deemed inadequate with the massive deployment of solar PV.

An illustration of the issue: if a consumer consumes 300 kWh a month in her house and has a solar panel installed which generates 200 kWh in that month. The electricity consumption in the house and the generation by the PV panel will not always coincide, but the consumer will have a net consumption from the grid that month of 100 kWh for which she will pay network charges. Thus by installing a PV panel, the consumer lowered her grid charges to 1/3 of what she originally would have paid (100 kWh/300 kWh). However, the consumer still relies on the distribution grid and her peak usage in the evening, the main cost driver of the network if coincident with the system peak usage, will not change much. Thus, the total grid costs do not lower in proportion to the reduced network charges paid by the PV adopter. Actually, this reduction in network charges could make the business case for solar PV more attractive, thus, by the way the network charges are designed the adoption of this technology could be over-incentivised from a purely economic point of view. Also, it would mean that if cost recovery is respected, other consumers, not having installed solar PV would have to contribute more. Note that support for solar PV or energy efficiency can be justified, but it is considered the better practice to provide direct support instead of via network tariffs. (CEER, 2017a) for instance, refers to the Dutch case for the disentanglement of network tariff design and energy efficiency goals. In 2009, fixed network charges were introduced for small electricity and gas users replacing volumetric tariffs. These charges were based on the connection capacity of a household. The consumer now paid less per kWh consumed, but the energy tax (also in €/kWh) was adjusted to compensate for reduced energy efficiency incentives. If more direct support for energy efficiency or renewables is politically sensitive, which is, for instance, more the case in the US, network tariffs could be used for these purposes Kolokathis et al. (2018). However, this is highly controversial among academics (see e.g. the blog post by Davis (2018)).

Next to solar PV, there are also breakthroughs in (stationary) batteries, heat pumps, electric vehicles, smart appliances etc. Consumers can monitor their interaction with the grid through smart meters, and these new controllable technologies can have not only significant effects on the volumes withdrawn from the network (in kWh) but also on the timing of withdrawn or injection, i.e. the network capacity utilised at each moment by a consumer (in kW).

There are empirical studies and pilots which confirm that consumers do react to (distribution) tariffs by changing their consumption or investing in PV panels. For example, Faruqui et al. (2017) carry out a meta-analysis of the results from 63 pilots containing a total of 337 electricity pricing treatments in nine countries located on four continents. They focus on the complete electricity bill, not solely the distribution network tariff and show that customers do respond to price signals and that these responses are predictable. More specifically, they show that consumers do reduce their peak load in response to higher peak to off-peak price ratios. Another interesting work in this regard is the paper by Gautier and Jacqmin (2018). In their study, they focus on the differences between the distribution network tariffs in place for different municipalities within Wallonia, the Southern region of Belgium, and its effect on solar PV adoption. Applying an econometric model, they find that one euro cent per kWh of tariffs increase leads to, all else equal, an increase of around 5 % in the number of new PV installations. In short, we are just at the beginning of this consumer-centric revolution, and we can expect that consumers will be able to react more and more to the way the network is priced. Enabled consumer response can create opportunities but also risks regarding cost-efficiency and fairness.

- **Cost-efficiency:** We said that until recently there was not much gain to be made from cost-reflective tariffs as consumers were not able to react strongly to price signals.
  - *Opportunity*: If an adequate cost-reflective tariff is set, consumers can adjust their consumption behaviour in a way that, for example, costly reinforcement can be avoided or postponed. A cost-reflective tariff will result in a benefit for active consumers and an overall lower total system cost.
  - *Risk*: wrong network pricing can have more severe consequences in terms of cost-efficiency as consumers can react stronger to the way the grid is priced. For example, high volumetric network charges with net-metering could over-reward people installing solar PV and therefore overly incentivise the adoption of a technology leading to more of this technology installed than would be optimal from a system point of view.

- **Fairness:** We said that volumetric network charges were perceived fair as high-usage correlated rather well with more affluent consumers.
  - *Opportunity:* If network charges are cost-reflective and consumers react to this tariff design, a reduction of the total cost to satisfy the electricity needs of all consumers could be realised. These gains could be shared with passive consumers thus actually leading to a situation where everyone is better off.
  - *Risk*: If the distribution network tariff is not cost-reflective and distortive, consumers can react to the way the tariff is designed and exploit privately beneficial opportunities without such actions having any system benefit. Such a situation would lead to a fairness issue as other grid users will have to contribute more in order to recuperate all grid costs as illustrated by the net-metering example at the start of this section.

Consumers being able to react to the way the network is priced also has implications regarding the third principle we addressed: cost-recovery. Until recently, with volumetric network charges in place, it was relatively easy to estimate the future consumption and thus to calculate the magnitude of the volumetric network charge needed to recover all the costs. With harder to forecast use of electricity and possibly more advanced network tariffs, the estimation of the tariff which will lead to the recuperation of the efficiently incurred grid costs is a more challenging task. Cost-recovery is also intertwined with the two other principles. The more consumers can actually reduce or increase the network costs due to their change in consumption, being it cost-efficient or not, the harder it becomes to determine what grid costs were efficiently incurred and thus to estimate the allowed revenue for the DSO. Also, political actions aimed at reducing fairness concerns which could result from an inadequate network tariff design could put grid cost recovery in danger.

Now, how to adapt the network tariff to these changing conditions? It can be said that there are three dimensions of distribution network tariff design:

- the what, the structure or format (in €/kWh, €/kW, and/or €/connection);
- the when of electricity generation and consumption (temporal granularity);
- the where of electricity generation and consumption (locational granularity).

These three dimensions can be seen as the tools that can be used to construct a tariff. There are many possible variations within the tariff structures, and the boundary between the different structures is not strict. Below in Table 1, several examples of more simple or advanced tariffs, categorised by tariff structure but with different implementation or temporal granularity are summarised. Please note that also combinations (so-called multi-part tariffs) can be opted for.

Table 1: Examples of implementations and different tariff structures with possible different temporal granularity

Volumetric	Capacity	Fixed
With net-metering	The connection (kVA)	Per connection
Gross withdrawal or bi-directional charges	The max capacity over a period (ex-ante determined or ex-post measured)	Per income of household
Increasing (progressive) or decreasing block pricing	Multiple measured max capacity in different periods ≈ Time-of-use pricing	Per square meters of property
Time-of-use pricing	…	…
…		

Another innovation in distribution network tariff design is Smart Connection Arrangements (SCA). Anaya and Pollitt (2015) describe that an SCA implies that grid users, mainly new connections for distributed generation such as a windmill connected to the distribution network, have interruptible connections rather than the conventional non-interruptible or firm connections. The idea is that grid users engaging in an SCA would have to pay fewer grid charges as they allow the DSO to curtail their connection a pre-determined number of times. By limiting these connections at times of possible network congestion, the DSO can avoid or postpone reinforcement. Thus a win-win situation results. Anaya and Pollitt (2015) show that the smart connection option is by far the best option when compared with Business as Usual (BAU) connections. Hadush and Meeus (2018) discuss another alternative to deal with congestion in distribution grids, namely tradable access rights between TSOs and DSOs or other borders in the distribution grid.

5. **What is the EU debate about?**

On 30 November 2016, the European Commission presented a new package of measures with the goal of providing the legislative framework needed to facilitate the clean energy transition – and thereby taking a significant step towards the creation of the Energy Union. This package was called the EU Clean Energy Package (CEP), also known as the Winter Package. As expected, distribution network tariffs are covered by the CEP. In Article 16(10) of the proposal by the EC for the Regulation on the Internal Market for Electricity (IME) it is said that (EC, 2016a):

'*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 transparent, take into account the need for network security and flexibility and reflect actual costs incurred insofar as they correspond to those of an efficient and structurally comparable network operator and are applied in a non-discriminatory manner. In particular, they shall be applied in a way which does not discriminate between production connected at the distribution level and production connected at the transmission level, either positively or negatively. They shall not discriminate against energy storage and shall not create disincentives for participation in demand response. Without prejudice to paragraph 3, those charges shall not be distance-related*.[14]'

Also, the CEP brings new proposals for distribution tariffs harmonization and links them to the transmission tariffs harmonization process. While the harmonization of transmission tariffs has been debated in the past (see e.g. ECN et al. (2017) and Glachant et al. (2017)), the harmonisation of distribution tariffs has not had a similar focus over the last years. The EC argues that harmonising the principles for distribution tariffs will help the establishment of a well-functioning internal market and limit its cross-border distortions. More precisely, the EC (2016a) states that widely divergent distribution tariff regimes may affect the development of the internal market as they affect the conditions under which Renewable Energy Sources (RES) or other generation resources can access the grid and participate in the national and cross-border energy markets.

In the CEP, the EC proposal for the Regulation on the IME suggested new rules for the harmonisation of the distribution tariffs (EC, 2016a). Concretely, in Article 55(1)(k) the harmonization of distribution tariffs is added to the areas to be covered by Network Codes:

[14] Paragraph 3: ''*Where appropriate, the level of the tariffs applied to producers and/or consumers shall provide locational signals at Union level, and take into account the amount of network losses and congestion caused, and investment costs for infrastructure*.''

Article 55: '1. The Commission is empowered to adopt delegated acts in accordance with Article 63 concerning the establishment of network codes in the following areas:

…

(k) harmonised transmission and ***distribution tariff structures*** *and* ***connection charges*** *including locational signals and inter-transmission system operator compensation rules;'*

….

Further, for the progressive convergence of transmission and distribution tariff methodologies, Art. 16 (9) of the EC proposal for the Regulation on the IME states that ACER shall provide a recommendation addressed to NRAs within three months of the Regulation entering into force (EC, 2016a). Several questions should be addressed in the recommendation such as the ratio of tariffs applied to producers and to consumers, temporal and locational signals and the relationship between transmission and distribution tariffs.

In the meantime, the Council of the European Union published a provisional position on this proposal which forms the basis for the negotiations with the European Parliament (EU Council, 2017). It is important to note that in this proposal the adoption of a network code for distribution network tariffs has been removed. Plus, it is stated that within three months of entering into force of the Regulation, '*the Agency shall provide a best practice report on transmission and distribution tariff methodologies while leaving sufficient room to take national specificities into account.*' A best practise report is expected to send a weaker signal for harmonisation than recommendations.

Like the Council, not everyone agrees with drafting a network code for the harmonisation of distribution network tariffs. CEER (2017b) clearly opposes, stating: '*The impact assessment published by the Commission* (EC, 2016b) *does not provide any justification that the benefits of further harmonisation of tariffs would outweigh the costs for implementation. We consider that harmonisation of both transmission and distribution tariffs at European level could be inefficient and not lead to the right outcomes for European consumers. NRAs are best placed to consider the best regulatory choices within the European framework. Implementing a "one size fits all" approach risks inefficient incentives for network use on a Member State level, particularly with the emergence of more local energy models.*' EDSO, one of the main organisations representing the DSOs in Europe, agrees with CEER on this point by stating: '*Network and geographical characteristics are very diverse throughout Europe, leading to diverging best practices in terms of network tariffs structures. Network codes do not seem to be the right tool to efficiently enhance distribution tariff structures at European level*.'

Another stakeholder, REScoop (2017), representing energy communities in Europe, provides a more nuanced view about the harmonisation of distribution grid tariff by saying: '*the Electricity Directive should provide national regulators with a duty to ensure that network tariffs for DER are calculated according to an objective and transparent long-term cost benefit analysis (CBA) that takes into account the wide range of benefits of DER to the energy system, society and the environment. To ensure a holistic approach towards such an analysis, the Electricity Directive must provide a definition of DER.'* Finally, BEUC (2017) the consumer voice in Europe, recommends the following: '*Network tariffs should better reflect real use of the grid. They should be redesigned in order to reward flexibility and trigger contribution of ancillary services by consumers who engage in self-generation or demand-side flexibility. However, the redesign of network tariffs must not unduly increase the financial burden of households with a low level of electricity consumption or households living in remote areas.*'

CHAPTER 2: FUTURE-PROOF TARIFF DESIGN: RECOVERING SUNK GRID COSTS IN A WORLD WHERE CONSUMERS ARE PUSHING BACK

Abstract

Traditional analysis of distribution network tariff design assumes a lack of alternatives to grid connection for the fulfilment of consumers' electricity needs. This is radically changing with breakthroughs in two technologies: (1) Photovoltaics (PV) enable domestic and commercial consumers to self-produce energy; (2) Batteries allow consumers and self-producers to gain control over their grid energy and capacity parameters. Contributing to the state of the art, the grid cost recovery problem for the Distribution System Operator (DSO) is modelled as a non-cooperative game between consumers. In this game, the availability and costs of the two named technologies strategically interact with tariff structures. Four states of the world for user's access to technologies are distinguished and three tariff structures are evaluated. The assessed distribution network tariff structures are: energy volumetric charges with net-metering, energy volumetric charges for both injection and withdrawal, and capacity-based charges. Results show that in a state of the world with new technology choices for grid users both efficiency and equity issues can arise when distribution network charges are ill-designed.

JEL classification : C7, D61, L94, L97, Q41, Q42

Keywords: Batteries, optimisation, distribution network tariff design, non-cooperative behaviour, photovoltaics

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1. Introduction

In Europe and the USA there is an observable trend towards volumetric network tariffs (in €/ kWh) being gradually replaced by capacity-based network tariffs (CEER, 2017a; European Commission, 2015a; Hledik, 2015). Especially a volumetric tariff accompanied with net-metering[15], the network tariff design historically in place, is challenged both in the media[16] and in academic circles (e.g. Comello and Reichelstein (2017); Darghouth et al. (2011); Eid et al. (2014) and Pérez-Arriaga et al. (2017a)). Volumetric network charges with net-metering are inefficient as they over-incentivise PV adoption. Namely, under net-metering active consumers installing PV panels see their electricity bill decrease not only because of lesser electricity consumption, but also because of significantly lowered network charges. This is an issue as their costs inflicted on the network do not necessarily change. Net-metering is also perceived unfair; the total network costs need to be recuperated, and therefore passive consumers without PV panels see their electricity bill increase by the network charges that active consumers manage to offset. In this paper, a game-theoretical model is applied to address the following two research questions:

(1) Do capacity-based network charges solve the efficiency problems experienced with volumetric charges with net-metering?

(2) Do capacity-based network charges allow active consumers, investing in PV and batteries when incentivised, to be better off at the expense of passive, sometimes vulnerable, consumers?

It is shown that the answers to both research questions depend on the technology cost scenario. The answers are further nuanced as a result of the chosen modelling approach. Conventionally, papers analysing network tariff design (e.g. Borenstein (2016); Brown et al. (2015); Hledik and Greenstein (2016a) and Simshauser (2016)) discuss qualitatively or exogenously consider the interaction between the adoption of in Distributed Energy Resources (DER) and network tariff design. In this paper, the grid cost recovery problem for the DSO is represented as a non-cooperative game between consumers. In this game, active consumers can strategically opt out of part of the grid use by investing in DER. Their investment in DER is endogenous and differs depending on the grid tariff design in place. By opting out of part of the grid use, active consumers shift grid costs to passive consumers and at the same time compete to reallocate the grid costs to one another. The added insight obtained from this modelling

[15] Net-metering is the practice by which consumers are accounted solely for their net electricity consumption from the grid when distribution charges are determined.

[16] E.g.: Pyper, Julia. 2015. "Ditching Net Metering Is in the 'Best Interest' of Solar, Say MIT Economists." *Greentech Media*. Accessed on 15/04/2017. www.greentechmedia.com/articles/read/MIT-Economists-Say-We-Should-Ditch-Net-Metering

approach is that it considers uncoordinated investment decisions by active consumers. Uncoordinated consumer decisions can result in an overall efficiency loss when price signals, in this case network charges, are not designed properly.

The reallocation effect is not captured by Borenstein (2016); Brown et al. (2015); Hledik and Greenstein (2016a) and Simshauser (2016). Hledik and Greenstein (2016a) and Simshauser (2016) argue that capacity-based charges (in € per kilowatt (kW) peak) are an attractive option to replace volumetric network tariffs. These authors contend that capacity-based grid charges would avoid inequitable bill increase and allow for better cost reflection. However, not everyone agrees. Borenstein (2016) reasons that challenges arise as a significant part of the network costs are residual or sunk costs.[17] He states that there is no clear guidance from economic theory on how to allocate such costs as cost causation is unclear. He argues that almost surely a combination of higher fixed charges and an adder to time-varying volumetric charges would be the least bad policy option. Similarly, Brown et al. (2015) do not identify any single best option for the recovery of residual costs. They state that the recovery of residual costs through fixed charges would result from prioritising the principle of efficient prices.

Typically, models with a similar mathematical structure as in this paper have been used to analyse imperfect competition in (power) markets (see e.g. Gabriel et al. (2012); Gabriel and Leuthold (2010)). In such equilibrium problems, the numerous optimisation problems are connected, e.g. via either an equilibrium constraint (supply equals demand) or the inverse-demand function in each agent's objective function. In the past, there was no need to apply a similar modelling approach when studying distribution network charges as consumers had little means to react strategically to the tariffs imposed on them. However, this assumption does not hold true anymore. This is mainly due to the sharply decreasing costs of two technologies: photovoltaics (PV) and batteries (see e.g. Lazard (2016b, 2016a); MIT Energy Initiative (2016a) and RMI (2015)). These two technologies allow grid users to react to the way electricity supplied by the grid is priced. PV enables consumers to self-produce energy and lowers the net energy need from the grid, while batteries enable self-producers to regulate both their grid energy flows and capacity parameters. Suddenly, network tariff design has become a concern. As described by Pollitt (2016): “The rise of distributed energy resources (DERs) offers increased opportunities to exploit the existing system of network charges in ways that were not originally envisaged.“ If network tariff design does not anticipate the new sets of actions available to consumers, grid cost recovery for the DSO and a fair allocation of costs are at risk.

[17] This is especially true in networks experiencing low or no load growth for which costs occurred in the past to dimension distribution grids to the expected peak capacity needed in the local system (Pérez-Arriaga and Bharatkumar, 2014).

In this new setup, instead of an equilibrium constraint or inverse-demand functions, the optimisation problems are linked by introducing a 'grid cost recovery (equilibrium) constraint'. More precisely, the stylised game-theoretical optimisation model presented in this work consists of linked individual optimisation problems of consumers which are minimising their cost to satisfy their electricity demand. The individual optimisation problems are linked with a 'grid cost recovery constraint', stating that the total network charges paid by all consumers should equal the total network costs to be recovered by the DSO. By doing so, the optimisation problem of one consumer is impacted by decisions of other consumers. An equilibrium is found when the grid costs are recovered by the DSO and the consumers have no incentive anymore to change their reaction to the network tariff.

Three illustrations have inspired this paper: Zugno et al. (2013), Momber et al. (2016) and Saguan and Meeus (2014). Zugno et al. (2013) build up a game between an electricity retailer and consumers who are reacting to the electricity price set by the retailer by shifting their load. Similarly, Momber et al. (2016) model an aggregator which takes decisions on optimal bidding strategies in the electricity market and on the retail price, while being subjected to decisions of cost-minimising electric vehicle (EV) owners. Saguan and Meeus (2014) introduce a competitive equilibrium model to calculate the cost of renewable energy in four states of the world, i.e. with renewable trade versus without renewable trade, and with national transmission planning versus international cooperation on transmission planning.

The remaining parts of the paper are structured as follows. In Section 2 the methodology of the paper is highlighted. In Section 3, the proposed model is described in detail. In Section 4, the setup of the numerical example, data and the technology cost scenario matrix is presented. The results are discussed in Section 5. Lastly, a conclusion is formulated and possibilities for future work are summarised.

2. **Methodology: three tariff structures, two metrics and four states of the world**

Three different tariff structures (TS) are analysed:[18]

- **TS1**: Volumetric network charges with net-metering.
- **TS2**: Volumetric network charges without net-metering, bi-directional metering is applied. Network charges are paid for both each kWh withdrawn and injected and at the same rate.

[18] No time or locational variation in the rates is assumed, solely the 'structure or format' of the tariffs differ. See Pérez-Arriaga et al. (2017a) for a discussion more focussed on the time and locational granularity of distribution tariffs.

- **TS3**: Capacity-based charges based on the observed individual peak power withdrawal or injection from the grid over a certain duration (e.g. hourly or quarter-hourly).[19]

The outcomes of the tariff structures are benchmarked with the application of fixed network charges. Fixed network charges serve as a reference as they do not distort the volumetric (€/kWh) and capacity (€/kW) price signal and grid costs are assumed sunk.[20] Going entirely off-grid is not considered an option for consumers in this paper. This is not a strong simplification as Hittinger and Siddiqui (2017) find that the financial case for grid defection is limited or non-existent given current costs and prevalent policies. Two metrics are introduced to quantify the results. Firstly, a proxy for (in)efficiency is used to quantify the increase of the total system cost as compared to the reference case with fixed network charges. Secondly, a proxy for equity is introduced by looking at the allocation of the sunk costs for different consumer's types under the different tariff structures.

A 'Technology costs matrix', with four extreme states of the world, is set up to analyse the impact of dropping investment costs in PV and batteries (Lazard (2016b, 2016a); MIT Energy Initiative (2016a) and RMI (2015)). This matrix is displayed in Table 2. Each state of the world represents a unique combination of costs related to the technologies.

Table 2: Matrix representation of the four states of the world related to technology costs

Technology cost matrix		Capital cost PV (€/kW$_p$)	
		High	Low
Capital cost batteries (€/kWh)	High	The past?	Today?
	Low	Unlikely?	The future?

In the past, a consumer did not have much means to react to electricity prices as DERs were too expensive to invest in. Today, residential PV becomes more and more competitive with electricity supplied from the central grid, while batteries are still relatively expensive. Nevertheless, a scenario with low PV and battery investment costs can be expected to materialise soon as pointed out by many studies (Lazard (2016b, 2016a); MIT Energy Initiative (2016a) and RMI (2015)). As an illustration, in the Utility of the Future Study by the MIT Energy Initiative (2016a) it is quoted that PV developers and industry analysts expect the installed cost of utility-scale PV to fall below $1000 per kW before the end

[19] Currently, in most cases, low voltage users are being billed by the contracted capacity, and not through an observed maximum capacity. However, with the envisioned mass roll-out of smart meters accurate maximum capacity charging of network users will be enabled (Eid et al., 2014).

[20] Other quantitative work on network tariff design (Brown et al., 2015; Hledik and Greenstein, 2016; Simshauser, 2016) assume 'revenue neutrality' for the network operator when assessing different tariff structures with a consumer database. Assuming revenue neutrality is from a modelling perspective not different than assuming grid costs are sunk.

of this decade, and that one major US automaker projects that lithium-ion battery cell costs will drop below $100 per kWh by 2022— an order of magnitude less costly than 2010 costs.

3. **Model: approach and mathematical formulation**

In this Section, the modelling approach is presented. This Section is split up into three Subsections. The first subsection explains the high-level functioning of the model shortly. Also, the limitations of the modelling approach are discussed. A second Subsection describes the mathematical formulation of the model. A third subsection explains the solution method applied.

3.1 Modelling approach

The stylised game-theoretical optimisation model consists of several individual optimisation problems which are linked by an equality constraint that needs to be satisfied, the so-called 'grid cost recovery constraint' in this context. The optimisation problem of one consumer is impacted by decisions of other consumers, as all optimisation problems are linked. For example, under volumetric charges with net-metering, if a consumer installs PV, it would mean that the total net volume of electricity requested from the grid is reduced. Consequently, the total amount of network charges paid would reduce. In reaction, the volumetric rate of the network charge must now be increased to allow total cost recovery for the DSO. This rate increase makes it possibly interesting to install additional capacity of PV and so forth. An equilibrium is found when the sunk costs are recovered and the consumers have no incentive anymore to change their reaction to the network tariff.

The formulation is split up into two parts:

- *The grid cost recovery constraint:* This equality represents the cost-allocation problem of a DSO. The sunk grid costs to be recovered by the DSO need to equal the network charges collected from the consumers. The network charges are set perfectly anticipating the reaction of the consumers to these charges.
- *The optimisation problems of individual consumers:* The consumers are split up as active and passive consumers and have the objective to minimise their electricity costs. Active consumers have the possibility to invest in solar PV and batteries, while passive consumers do not. The network charges are the variables linking all individual optimisation problems through the grid cost recovery constraint.

It should be added that this modelling approach has certain limitations. Firstly, the investment decisions by the consumers and the setting of the network tariffs are treated as a 'single-shot problem', instead of multi-stage. Further, no stochasticity in the parameters is accounted for. Returns for consumers from investment in DER might be uncertain. Also, eventual future decline in DER investment costs could be anticipated by consumers; there is an option value for waiting. An example of a paper tackling these issues is the risk-constrained multi-stage stochastic programming model proposed by Baringo and Conejo (2013). Addressing these limitations in this context could be a line for further research. Alternatively, an agent-based modelling approach could be used, see e.g. Saguan et al. (2006) for a discussion between equilibrium and agent-based modelling to study imperfect competition in electricity markets and Weidlich and Veit (2008) for a critical survey of agent-based wholesale electricity market models.

3.2 Mathematical formulation[21]

In this Subsection, the two parts of the mathematical formulation and how they are connected are described in more detail. Firstly, the grid cost recovery constraint of the DSO is described. Secondly, the optimisation problem of the individual consumers connected to the distribution network is described.

(a) The grid cost recovery constraint

The cost recovery constraint of the simplified DSO is displayed by Equation 1. The equation states that the total network costs to be recovered have to equal to the total network charges collected by the DSO to recover their costs.[22] This equation should hold while minimising the coefficient of the volumetric (vnt) or capacity-based (cnt) network tariff. By minimising the coefficients of the network charges, the increase in network cost reallocated to passive consumers, not installing DER, are most limited. By assuming grid costs to be sunk, the change in aggregated consumption/injection behaviour of the active consumers connected to the distribution grid does not have an influence on the total network costs to be recovered. In other words, costs occurred in the past, anticipating future usage. The sunk cost assumption will be relaxed in future work. To ensure full cost recovery for the DSO, the coefficient of the network tariff will increase in almost all cases when having consumers installing DER when compared to a default situation where all consumers fulfil their electricity needs solely with power from the grid. This increase is minimised by this formulation, while cost recovery is ensured.

The total network charges collected from the consumers are calculated by the right-hand side of the equation. The network charges can be volumetric, capacity-based or fixed charges. α, β and NM

[21] Variables are represented by italic lower case Latin letters, for parameters upper case Latin or lower case Greek letters are used.

[22] For computational reasons, an error margin δ (e.g. 1% of the network costs) is applied, allowing for a limited deficit or excess.

parameterise the different tested tariff structures. Please find an overview of all notations in Appendix A.

$$\text{Network costs} = \sum_i \Big[\mathrm{N_i} * \Big(\underbrace{\alpha * vnt * \sum_t (qw_{t,i} - qi_{t,i} * \mathrm{NM}) * \mathrm{WDT}}_{\text{Volumetric}} + \underbrace{\beta * cnt * qmax_i}_{\text{Capacity}} + \underbrace{(1 - \alpha - \beta) * \mathrm{FNT}}_{\text{Fixed}} \Big) \Big] \quad (1)$$

With minimal vnt or cnt

The parameter $\mathrm{N_i}$ stands for the number of consumers represented by representative consumer i.[23] Representative consumers standing for homogenous groups are used to limit the computational time. The variables set by the grid cost recovery level are vnt the coefficient of the volumetric charge in €/kWh, and cnt the coefficient of the capacity-based charge in €/kW. Depending on the tariff structure, a coefficient can be forced equal to 0. Further, $qw_{t,i}$ represents the energy withdrawn from the grid at time step t by consumer i, $qi_{t,i}$ the energy injected into the grid at time step t by consumer i. WDT is a scaling factor for the annualization of all costs. $qmax_i$ is the peak use of the network by consumer i. It is a proxy for the maximum capacity required to service consumer i's network requirements. Finally, FNT is a parameter and represents the fixed network charge per connection, uniform over all consumers.

In Table 3 the different network tariff structures and their parameter settings are displayed. In cases where TS1 or TS2 are applied, the second term of the summation on the right-hand side of Equation 1 will equal zero as cnt is forced to zero. The third term of the equation, representing fixed network charges, will also be zero as α equals 1. By setting parameter NM to 1 the power withdrawn from the grid ($qw_{t,i}$) is netted out with the power injected into the grid ($qi_{t,i}$), representing net-metering. If NM is set to -1, no netting out takes place, and both power withdrawal and injection are subjected to network charge vnt. When applying TS3 vnt will be forced to zero and again the third term of the summation will equal zero as β is set to 1. Lastly, when fixed network charges are applied the first two terms of the summation will equal zero as α and β are set equal to zero. Please note that other implementations can be tested with this model, for example a 3-part network tariffs with a volumetric, a capacity and a fixed component. This can be done by setting α and β to a value between 0 and 1, with the sum of α and β being less (3-part tariff) or equal to 1 (2-part tariff, no fixed component). In this work, we chose to report the more extreme implementations.

[23] Alternatively, proportions of consumer groups relative to all consumers connected could be used. In that case, the total network costs are scaled accordingly.

Table 3: The different network tariff options - description and parameter settings for Equation 1

	Network tariff structure	Description	α Volumetric	β Capacity	NM Net-metering
TS1	Volumetric charges with net metering	Only the net consumption is used to calculate the network charges to be paid by the consumer.	1	0	1
TS2	Volumetric charges without net metering	The sum of the withdrawal and injection into the grid is used to calculate the network charges paid by the consumer. Charge for withdrawal and injection is equal.	1	0	-1
TS3	Capacity-based charge	The withdrawal or injection peak (in kW) measured over the length of the full-time horizon is used to calculate the network charges paid by the consumer.	0	1	0
Ref.	Fixed network charges	The fixed charge is uniform and equal to the sunk cost to be recovered divided by the number of consumers.	0	0	0

(b) Optimisation problem of consumers

The consumer's optimisation problem is a linear programme (LP). The objective function is presented by Equation 2. Each consumer minimises its (annualised) total cost of servicing its electricity requirements. The total costs consist of four parts; the energy costs, the network charges and other charges that constitute the electricity bill, and the investments costs in DER technology.[24] In the case where a consumer is passive, the investment costs will always be zero. For an active consumer, investment costs might be positive. This will be the case if additional investment costs are lower than the decrease in the electricity bill due to the DER investment. With 'other charges', e.g. RES levies are meant. It is assumed that these charges are paid as a fixed fee, and do not influence the optimisation problem of an individual consumer.

$$\text{Minimise } \; energy\ costs_i + network\ charges_i + other\ charges + investment\ costs_i \tag{2}$$

With:

$$energy\ costs_i = \sum_t \left(qw_{t,i} * \mathrm{EBP_t} - qi_{t,i} * \mathrm{ESP_t}\right) * \mathrm{WDT} \tag{3}$$

$$network\ charges_i = \sum_t (qw_{t,i} - qi_{t,i} * \mathrm{NM}) * vnt * \mathrm{WDT} + qmax_i * cnt + (1 - \alpha - \beta) * \mathrm{FNT} \tag{4}$$

$$investment\ costs_i = is_i * \mathrm{ICS} * \mathrm{AFS} + ib_i * \mathrm{ICB} * \mathrm{AFB} \tag{5}$$

Equation 3 describes the calculation of the energy cost. $\mathrm{EBP_t}$ represents the price paid by a consumer for withdrawing one kWh of electricity at time step t from the grid, excluding the network or other charges. $\mathrm{EBP_t}$ can be thought of as the wholesale electricity price plus a retail margin. $\mathrm{ESP_t}$ stands for the price received for injecting one kWh of electricity into the grid. Depending on the country context $\mathrm{ESP_t}$ may be labelled the feed-in tariff, again excluding possible network other charges. The energy costs are annualised using a scaling factor WDT.

[24] No costs for operation or maintenance of DER technology is assumed.

In Equation 4 the network charges paid by consumer i are calculated. Depending on the applied tariff structure, two of the three terms of the summation will be forced to zero. When TS1 or TS2 is applied, only the first term will be greater or equal than zero, in the case of TS3, the second term can be positive and finally when TS4 is applied the third term will be greater than or equal to zero.

The investment costs of DER installed by a consumer are described by Equation 5. Variable is_i represents the capacity of installed solar PV (kWp), and variable ib_i represents the installed battery energy capacity of the battery (kWh). In the case of a passive consumer both is_i and ib_i are forced to zero. Capacities of PV and batteries are represented as continuous variables in this formulation, while in reality there may be only discrete choices. ICS and ICB are the investment costs per kWp solar capacity and kWh battery capacity respectively and AFS and ABS are the annuity factors for both technologies.

Consumers are subjected to a set of constraints, shown by Equations 6-16. Equation 6 represents the demand balance, meaning that demand should equal supply at all moments. $\mathrm{D_{t,i}}$ is the demand of consumer i at time step t.[25] The supply of electricity consists of the summation of electricity withdrawn from the grid, the electricity generated from PV and the energy discharged from the battery, minus the summation of the electricity injected into the grid and the electricity used to charge the battery. It is not possible to buy and sell electricity or discharge and charge the battery simultaneously. As such, $qw_{t,i}$ will be equal to zero if $qi_{t,i}$ is positive and vice-versa and the same holds for $qbout_{t,i}$ and $qbin_{t,i}$.[26] $\mathrm{SY_{t,i}}$ stands for the time-varying PV yield in kWh per KWp PV installed, which depends on the observed irradiation and the efficiency of the PV panel. $qbout_{t,i}$ and $qbin_{t,i}$ are variables standing for the energy output and input respectively of the battery of consumer i at time step t.

$$\mathrm{D_{t,i}} = qw_{t,i} - qi_{t,i} + is_i * \mathrm{SY_{t,i}} + qbout_{t,i} - qbin_{t,i} \quad \forall\, t \tag{6}$$

$$soc_{1,i} = qbin_{1,i} * \mathrm{EFC} * \mathrm{DT} - \ (qbout_{1,i}/\mathrm{EFD}) * \mathrm{DT} + \mathrm{SOC_0} \tag{7}$$

$$soc_{t,i} = qbin_{t,i} * \mathrm{EFC} * \mathrm{DT} - (qbout_{\mathrm{t,i}}/\mathrm{EFD}) * \mathrm{DT} + soc_{t-1,i} * (1 - \mathrm{LR} * \mathrm{DT}) \quad \forall\, t \neq 1 \tag{8}$$

$$soc_{tmax,i} = \mathrm{SOC_0} \tag{9}$$

$$qw_{t,i} + qi_{t,i} \ \leq qmax_i \qquad \forall\, t \tag{10}$$

$$soc_{t,i} \leq ib_i \qquad \forall\, t \tag{11}$$

$$qbout_{t,i} \leq ib_i * \mathrm{BRD} \qquad \forall\, t \tag{12}$$

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[25] In this paper, the household power demand ($\mathrm{D_{t,i}}$) is an exogenous parameter and instead the way the demand is met (grid, solar panel or battery) is an optimised decision for a active consumer. In future work, also the household power demand could be modelled as a variable e.g. by introducing a price sensitivity of demand for electricity as in Van Den Bergh and Bruninx (2015).

[26] Binaries could be introduced to force this. In this paper, the validity of the LP solution is checked ex-post.

$$qbin_{t,i} \leq ib_i * \mathrm{BRC} \qquad \forall\, t \tag{13}$$

$$is_i \leq \mathrm{MS_i} \tag{14}$$

$$ib_i \leq \mathrm{MB_i} \tag{15}$$

$$qw_{t,i}, qi_{t,i}, soc_{t,i}, qbout_{t,i}, qbin_{t,i}, is_i, ib_i, qmax_i \geq 0 \tag{16}$$

Equations 7-9 describe the battery balance. $soc_{\mathrm{t},i}$ stands for the state of charge of the battery of consumer i at time step t, $\mathrm{SOC_0}$ is the initial energy content of the battery, EFC and EFD are the efficiencies of charging and discharging respectively, LR is the leakage rate of the battery and DT is the length of time step as a fraction of an hour. By Equation 10 the peak withdrawal or injection $qmax_i$ over all time steps is determined. Equations 11-13 limit the energy stored, power discharged at a time step and power charged at a time step respectively. The parameters BRD and BRC define the maximum rate of power discharged/charged over the energy capacity of the battery. The capacities of solar and batteries to be installed by a consumer i are capped by Equation 14-15. Equation 16 forces all consumer variables to be non-negative. This formulation of the optimisation problem of a consumer can be considered as a linearised version of a DER sizing problem with possibilities to invest in solar and batteries (See for example: Schittekatte et al. (2016)).

3.3 Solution method: connecting the equilibrium constraint and the individual optimisation problems

All individual consumers are connected to one another through Equation 1. An equilibrium is obtained if this equality holds and none of the consumers, for which the optimisation problems are described by Equations 2-16, has an incentive to adapt their electricity withdrawal and injection pattern from the grid by e.g. by installing more solar panels or using installed batteries in an alternate fashion.

Different methods to solve the linked optimisations problems that are described by Equations 1-16 exist. For example, the problem could be reformulated as a Mathematical Program with Equilibrium Constraints (MPEC) by transforming the equality described by Equation 1 into an upper level (UL) optimisation problem of a bi-level structure. The lower level (LL) problem, in this case the cost minimisation problems of consumers, can be completely recast as also described in Momber et al. (2016). This involves replacing the LL objective function with a set of optimality conditions, combining first-order stationarity with strong duality. Since the LL is linear and thus convex, its recast can be directly included as constraints of the UL. A single level non-linear MPEC would result. The problem can be linearized and reformulated as a Mixed Integer Linear Program (MILP) as for example described in Zugno et al. (2013). The resulting MILP can be solved using commercial off-the-shelf optimisation software. For a complete treatment of different solution methods see Gabriel et al. (2012).

In this paper, a solution is found through the application of an equivalent iterative approach. Depending on the tariff structure applied, the coefficient of the network tariff (vnt or cnt) is tuned until an equilibrium is attained. First, the consumer optimisation problems are solved for an initial value of the network tariff coeffient. Then, the optimised consumer variables, i.e. electricity consumed ($qw_{t,i}$), electricity injected ($qi_{t,i}$) or the peak withdrawal or injection ($qmax_i$), are plugged into Equation 1. If the equality described in Equation 1 holds, an equilibrium is found, if not, the network tariff coefficient is increased. By starting from an initial low value (typically 0) of the network tariff coefficient and incrementally adjusting this value, we find the equilibrium with the minimal network tariff coefficient under which cost recovery for the DSO holds. The flow chart of the algorithm underlying the proposed iterative approach is presented in Figure 7.

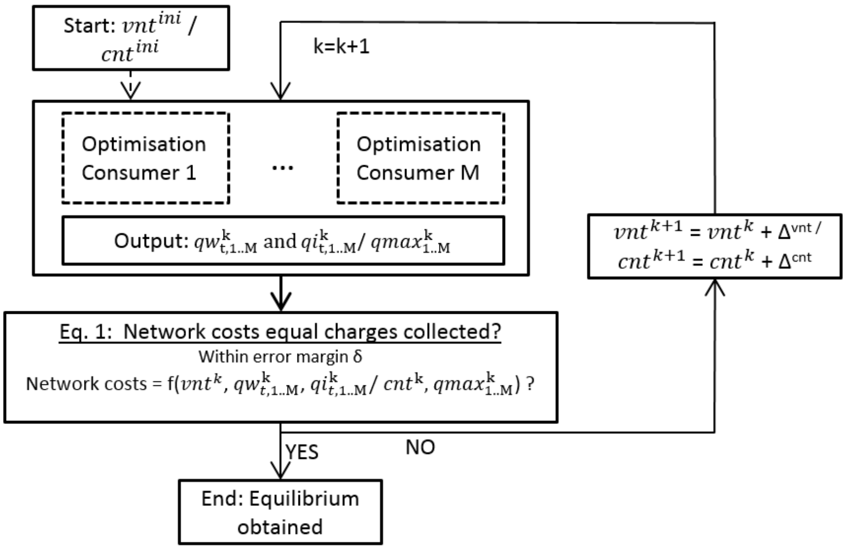

Figure 7: Flow of the calculations to obtain the equilibrium

The computational time needed to obtain a solution is sensitive to the number of unique consumers modelled and the length of the time series used to represent demand and solar yield. The algorithm was formulated and solved in GAMS© BUILD 24.3.3 employing the CPLEX™ 12.6.0 solver on a standard laptop 64-bit with 8 GB of RAM and an Intel© Core™ i7-7600 CPU clocked at 2.8 GHz with 4 threads. The computational time to do one run with the setup and parameters assumed in the numerical examples is on average around one minute.

4. **Numerical example, result metrics and data**

In this Section, firstly, the setup of the numerical example of the model is described. Secondly, the metrics to analyse the results are explained. Thirdly, the parameters which remain constant over all four states of the world are presented. Lastly, the parameters which change over the four states of the world are presented in the form of a technology cost matrix.

4.1 Setup

For simplicity, only two consumer types are modelled: passive and active consumers. Both consumer types have the same original electricity demand from the grid. The sole difference between the two consumer types is that a passive consumer does not have the option to invest in solar PV and batteries, unlike an active consumer, who can opt to invest in DER. Passive consumers are uninformed about the possibility to invest in DER. They either do not have the financial means, are strongly risk averse or simply do not have space. Active consumers are economically rational, i.e. they minimise their costs to meet their electricity demand, and may invest in DER if optimal. Note that the relative proportion of each consumer type is an important parameter for the sensitivity analysis of the results.

4.2 Proxies for efficiency and equity

Depending on the network tariff design in place, active consumers can offset their contribution to the sunk grid costs by investing in DER. In this case, the avoided contribution is reallocated to the passive consumers. However, the total costs to be recovered by the DSO remains the same, only the allocation of the contributions changes.

More precisely, if an active consumer invests in DER technology, its electricity bill reduces due to the avoided energy costs *and/or* network charges. The active consumer will invest in DER if the difference between the reduction of the electricity bill and the DER investment cost is positive. The net reduction in the total electricity cost will be exactly this difference. The passive consumer does not invest in DER technology and will possibly see its electricity costs increase with the sunk costs reallocated by the active consumer. As an illustration, assume one active and one passive consumer. When no one invests in DER, the total electricity cost of all consumers is assumed the same as the consumers are identical. However, when investment in DER is allowed for an active consumer, the respective change in electricity cost can be:

- Change for active consumer = – avoided energy cost by the active consumer – avoided network charges by the active consumer + investment cost in DER
- Change for passive consumer = + avoided network charges by the active consumer

The net aggregated decrease or increase in total electricity cost for the two consumers, referred to as the change in system costs, will be:

- Change system costs = – avoided energy cost by the active consumer + investment cost in DER

Price signals are distorted if the avoided energy cost by the active consumer is lower than the investment cost in DER. This would mean that the system cost increases. In simple terms, 'the losers' (passive consumers) lose more than 'the winners' (active consumers) win. The system cost is calculated in this model as the summation of the objective function of both consumer types weighted with their respective proportion $\mathrm{P_i}$[27]:

$$System\ cost = \sum_i \mathrm{P_i} * (energy\ costs_i + network\ charges_i + other\ charges + investment\ costs_i) \quad (17)$$

Fixed charges do not have a distortive effect in this model. Therefore, as a proxy for efficiency or 'non-distortionary', the system cost for a tariff structure is benchmarked with the system cost when fixed network charges are applied.

A proxy for the equity is introduced by looking at the allocation of the sunk costs to the two consumer's types. It is assumed that in the most equitable situation the sunk costs allocated to both consumer types are the same, as their original electricity demand before installation of DER from the grid is identical. When an active consumer invests in DER part of the sunk costs can be reallocated to the passive consumer. The increase in network charges paid by the passive consumer compared to a situation where both consumer types pay the same fixed network charge serves as a proxy for equity.

4.3 Data

In this stylised example, the consumer demand and yield of a PV panel is represented using a time series of 24-hours with hourly time steps. (See Table 4 (middle and right)). The household demand for electricity shows a small peak in the morning and a stronger peak in the evening. The fulfilment of the demand is a hard constraint. The scaled annualised consumption of a consumer is 6.500 kWh with an annual peak of 3 kW. The relationship between the annual consumption and peak is based on Blank and Gegax (2014).[28] As a reference, in Europe average annual electricity consumption per household in 2015 ranged from 20.000 kWh (Sweden) to 1.400 kWh (Romania) (ACER and CEER, 2016). In the same year, the average electricity consumption per household in the USA was about 10.800 kWh (EIA, 2016). This is a stylised example, and the intention of this paper is not to analyse the impact of tariff design on consumers from a specific region. However, the adopted approach does not exclude such an analysis in the future. In Appendix B.1, the data used for the sensitivity analysis with longer time series and additional demand and solar yield profiles can be found.

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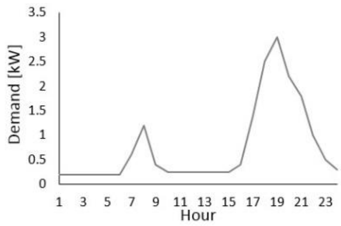
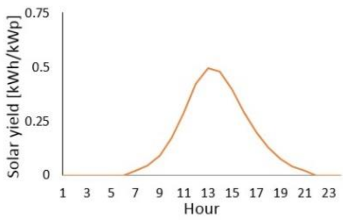
[27] The proportion of a consumer group is defined by the number of consumers represented by a consumer group i ($\mathrm{N_i}$) divided by the total number of consumers connected to the distribution grid (N): $\mathrm{P_i} = \frac{\mathrm{N_i}}{\mathrm{N}}$

[28] In that paper, a regression analysis using a small data sample of households in Alaska is done. The authors find that an increase in monthly energy use by 1,000 kWh would increase maximum monthly demand by 5.5 kW. For the sake of simplicity these findings are extrapolated to a yearly basis.

Table 4: Technical DER Parameters (left), original demand profile (middle) and PV yield profile (right)

Parameters active consumer	Value
Lifetime PV	20 years
Lifetime battery	10 years
Discount factor PV and batteries	5 %
Maximum solar capacity installed	5 kWp
Maximum battery capacity installed	No limit
Efficiency charging & discharging	90 %
Leakage rate	2 %
Price received for electricity injected into the grid (% of wholesale price)	90 %





The yield per kWp PV installed scales up to 1160 kWh per year with the profile shown in Table 3 (right). This level is similar to the average yield in the territory of France (Šúri et al., 2007). As a reference, Formica and Pecht (2017) found a yield of 1300 kWh/kWp for a PV installation in Maryland, USA and Mason (2016) finds that in the UK the average yield equals 960 kWh/kWp. Remaining other relevant parameters are shown in Table 3 (left). Technical DER data is in line with Schittekatte et al. (2016). Finally, the price received for electricity injected into the central grid (also called the 'feed-in tariff') is set to 90 % of the assumed price paid for energy from the grid, excluding network cost or any other charges. The energy price paid for energy relates to the electricity wholesale price and includes a retailer margin.

In Table 5 the composition of the consumer bill is presented. This is the consumer bill in the default setting, i.e. a situation without investment in DER technology by any consumer. If active consumers decide to invest in DER, the relative proportion and absolute values of the bill components will change for both the active and the passive consumer. The consumer bill is based on information from the market monitoring report for electricity and gas retail markets by ACER and CEER (2016). There, the breakdown of the different components of the electricity bill for an average consumer in the EU for the year 2015 is presented. The energy component of electricity prices in the EU in 2015 is estimated to be 37%. In nominal terms, this means a cost of 0.074 €/kWh. Further, 26 % of the bill consisted of network charges, and 13 % are RES and other charges. Finally, an important chunk (25%) of the bill consists of taxes. A value-added tax (VAT), averaging 15%, must be paid and additional (ecological) taxes, averaging 10 %, are raised on the use of power in some countries.

Taxes are integrated into the remaining three components: energy costs, network charges and other charges. The default electricity bill of the consumer consists of 45% energy costs, 35% network charges and 20% other charges. The energy price is set at 0.08 €/kWh consumed.[29] Other charges are recovered

[29] In this work, the energy cost component is modelled exogenously. In cases with high PV adoption this might be a strong simplification as a higher penetration of PV can have a depressing effect on wholesale prices (see e.g. Darghouth et al. (2016)).

through a fixed fee and as such do not interfere with the analysis. However, this is not always the case, as described in Frondel et al. (2015). The question of how to collect such charges, or even whether they belong in the electricity bill at all, is out of the scope of this work. The network charges, the focus of this work, are recovered through the different network tariff designs.

Table 5: Consumer bill for in the default case, when no investment in DER by any consumer is made

Default consumer bill	Proportion of the bill	Cost per year	Recovery
Energy costs	45 %	520 €/year	0.08 €/kWh
Network charges	**35 %**	**404 €/year**	**Through the different network tariffs**
Other charges	20 %	231 €/year	Fixed fee (does not interfere)
Total electricity cost	Average of 0.18 € per kWh delivered	1155 €/year	

The total annual electricity cost, including also the network and other charges, equals 1155 €/year or 0.18 €/kWh delivered. This total cost is near to the average electricity cost for EU households in 2015 that was estimated around 0.21€/kWh (Eurostat, 2016). In the USA the average electricity cost in 2015 for residential use was lower, namely around 0.125€/kWh (EIA, 2016).

Also, a typical consumer bill varies widely over time and, additionally, is country context dependent. The energy cost component in the EU has fallen since 2012, both in nominal terms, from 0.08 to 0.074 €/kWh, and as a percentage of the final consumer bill (ACER and CEER, 2016). The proportion of the energy component of a typical residential electricity bill ranges from 78 % in Malta to solely 14-13 % in Norway and respectively Denmark. Not only the energy component but also the proportion of grid costs in the final bill was found to vary significantly. According to a recent European Commission (2015) report, the share of distribution cost paid by residential users in the EU ranges from 33% to 69% in the final consumer bill. High network charges are not always related to high costs of physical grids, but might be ‘artificially’ inflated. In some countries, costs have been added to the DSO’s costs that are not directly tied to providing an incremental kWh of electricity, e.g. costs for energy efficiency programs and subsidies for installing distributed generation (Borenstein, 2016; European Commission, 2015a; Huijben et al., 2016). In future work, the sensitivity of the results to the country context will be investigated.

4.4 The technology cost matrix

The values of the key parameters for the different states of the technology cost matrix are displayed in Table 6. The numbers for the investment cost in residential PV are coherent with the low and high estimates of prices found in RMI (2015). As the cost of a kWh generated by 1 kWp of PV installed is a function of several parameters, the levelised cost of energy (LCOE) is calculated as an additional reference value.[30] The LCOE for the high and low PV cost scenario is equal to 0.18 €/kWh, and 0.09 €/kWh respectively and these LCOE estimates are in line with the ranges presented in Lazard (2016a). The same sources (Lazard, 2016a; RMI, 2015) are used to obtain the high and low investment cost scenario for lithium-ion battery packs. It is further assumed that the minimum time needed to fully (dis)charge the energy capacity of the battery is one hour. No investment subsidies for PV or batteries are introduced.

Table 6: Main parameter settings of the technology cost matrix

	High technology costs	Low technology costs
Investment cost PV	2600 €/kWp (LCOE: 0.18 €/kWh)	1300 €/kWp (LCOE: 0.09 €/kWh)
Investment cost batteries	600 €/kWh (full (dis)charge in 1 hour)	200 €/kWh (full (dis)charge in 1 hour)

Please note that high investment costs for PV panels could also be interpreted as installing those panels in parts of the world with less solar irradiance and vice-versa. It is harder to come up with a similar interpretation for the battery investment costs. However, the battery is used to shift power demand from the grid in time, a function which could also be provided by demand response.[31]

5. Results and discussion

The results obtained for the different tariff structures are displayed in Figure 8. Figure 8 provides answers to the two research questions posed at the introduction of this paper, namely:

(1) Do capacity-based network charges solve the efficiency problems experienced with volumetric charges with net-metering?

(2) Do capacity-based network charges allow active consumers, investing in PV and batteries when incentivised, to be better off at the expense of passive, sometimes vulnerable, consumers?

The answers to these questions depend on the quadrants in which the graph is split up, representing the four states of the world. The proportion of active consumers, able to invest in PV and batteries when economically rational is assumed to be 50 %. The proportion of active consumers is further discussed when the results are described. For each state of the world, the performance of the three tariff structures for the efficiency proxy is shown on the horizontal axis, and for the equity proxy on the vertical axis. The closer the result of a tariff structure is to the origin along one axis, the better its performance for the metric displayed on the other axis.

[30] In the model applied, the LCOE of PV is a function of the investment cost of the PV panel, lifetime, discount factor, the PV system performance ratio and the solar irradiation profile.
[31] Demand response is not modelled. The cost of demand response would be dependent on the value a consumer attributes to the need of power at a particular time. Such an analysis is out of the scope of this work.

The results shown in the quadrant in Figure 8 are the ones computed for the numerical example. However, the absolute magnitude for the efficiency and equity metric can be overestimated or underestimated dependent on the data and the assumptions made. In Appendix B.2. the results for longer and additional time series for demand and solar yield are shown and discussed briefly. Overall, the intuition behind the results presented in the body of the paper is confirmed. For example, the impact of seasonality in PV yield is highlighted in Appendix B.2. It is illustrated that the dispatch decisions of an active consumer can differ depending on the season and that by using short time series and an average PV yield profile the synergistic value of batteries and PV can be assumed higher. This can lead to slight overestimations in the presented results. On the other hand, it assumed that other charges, e.g. including charges relating to support schemes for RES and other policy costs, are recuperated through a fixed charge, while often these charges are recuperated from consumers with volumetric charges or included in the distribution network tariff (see e.g. Borenstein (2016) or European Commission (2015)). By recuperating these charges with a fixed charge, the allocation of these charges among consumers does not distort consumer decisions. This assumption can lead to slight underestimations in the presented results.

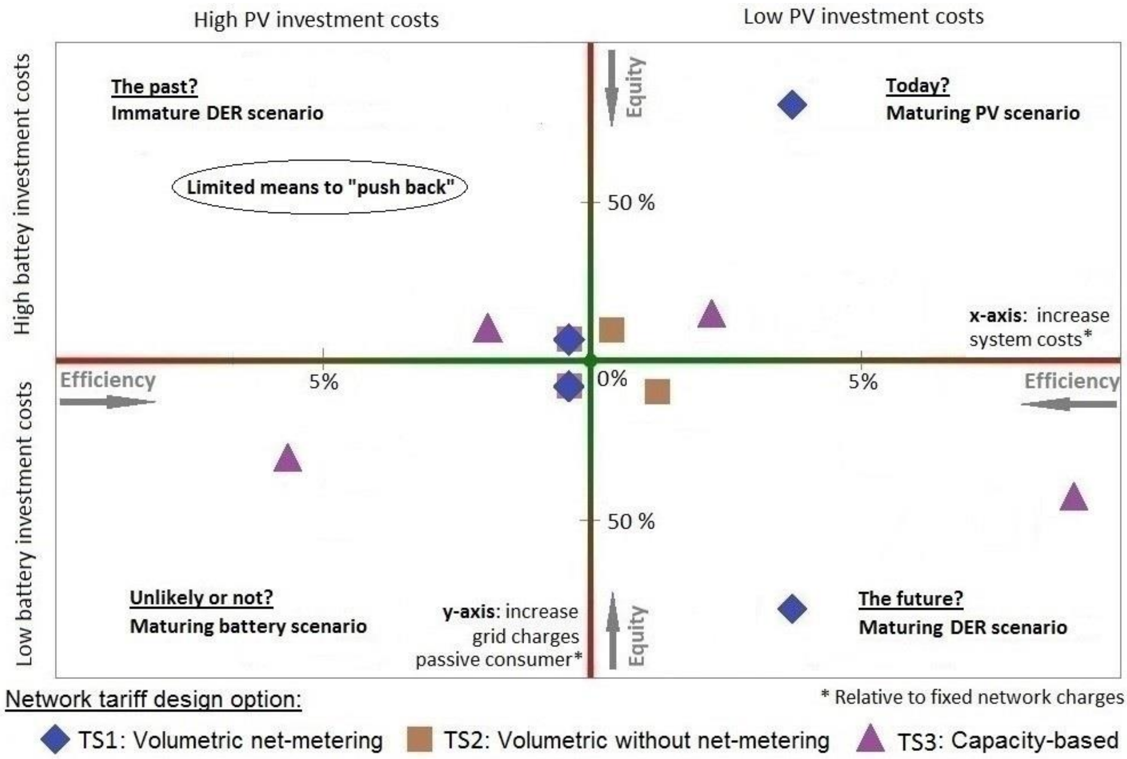


Figure 8: The results for the four scenarios of the technology matrix with 50 % active consumers connected to the grid. Results of the efficiency (horizontal) and equity (vertical) proxy are shown. The more the result of a tariff structure is situated near the origin along one axis, the better its performance for the metric on the other.

The results for the different tariff structures can be compared to each other in a specific state of the world. Also, the relative performance of certain tariff structures in the different state of the worlds can be assessed. This work does not attempt to discuss the trade-off between efficiency and equity. Only if a tariff structure dominates another tariff structure for both the efficiency and the equity metric, it can be said that one outperforms the other. In the next Subsections, the results are described per state of the world. The dynamics behind the results are described in detail for the 'Maturing DER scenario'. This Section ends with a short discussion on the implementation of capacity-based charges.

5.1 Immature DER scenario, the past?

Two observations are made in this reference state of the world. Firstly, the results show that applying volumetric network charges with net-metering, the network tariff design historically in place, does not create efficiency or equity issues for the recovery of the sunk costs. The same result is found for volumetric network charges without net-metering. This can be explained by consumers not having means to react to prices as PV is simply too expensive to invest in. A second observation is that with capacity-based network charges some inefficiencies, but very limited equity issues arise. This can be explained by investment in small but expensive batteries by the active consumers to shave their peak consumption. As the batteries are small, only a small proportion of the sunk costs are reallocated to the passive consumers.

5.2 Maturing battery and expensive PV scenario, unlikely scenario or not?

A state of the world with high PV investment costs and low battery costs is rather unlikely. However, this state of the world with associated technology cost could be the thought of as the future for places where electricity generated by PV is too expensive due to low levels of solar irradiation combined with few government subsidies. Alternatively, an unexpected battery R&D breakthrough could bring forward this scenario. Two observations from this state of the world are described below.

Firstly, results for volumetric charges with and without net-metering do not change. Net-metering does not incentivize investments in batteries for active consumers. [32] Under volumetric network charges without net-metering, there is an incentive to install batteries. A consumer must pay network charges both for withdrawal and injection of energy into the grid. This means that a consumer is incentivised to self-consume his electricity generated on-site by PV. Consequently, when a consumer installs PV, it can make sense to install additional batteries to limit the amount of electricity injected into the network when PV generation is high and demand low. The energy collected in the batteries can then be used to serve the electricity demand when the situation is reversed. As such, the exchange of electricity with the grid, and thus the network charges paid, will be limited. However, in this state

[32] When energy prices or network charges would be time-varying also batteries adoption could result with volumetric charges without net-metering.

of the world PV is expensive and therefore no PV is installed by the active consumer. As no PV is installed, also no batteries will be installed, and therefore the results do not differ from those of the previous state of the world.

Secondly, increased inefficiencies and a more severe equity issue resulted with capacity-based charges when compared with the previously described state of the world. The proxy for efficiency, the system cost, is a function of two forces: the capacity of batteries installed and their costs. Active consumers install batteries with a higher capacity as these are rather inexpensive. However, since batteries are cheap, the increase in system costs is dampened. An equity issue results as the active consumers can shave their peak demand more significantly with the higher battery capacity installed per active consumer.

5.3 Maturing PV scenario, today?

Three observations can be made for this state of the world. Firstly, volumetric network charges with net-metering create severe equity issues and inefficiencies. Since active consumers install the maximum amount of PV of which the excess generation is fed into the grid, the netted-out electricity consumption of the active consumers from the grid is significantly lowered. Consequently, the network charge coefficient in €/kWh must increase to ensure cost recovery. This means that the network charges paid by the passive consumers increase strongly. Additionally, investment distortions are created with this network tariff structure. More precisely, the LCOE of PV for this scenario is slightly higher than the energy cost of electricity and the price received for injecting electricity into the grid. In the case a network tariff does not interfere with the volumetric (€/kWh) or capacity (€/kW) price signal, no investment in PV is expected from the rational cost minimising consumer. With volumetric network charges with net-metering in place, investing in PV becomes a lot more attractive as not only energy costs can be avoided but also network charges. These results confirm the findings of Eid et al. (2014). They concluded that net-metering creates significant equity issues for passive consumers and acts as an implicit subsidy for the adoption of PV.

A second observation is that the result for volumetric network charges without net-metering almost does not change when compared to the previously discussed scenarios. PV is inexpensive, and if active consumers install PV, they will avoid paying network charges for withdrawing electricity from the grid. However, the electricity demand is not always at the same level as the PV production and vice-versa. Therefore, the business case for an active consumer to install a large capacity of PV is not attractive, and only a very limited capacity of PV is installed. Batteries can increase the amount of electricity produced on-site that could be used for self-consumption. However, in this state of the world, these are expensive, and no batteries are installed.

The last observation is that the performance of capacity-based charges is impacted by a change in the PV investment cost while keeping the battery investment cost constant. This effect can also be observed when comparing the two states of the world with low battery costs and different PV investment costs. Lowered PV costs incentivise investment in PV under this tariff structure and consequently also an investment in batteries becomes more attractive. This is rather surprising as can be seen from the demand and solar yield profile on Table 4 (middle and right) that the solar profile and peak demand are highly uncorrelated. This dynamic shows that there is added value in considering both investment possibilities in PV and batteries simultaneously when studying capacity-based charges in a setting with active consumers. Equity issues are limited as the capacity of batteries installed is small, and the correlation of the solar yield profile and the peak demand of the consumer is low.

5.4 Maturing DER scenario, the future?

Three highlights are described for this state of the world. To begin with, Figure 8 shows that the results for volumetric charges with net-metering in this state of the world do not change when compared to the previously described state. This is expected as the only parameter changing between those two states is the battery investment cost, and with net-metering and no time-varying prices in place, an active consumer has no reason to install batteries.

Secondly, the results for volumetric charges without net-metering change slightly. In this state of the world, the active consumers invest in PV and batteries. Inexpensive batteries increase the amount of electricity produced by PV that can be used for self-consumption. As such, the total amount of network charges paid by the active consumer decreases. However, the amount of avoided network charges is limited, and the installed capacities of both PV and batteries remain very small. This tariff structure could be regarded as an extreme case of the British tariff design as described by Green and Staffell (2017). In their paper, the authors investigate the business case of batteries and self-sufficiency for domestic electricity consumers. The obtained results are in line with their conclusion for GB. Namely that, even with low-cost storage available and a (volumetric) tariff design that seems to encourage the technology, energy arbitrage does not make consumer-based storage economic.

Thirdly, the results for capacity worsen significantly, both in terms of efficiency and equity, when comparing to the other states of the worlds. This result is elaborated on more deeply to demonstrate why this is happening. In Figure 9 the results for efficiency and equity proxy with sensitivity for the proportion of active consumers connected to the grid is shown. For all three tariff structures, the magnitude of the inefficiencies and equity issues increases with an increased share of active consumers. This is relatively straightforward because there are simply more active consumers with distorted investment incentives who are trying to reallocate the grid costs to a smaller share of passive consumers. This dynamic could be labelled as an effect of big numbers and is also captured by more static quantitative models as Hledik and Greenstein (2016)[33] and Simshauser (2016).

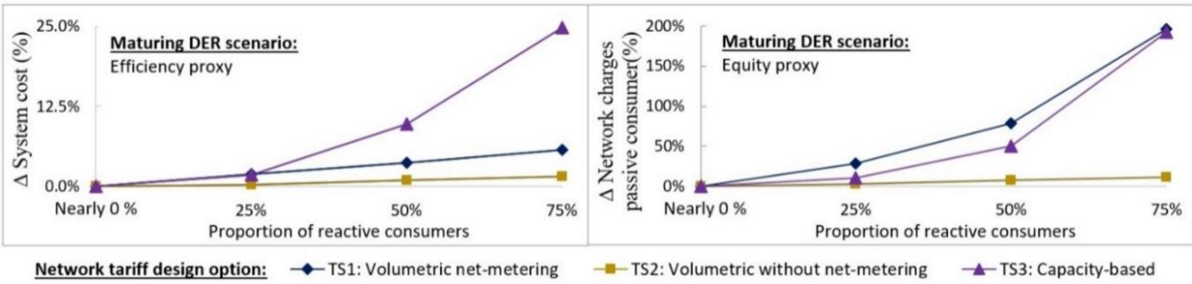


Figure 9: Results for the efficiency proxy (left) and the equity proxy (right) with sensitivity analysis for the proportion of active consumers.

However, a second effect makes the increase in inefficiencies and equity issues very non-linear and unpredictable. The origin of this effect is non-cooperative behaviour between consumers and the result is that *the capacity of DER technology installed per individual active consumer can increase with an increased share of active consumers connected to the grid*. In this scenario and under capacity-based charges, the optimal battery capacity installed per active consumer increased from 2.5 kWh with nearly no active consumers, to 5.5 kWh with 50 % active consumers connected to the grid.

Figure 10 helps to further explain the adverse effect of non-cooperative behaviour on the efficiency and equity proxy. In Figure 10 the annual electricity cost of the two consumer types, relative to the baseline case with non-distortive fixed network charges, is shown. Additionally, system cost, calculated as the weighted average electricity cost and used as a proxy for efficiency, is shown.[34] Please note that the scale of the vertical axis for the middle panel of Figure 10 differs from the other two panels.

[33] In their paper, the authors develop a preliminary understanding of the relationship between capacity-based charges and storage. A battery with a certain size is assumed and the cost of the battery for the consumer is not accounted for. The optimal sizing of the battery and the interaction between the sizing and the proportion of active consumers connected to the grid is not attempted, however, mentioned to be a valuable area of research.

[34] Indirectly also the results for the equity proxy can be calculated from Figure 10.

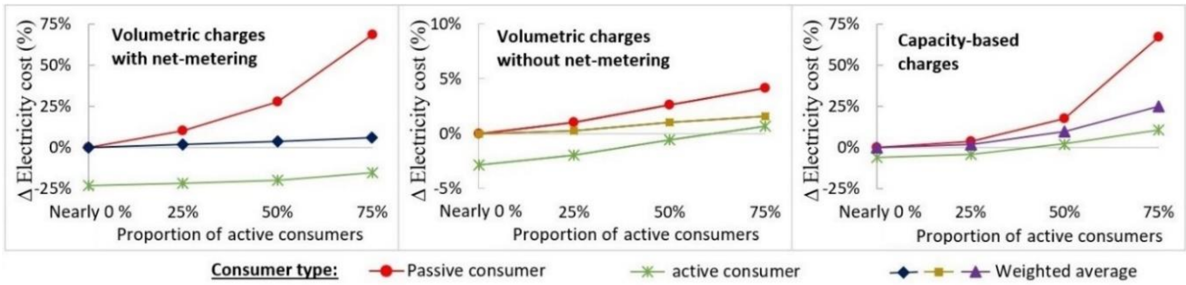


Figure 10: Difference in annual electricity cost per consumer type for the three network tariff structures compared to the application of non-distortive fixed network tariffs. Additionally, the weighted average electricity cost (or system cost) which serves as the proxy for efficiency is shown.

When the proportion of active consumers connected to the grid is very limited, an active consumer can lower his electricity bill under all tariff structures. Active consumers can profit the most under volumetric charges with net-metering by installing the maximum capacity of PV. The decrease in the electricity bill of the active consumer, compared to the baseline case, is the result of the low DER investment costs. As the proportion of active consumers is limited, the total grid costs reallocated to the numerous passive consumers and the rate increase of the network charge needed to ensure cost recovery for the DSO is minimal. Therefore, the increase in the electricity cost for the passive consumer is limited. It can also be observed that the electricity cost of an individual active consumer increases with an increased share of active consumers connected. It is surprising to see that under volumetric charges without net-metering and capacity-based charges the electricity cost of the active consumer surpasses the electricity cost for that same consumer in a situation where all consumers are passive and do not invest in DER at all. On first sight, this outcome might seem counter-intuitive: *Why would a consumer invest in DER when everybody, including himself, is better off when nobody invests in DER?*

This dynamic can be explained by the fact that cost-minimizing active consumers take uncoordinated investment decisions by following their own self-interest. The results of the model can be interpreted as a Nash equilibrium, defined as a solution of a non-cooperative game involving two or more players in which each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing only his or her own strategy (Nash, 1951; Osborne and Rubinstein, 1994). In this context, a Nash equilibrium implies that no consumer has anything to gain by changing only his own operational and investment decisions. Concretely, for a certain share of active consumers, an individual consumer would not install more DER as in this case the additional investment does not justify the decrease in network charges and/or energy costs. On the other hand, for the same share of active consumers, an individual consumer would also not install less DER as that would mean his total electricity cost goes up as he would have to pay more network charges and/or energy costs. In a setting where all active consumers would jointly make an investment decision, a lower amount of DER would be installed than in the case they make an individual decision. This would be an optimal solution as the overall efficiency would increase. With the game-theoretical model applied in this work, it is possible to capture and quantify the adverse effect of non-cooperative behaviour between active consumers.

Uncoordinated decision making does not only have an adverse effect on the aggregated electricity cost of all consumers but also on the electricity cost of the group of active consumers. In other words, active consumers are cannibalising their own 'profit' by competing against each other. *This adverse effect, which leads to a race (to the bottom) of DER adoption, can be minimised or enabled by adequate network tariff design.* For this scenario, the results show that capacity-based charges are more prone to enable this loop, which creates severe efficiency and equity issues. It can also be seen that this effect kicks in for volumetric charges without net-metering, however, less intense and delayed when compared to capacity based charges.[35] The same effect does not affect volumetric charges with net-metering for this scenario simply because the active consumer already had installed the maximum amount of PV capacity (5 kWp) when the proportion of active consumers was negligible.[36]

5.5 Implementation matters: on limitations of capacity-based charges to recover sunk costs

With capacity-based charges in place, investment in batteries and PV are strongly (over)incentivised in some scenarios. This network tariff structure is found to be prone to adverse effects of non-cooperative behaviour, leading to an increased capacity of DER installed per individual consumer when the share of total active consumers increases. The reacting consumers are competing and try to reallocate the sunk cost burden to the passive consumers, but also to one another. Hledik (2014) and Hledik and Greenstein (2016)point out that there is no single type of capacity-based network charges, but that many variants exist. Depending on the implementation of the capacity-based charge results could resemble or depart from the outcomes presented.

In this work, a capacity-based network charge measuring the observed peak demand during one hour was used. A 24-hour deterministic profile including the demand peak was used in this work and results were annualised. By doing so, it is assumed that the battery can perfectly anticipate when the peak demand takes place. Two design parameters of the capacity-based network charge can determine the level of (in)accuracy of the assumption of perfect foresight of the peak demand. Firstly, 'the ratchet or billing cycle' of a capacity-based charge, i.e. the peak demand is determined on a daily, monthly,

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[35] Additional sensitivity runs were conducted and strong adverse effects of non-cooperative behavior were found for volumetric charges without net-metering in a scenario with very high grid costs (€ 1000/consumer) and high energy cost (0.15 €/kWh). These cases are further developed in Chapter 4 of this thesis.

[36] For more details on the interaction between net-metering and PV adoption see e.g. Cai et al. (2013) and Darghouth et al. (2016). In those works, models are used to simulate PV adoption and rate adjustments over 20 and 35 years, respectively.

seasonally or annual basis to calculate the network charges. Logically, the longer the period over which the peak demand is observed, the more inaccurate perfect foresight of the peak demand would be. Secondly, the duration over which the peak demand is measured, i.e. instantaneously, averaged over fifteen minutes, averaged over one hour, or averaged over several hours, etc. The shorter the period over which the peak measurement is averaged, the more inaccurate a perfect forecast of the peak demand is. Shorter averaging period increases uncertainty around the forecast. Thus 'badly designed' capacity charges for sunk cost recovery, e.g. based on the hourly peak demand over a monthly period, could resemble the results of this analysis. While capacity based charges based on the peak demand during 15-minutes with a seasonal or annual ratchet would perform better than the results shown in this analysis. However, if the investment cost of batteries is low enough or grid costs to be recovered through the tariff are high, similar dynamics would result, independent of the design of the capacity-based charge.

6. **Conclusion**

Low-voltage consumers cannot be considered as passive anymore after two technology breakthroughs: (1) PV enables domestic and commercial consumers to self-produce energy; (2) Batteries enable self-producers to choose both their grid energy and capacity parameters. The availability and costs of these new technologies strategically interact with tariffs to recover grid costs, as active consumers will react with their profit-maximising actions to any network tariff charged to them. In this paper, a game-theoretical model has been applied to assess whether:

(1) capacity-based network charges solve the efficiency problems experienced with volumetric charges with net-metering? And if,

(2) capacity-based network charges allow active consumers, investing in PV and batteries when incentivised, to be better off at the expense of passive, sometimes vulnerable, consumers?

Insights were gained with the help of three different distribution network tariff structures evaluated in four states of the world. This applied modelling approach allowed to capture the uncoordinated reaction of consumers to different tariff design by the adoption of DER technologies. Energy volumetric charges with net-metering, energy volumetric charges for both injection and withdrawal and capacity-based charges were assessed with a proxy for efficiency and equity. A central assumption was that grid costs to be recovered by the DSO were sunk, i.e. the adoption of DER technology by consumers does not influence the total grid costs to be recovered.

Regarding the first question, the results confirm that in a world with an increasing share of consumers connected to low voltage distribution networks reacting to price signals, simple netted out volumetric network charges to recover grid costs cannot be considered as the adequate network tariff design. Net-metering is an implicit subsidy for the adoption of PV. However, depending on the state of the world and its implementation, also capacity-based charges can severely distort the investment decisions of consumers. These results nuance the findings of the pro-capacity-based camp, e.g. Hledik and Greenstein (2016) and Simshauser (2016) and add a critical note to the observed trend towards being capacity-based tariffs replacing volumetric tariffs.

The observed dynamics confirm the suggestion made by Simshauser (2016), namely that if the capacity-based charge overstates the value of peak load, it may pull-forward battery storage and create a new dimension to the sunk cost recovery problem. Simply abolishing net-metering and applying so-called 'bi-directional' volumetric charges; an option also brought forward by Eid et al. (2014), can outperform capacity-based charges to recover sunk costs in a scenario of low technology costs with high proportions of active consumers. This tariff design is found to be more robust against the adverse effects of non-cooperative behaviour, and investment decisions are less distorted.

Regarding the second question, both under volumetric charges with net-metering and capacity-based charges active consumers make uncoordinated investment decisions and push sunk grid costs to one another which can lead to overinvestment in DER and subsequently raise equity issues. Equity issues are found acuter under net-metering. However, paradoxically, under capacity-based charges, a situation can occur in which not only passive but also active consumers, end up paying more than in a situation where nobody invests in DER. This is due to competitive pressure among active consumers in allocating sunk cost. This effect was captured by modelling the grid cost recovery problem as a non-cooperative game between consumers, unprecedented in the existing body of literature.

By considering grid costs to be sunk, we focused on the limitations of capacity-based charges. Admittedly, this assumption presents a simplification in countries where the distribution network is in full expansion, and therefore it will be challenged in future work. By doing so, the total costs to be recovered by the DSO will become a function of network usage. In that setting, with low sunk costs and high future demand-driven investment, intelligently designed capacity-based charges could be of use. Lowered future grid costs due to intelligent grid charges could dampen the effects of non-cooperative behaviour. Another potential future research line would be to investigate the risk of grid defection when fixed charges would be increased strongly. Also, the effect of time-varying price signals, which would add value to the battery, would provide interesting insights.

CHAPTER 3: LEAST-COST DISTRIBUTION NETWORK TARIFF DESIGN IN THEORY AND PRACTICE

Abstract

In this paper, a game-theoretical model with self-interest pursuing consumers is introduced to assess how to design a least-cost distribution tariff under two constraints that regulators typically face. The first constraint is related to difficulties regarding the implementation of cost-reflective tariffs. In practice, so-called cost-reflective tariffs are only a proxy for the actual cost driver(s) in distribution grids. The second constraint has to do with fairness. There is a fear that active consumers investing in distributed energy resources (DER) might benefit at the expense of passive consumers. We find that both constraints have a significant impact on the least-cost network tariff design, and the results depend on the state of the grid. If most of the grid investments still have to be made, passive and active consumers can both benefit from cost-reflective tariffs, while this is not the case for passive consumers if the costs are mostly sunk.

Keywords: Batteries, distributed energy adoption, distribution network tariff design, game-theory, non-cooperative behaviour

JEL classification : C7, D61, L94, L97, Q41, Q42

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1. Introduction

Technological breakthroughs at the consumer-side are challenging the use of volumetric distribution network charges (€/kWh). Specifically, volumetric charges with net-metering, implying that a consumer's network charges are proportional with its net consumption from the grid over a certain period (e.g. month), are deemed inadequate with the massive deployment of solar PV. Consumers with solar PV pay significantly lower network charges but still rely on the distribution grid as much as they did before. This means that if cost recovery is respected, consumers that have not installed solar PV would have to contribute more.

There is no easy fix for distribution network tariff design. Regulators in many European countries are thinking to suspend net-metering and move more towards capacity-based (€/kW), fixed network tariffs (€/connection) or a combination of both (CEER, 2017a). However, many practitioners as well as academics, e.g. Abdelmotteleb et al. (2017), Batlle et al. (2017) , Passey et al. (2017), Pollitt (2018), Pérez-Arriaga et al. (2017) and Simshauser (2016), warn for possible issues constraining the implementation of improved or more efficient distribution tariffs. In this paper, we go one step further by demonstrating quantitatively how such constraints affect distribution network tariff design. We focus on two often-discussed constraints which are of a different nature: implementation issues with cost-reflective charges and fairness in the allocation of network costs among consumers.

To capture the impact of these two constraints on network tariff design in this new reality with active consumers investing in DER, it is indispensable to consider how consumer incentives change as a function of network tariff design. Therefore, we introduce a game-theoretical model which closes the loop between network tariff design, incentives for self-interest pursuing active consumers, and the aggregate effect of consumer actions on the total network costs which again need to be recovered by the network charges. Although the rise of active consumers is rightly welcomed, the model takes into account the fact that it can also be a double-edged sword. On the one hand, the more consumers have the ability to react to price signals, in this case network charges, the more welfare gains can be made from efficient consumer behaviour as an alternative to the historical practice of 'fit-and-forget' (Ruester et al., 2014). On the other hand, the more significant negative welfare impacts can result if these price signals are badly designed and are 'guiding' consumers in the wrong direction. In that case, the avoided network charges by active consumers will be simply transferred to more vulnerable passive consumers who see their electricity bill increase. The more consumers have the possibility to react to price signals, the more important it becomes to get the network tariff design right.

The mathematical structure of the presented model is a bi-level optimisation problem which is reformulated as a Mathematical Program with Equilibrium Constraints (MPEC). In the upper-level, a regulator sets the distribution network tariff. Besides volumetric charges, the regulator has two other traditional network tariff design options: capacity-based and fixed network charges, or she can opt for a combination of the three. The regulator anticipates the reaction of the consumers represented in the lower-level and the network tariff is determined in a way that the total system costs (incl. network costs, energy commodity costs and DER investment costs by consumers) are minimised. The regulator is subject to the constraint that the total network charges collected need to equal the network costs.[37] Modelled consumers can be passive or active. Passive consumers are assumed not to react to prices; active consumers pursue their own self-interest, i.e. their objective is to minimise their cost to satisfy their electricity demand. They have the option to invest in two technologies: solar PV and batteries.

Using a numerical example, we illustrate a trade-off between cost-efficiency, for which the proxy is the total system costs, and fairness, for which the proxy is the increase in grid charges for passive consumers compared to a baseline. We find that some cost-efficiency can be sacrificed to limit the distributional impact resulting from network tariff redesign and we show how this trade-off is impacted by the implementation issues with cost-reflective network tariffs. However, our main finding is that if the regulatory toolbox is limited to the three considered traditional tariff design options; it will be hard to design a distribution network tariff that is cost-reflective and future-oriented, while at the same time also fair in the allocation of costs between active and passive domestic consumers. We argue that other, more creative, regulatory tricks are needed to combine and satisfy different policy objectives.

The paper is structured as follows. In Section 2, we discuss the two considered constraints a regulator faces when designing the distribution network tariff and include relevant literature. In Section 3, we introduce the modelling approach. In Section 4, the setup and data for the numerical example are introduced. In Section 5 and 6, the two considered tariff design constraints are introduced, their modelling implication is described, and the results for the numerical example are presented to gain

[37] We consider an institutional setting with a fully unbundled distribution system operator (DSO) that does not own or operate any generation assets. The consumer reacts to the aggregated electricity bill but the accounting of the cost components (retailer energy price and network charges but also taxes and levies) is separate. Namely, consumers buy electricity, the commodity, from a retailer who bought this energy in the wholesale market and sells it to downstream consumers for a given exogenous price. The network charges, on the other hand, are considered endogenous. These are set by the regulator and the revenues are collected by the DSO equaling its network costs. Finally, next to the retailer energy price and the network charges, a consumer also pays taxes and levies; it is assumed that the total level of these costs is invariant and that the way these are collected does not interfere with the analysis.

insights into their impact on network tariff design. In Section 7, we discuss the results and derive policy implications. Lastly, a conclusion is formulated, and future work is proposed.

2. Practical constraints when redesigning the distribution network tariff

Pérez-Arriaga et al. (2017)[38] discuss and Abdelmotteleb et al. (2017) show with simulations and numerical examples that in a new world with active consumers the least-cost distribution network tariff consists of a forward-looking-peak-coincident capacity charge plus a fixed charge. If the capacity-based charge is computed as the incremental cost of the network divided by expected load growth, the tariff is cost-reflective; consumers will make optimal choices with regard to the trade-off between their consumption levels and grid reinforcements. A fixed network charge complements the capacity-based charge to collect the remaining residual network cost in a non-distorting manner.

However, there are many difficulties which constrain the implementation of this theoretical optimal tariff, a first constraint relates to the implementation difficulties with cost-reflective tariffs. In practice, so-called cost-reflective tariffs are only a proxy for the actual cost driver(s) in distribution grids because it would be too complex to consider all of them or because we simply lack the necessary information. Gómez (2013) describes how a distribution network is more difficult to oversee than a transmission network as it involves a much larger number and a wider variety of equipment and components. Cohen et al. (2016) use actual load and load growth data to show that grid usage is very heterogeneous in California. They also show that the costs of accommodating incremental demand/injection can be very location specific. Passey et al. (2017) analyse a dataset of 3,876 residential consumers in the Greater Sydney Area in Australia and observe that demand profiles and the timing of the network peaks vary widely across networks and at different voltage levels, depending on the mix of consumers connected. Designing a truly cost-reflective capacity-based charge is a challenging task. The coincident-peak of a distribution system, identified as the main network cost driver, is hard to target. Targeting the wrong network peak implies an efficiency loss, e.g. DER adoption can be under- or over-incentivised without resulting in much change in the total grid costs.

Pérez-Arriaga et al. (2017) and Pollitt and Anaya (2016) agree that from an efficiency point of view, a network tariff with very fine temporal and locational granularity would be more optimal. Examples are critical peak-pricing (mainly temporal) or even user-by-user charges as an extreme case (temporal and locational). However, such dynamic charges with fine locational granularity are hard to attain in the current context. This is mainly true due to a lack of information about the network flows in real-time,

[38] See e.g. also Box 4.6 (p. 115-116) in the Utility of the Future report by the MIT Energy Initiative (2016a).

requiring significant investments in IT infrastructure. Moreover, even if the distribution network became extremely 'smart', the implementation constraint could persist as in most countries regulation requires that a uniform distribution tariff should be in place on a regional level or per area operated by a Distribution System Operator (DSO) (European Commission, 2015a). This regulatory requirement is mainly based on arguments of simplicity and predictability for the consumer. Therefore, in this work, we limit ourselves to the application of the three traditional tariff design options: volumetric charges (€/kWh), capacity-based (€/kW) and fixed network charges (€/connection). Besides simplicity and predictability, fairness is an important regulatory requirement (e.g. Batlle et al. (2017) and Neuteleers et al. (2017)), thereby leading us to the second considered constraint in this paper.

There is a fear that network tariff reforms, which aim to increase cost-efficiency, will result in an unfair allocation of the network costs, i.e. passive, often smaller or poorer, consumers would see their electricity bills increase. Pollitt (2018) notes that under some conditions, e.g. where there is an over-dimensioned network combined with low load growth, a limited possibility to fully disconnect from the grid and when all externalities are incorporated into the other components of the electricity bill, then it can be optimal from an efficiency point of view to recover a large share of the network costs through fixed network charges. However, in many countries, there is strong opposition to high fixed network charges. This concern is not unique to the electricity sector but is acute in all markets with large fixed costs, such as energy, water, transportation, and telecommunications. For example, Borenstein and Davis (2012) use relevant microdata to characterize the effect of a transition to marginal cost pricing from volumetric charges which were on average about 30 % higher in the U.S. residential natural gas market. Marginal cost pricing does not guarantee cost recovery and consequently fixed monthly fees would need to be raised to recuperate the residual infrastructure costs.

It is often argued that if fixed network charges replaced the historic volumetric network charges, network costs would be shifted from often richer high-usage consumers to often poorer lower-usage consumers. Kolokathis et al. (2018) analyse German electricity demand data and show that, by introducing a high uniform fixed network charge, low-usage consumers can pay up to two and a half times as much per unit of electricity compared to high-usage users. Such discrepancies in price per kWh could raise acceptability issues. As a consequence, increases in uniform fixed network charges are often rejected or capped.[39] Although increased fixed network charges could be welcomed by DSOs as

[39] For example, a media article published in November 2014 mentions that there were 23 ongoing 'state fights' between utilities and regulators over increased fixed charges in the US: https://www.utilitydive.com/news/the-fight-over-solar-moves-from-net-metering-to-rate-design/327742/, accessed on 19/02/18.

they would allow for a better alignment of the network tariff with the network cost structure, DSOs can also be averse towards the risk of raising fairness concerns. Political actions aimed at reducing discontent could eventually put grid cost recovery in danger.

However, if higher fixed network charges are not acceptable even when cost-efficient, other network tariff components (e.g. volumetric or capacity-based) will be needed to recover the residual grid costs. By resorting to these, the network tariff will be distorted, implying that active consumers could exploit opportunities that might be beneficial in terms of reduced private network charges but not necessarily optimal from a system point of view. Moreover, the benefits active consumers obtain could be at the expense of passive consumers. Brown and Sappington (2017a) estimate the welfare and distributional impact of a vertical utility not being allowed to recover its costs by raising fixed charges in addition to volumetric charges with net-metering. Indeed, they find that in a context with active consumers investing in solar PV, negative distributional and aggregate welfare effects can be more pronounced when the regulator is not allowed to raise fixed charges. In short, a trade-off exists between a fairness issue with increased fixed charges, i.e. raising the network charges for smaller households, and sustaining a distortion in the network tariff which could finally also lead to a fairness issue due to active consumers reacting to the distortive network tariff. With the help of the game-theoretical model, introduced in the next section, we demonstrate this trade-off quantitatively.

3. **Model formulation**

In this section, the game-theoretical model is described. In theory, a centralised planner, optimising social welfare by deciding unilaterally on the optimal trade-off between the utilisation of the network and the adoption of DER by consumers, would lead to the lowest total system costs. However, in reality, there is no central planner that has information about the network cost function and at the same time decides on behalf of the consumers what technology to install in order to minimise the total system costs. On the contrary, decision-making is decentralised and coordinated by price signals.[40] In the following of this section, the description of the implemented model is split into three parts. First, the upper-level problem is described. Then, the lower-level problem is introduced. Last, the applied solution technique is explained.

3.1 The upper-level regulator

The upper-level of the model represents the network tariff design problem of the regulator. It is assumed that the regulator can set the network tariff and that it aims at minimising total system costs

[40] For a comparison between a centralized planner model and the game-theoretical model introduced in this paper, please consult Appendix B.

(here equivalent to maximising social welfare).[41] This is a simplification, as in some European countries the National Regulatory Authority (NRA) is responsible for network tariff design, while in other European countries the NRAs and DSOs share the responsibility. However, the final approval remains with the NRA (European Commission, 2015). The objective function of the regulator is shown by Eq. 1. The total system costs consist of four components: total energy costs, total DER investment costs, total grid costs, and other costs. Other costs represent taxes and levies recovered from consumers; it is assumed that the total level of these costs is invariant. The three variable components of the objective function are displayed by Eq. 2-4. All costs are annualised and normalised per (average) consumer. All introduced variables are positive continuous variables. Variables are represented in italics, parameters in standard style. An overview of the nomenclature used can be found in Appendix 0.

$$\boldsymbol{Minimise}\ \ TotalEnergyCosts + TotalDERcosts + TotalGridCosts + \ TotalOtherCosts \tag{1}$$

The total net energy costs to meet the electricity demand of all consumers are calculated by Eq. 2. Assuming one retailer for all consumers, $TotalEnergyCosts$ equals the revenue of the retailer minus the money received by consumers for the electricity injected in the grid (so-called feed-in remuneration).

$$TotalEnergyCosts = \ \sum_{\mathrm{t}=1}^{\mathrm{T}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{PC_i} * \left(qw_{\mathrm{t,i}} * \mathrm{EBP_t} - qi_{\mathrm{t,i}} * \mathrm{ESP_t}\right) * \mathrm{WDT} \tag{2}$$

The index i stands for a representative consumer of type i, PC_i is a parameter indicating the proportion of a consumer type relative to the total consumers. $\mathrm{EBP_t}$ stands for the price to buy a kWh of electricity from the retailer and $\mathrm{ESP_t}$ is the price received when feeding in a kWh of electricity (excluding grid or other costs). Further, $qw_{\mathrm{t,i}}$ and $qi_{\mathrm{t,i}}$ represents respectively the quantities of electricity withdrawn and injected from the network by a consumer i for a certain time step t. Please note that $qw_{\mathrm{t,i}}$ can only be positive if $qi_{\mathrm{t,i}}$ is zero and vice-versa. For a passive consumer $qw_{\mathrm{t,i}}$ will always equal its demand and $qi_{\mathrm{t,i}}$will always be equal to zero. This does not hold for an active consumer. For example, if an active consumer installs solar PV, it could be that at a given time step the PV production exceeds the consumer's demand. For that time step, $qw_{\mathrm{t,i}}$ will be zero and $qi_{\mathrm{t,i}}$ will be positive and equal to the excess PV production over demand. If that active consumer also installs a battery next to solar PV, it would have the choice to inject the excess electricity directly into the network ($qi_{\mathrm{t,i}}$) or store it in the battery to lower the need to withdraw from the grid ($qw_{\mathrm{t,i}}$) at a later moment. Finally, WDT is a factor to annualise the values and is a function of the length of the utilised time series (T). Please note that if the price for buying a kWh of electricity from the retailer ($\mathrm{EBP_t}$) equals the price received by an active

[41] We assume that electricity demand elasticity is zero. Instead, we allowed consumers to fulfil their electricity demand by other means than the grid (solar PV and/or batteries). This implies that demand response is not included. This assumption is further discussed in Section 7.1.

consumer when injecting a kWh of electricity ($\mathrm{ESP_t}$) (excluding grid or other costs), Eq. 2 can be simplified. In that case, the total energy costs equal the aggregate net demand scaled over all consumers multiplied by the retailer's energy price.

The total investment cost in solar PV and batteries by consumers is described by Equation 3. is_i stands for the capacity of solar PV (in kWp) installed by consumer i and ib_i is the capacity of batteries (in kWh) installed by consumer i. AICS and AICB are the annualised investment costs for respectively solar PV and batteries. No maintenance costs for the DER technologies are assumed.

$$TotalDERcosts = \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{PC_i} * (is_i * \mathrm{AICS} + ib_i * \mathrm{AICB}) \tag{3}$$

Finally, the function describing total grid costs is displayed by Eq. 4. Sunk grid costs are the costs of grid investments made in the past to be able to cope with electricity demand in the future. Sunk grid costs are represented by a parameter as these costs are unaffected by the utilisation of the network. Schittekatte et al. (2018) also discuss network tariff design with active consumers and grid costs are assumed to be all sunk throughout that work. This means the objective of a network tariff is mainly allocative, i.e. socialising the grid costs in a non-distortive and fair manner. In this work, also a term for prospective grid costs ($\mathrm{IncrGridCosts} * CoincidentPeak$) is added in Eq. 4.[42] These grid costs are variable (in the long-run) and a function of the maximum coincident network utilisation of all consumers ($CoincidentPeak$). The higher the coincident peak, the higher the network costs to be recovered. The parameter $\mathrm{IncrGridCosts}$ describes the cost per kW of increase/decrease in the coincident peak. This parameter resembles the incremental network cost as in MIT Energy Initiative (2016a). In case reactions of the consumers in terms of consumption from the grid (or injection) affect the network cost and in its turn the network charges, the network tariff should guide consumers to cost-efficient behaviour apart from purely allocating network costs.

$$TotalGridCosts = \mathrm{SunkGridCosts} + \mathrm{IncrGridCosts} * CoincidentPeak \tag{4}$$

Abdelmotteleb et al. (2017), Pérez-Arriaga et al. (2017) and Simshauser (2016) describe that the coincident peak demand (or injection if higher) is generally considered as the main cost driver of a distribution network. Brown and Sappington (2018) apply a similar formula by stating that the network costs are a function of the maximum potential demand for electricity supplied by centralised generation. In Brown and Sappington (2017a) a different approach is used, and it is assumed that the network costs are a function of the capacity of centralised generation and solar PV installed, with a

[42] We label these grid costs 'prospective' as they are ideally reflected to grid users by 'forward-looking grid charges', meaning the element of network charges that looks to provide signals to users about how their consumption pattern can increase or reduce future network costs (Ofgem, 2017b). However, in the longer-run equilibrium we are modelling, these costs become part of the grid costs to be recovered by the DSO. Therefore, they are included in Eq. 4.

higher weight for solar PV.[43] Next to the coincident peak demand, other network cost drivers can be identified, such as thermal losses and investment cost to replace electronic components (e.g. protection) to deal with bi-directional flows due to high concentrations in PV adoption (see e.g. MIT Energy Initiative (2015) and Cohen et al. (2016)). These other network cost drivers are not included in the current analysis.

How the coincident peak demand (or injection) is obtained is shown by Eq. 5-7. $CPeakDemand$ stands for the coincident peak demand, i.e. the maximum value of the sum of the consumer demands ($qw_{\mathrm{t,i}}$) minus injections ($qi_{\mathrm{t,i}}$) at a certain time step t. Similarly, the coincident peak injection of the network $CPeakInjection$ is obtained. The $CoincidentPeak$ is determined as the maximum of the two. In the most likely scenario, and also in the numerical example used in this paper $CPeakDemand > CPeakInjection$ and thus $CoincidentPeak \equiv CPeakDemand$.

$$CoincidentPeak \equiv \mathrm{Max}\{CPeakDemand, CPeakInjection\} \tag{5}$$

$$CPeakDemand \equiv \mathrm{Max}\left\{\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{PC_i}\left(qw_{\mathrm{t,i}} - qi_{\mathrm{t,i}}\right)\ \forall \mathrm{t}\right\} \tag{6}$$

$$CPeakInjection \equiv \mathrm{Max}\left\{\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{PC_i}\left(qi_{t,i} - qw_{\mathrm{t,i}}\right)\ \forall \mathrm{t}\right\} \tag{7}$$

The relative magnitude of the three variable system cost components (retailer energy costs, DER investment costs and grid costs) are a function of how the electricity demand of the consumers is met, i.e. the mix of the energy sourced from the retailer and delivered by the grid and the energy delivered directly from installed DER at the consumer side. A regulator cannot directly decide on the optimal trade-off. Instead, he can only indirectly influence the consumer decisions by setting a network tariff which anticipates their reactions. Eq. 8 expresses the need for total grid costs to be equal to the total grid charges collected. With this formulation, the unbundled DSO recovers its grid costs with a combination of a volumetric charge vnt (€/kWh), a capacity-based charge cnt (€/kW) and a uniform fixed charge fnt (€/connection). vnt, cnt and fnt are the decision variables of the upper-level, while $qw_{\mathrm{t,i}}$, $qi_{\mathrm{t,i}}$ and $qmax_{\mathrm{i}}$ are decision variables of the lower-level. $qmax_i$ is the maximum observed capacity (for withdrawal or injection) of consumer i over the considered time series.

$$TotalGridcosts = vnt * \sum_{\mathrm{t=1}}^{\mathrm{T}} \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{PC_i} * \left(qw_{\mathrm{t,i}} - \mathrm{NM} * qi_{\mathrm{t,i}}\right) * \mathrm{WDT} + cnt * \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{PC_i} * qmax_{\mathrm{i}} + fnt \tag{8}$$

[43] Brown and Sappington (2017a, 2017b, 2018) also apply a welfare analysis to gain insights into the issue of optimal tariffs in a setting where consumers with a certain elasticity are adopting distributed generation (DG). An important difference with our work is the institutional setting. Brown and Sappington focus on the design of the entire retail tariff and model one vertically integrated utility responsible for generation, transmission and distribution. We consider a setting with a fully unbundled distribution network company that does not own or operate any generation assets. A second important difference is that Brown and Sappington (2017a, 2017b, 2018) do not use inter-temporal data series. As a consequence, batteries at consumer level cannot be modelled.

NM is a parameter and determines the type of volumetric charge.[44] If NM is set as equal to 1, volumetric charges with net-metering result. With NM set equal to 0, solely charging for the total volume of electricity withdrawn are in place, these type of volumetric charges are so-called net-purchase volumetric charges. Please note that for the latter a bi-directional meter, measuring separately electricity withdrawn from and injected into the grid is a necessary requirement. Further, the capacity-based charge cnt accounts for maximum observed capacity (for withdrawal or injection) of a consumer i ($qmax_{\mathrm{i}}$). The fixed network charge fnt is assumed to be uniform for all consumers.

3.2 The lower-level consumers

The objective of the individual consumers' optimisation problems is to minimise the cost of meeting their electricity demand. Active consumers are enabled to invest in solar PV or batteries to lower their dependency from the grid when they have the financial incentive to do so. The objective function of a consumer i is represented by Eq. 9. The total electricity cost per consumer also consists of four components, similar to the upper-level, but now for an individual consumer: grid charges, the investment cost in DER, the energy cost and other charges, again representing taxes and levies. It is assumed that the amount of taxes and levies per consumer is not a function of its grid usage but recovered through a fixed charge per consumer. The other three components of the consumers' electricity costs are variable.

$$\textbf{Minimise } \ GridCharges_{\mathrm{i}} + DERCosts_{\mathrm{i}} + EnergyCosts_{\mathrm{i}} + \mathrm{OtherCharges} \tag{9}$$

Eq. 10-13 describe the different components of the total electricity costs in more detail. The grid charges are the sum of volumetric, capacity-based and fixed grid charges. The coefficients of the different grid charges are set by the upper-level regulator. The DER investment costs are the sum of the annualised investment cost of solar PV and batteries installed as shown in Eq. 12. Eq. 13 calculates the retailer energy costs for a consumer minus the feed-in remuneration.

$$GridCharges_{\mathrm{i}} = \sum_{\mathrm{t=1}}^{\mathrm{T}} (qw_{\mathrm{t,i}} - qi_{\mathrm{t,i}} * \mathrm{NM}) * vnt * \mathrm{WDT} + qmax_{\mathrm{i}} * cnt + \ fnt \qquad \forall\ \mathrm{i} \tag{10}$$

$$\text{with } qmax_{\mathrm{i}} \equiv \mathrm{Max}\left\{qw_{\mathrm{t,i}} - qi_{\mathrm{t,i}}\ \forall \mathrm{t}\right\} \qquad \forall \mathrm{i} \tag{11}$$

$$DERCosts_{\mathrm{i}} = is_{\mathrm{i}} * \mathrm{AICS} + ib_{\mathrm{i}} * \mathrm{AICB} \qquad \forall\ \mathrm{i} \tag{12}$$

$$EnergyCosts_{\mathrm{i}} = \sum_{\mathrm{t=1}}^{\mathrm{T}} \left(qw_{\mathrm{t,i}} * \mathrm{EBP_t} - qi_{\mathrm{t,i}} * \mathrm{ESP_t}\right) * \mathrm{WDT} \qquad \forall\ \mathrm{i} \tag{13}$$

[44] In Brown and Sappington (2017a) the optimality of net-metering is investigated. The setup in their paper is different but one could say that they model the term NM as a continuous variable. Namely, they investigate the optimal value of the compensation in kWh for DG compared to the full retail rate under different industry conditions. In this work, NM can only take two values, 1 and 0. This assumption is also briefly referred to in Section 7.1.

A consumer is subject to a number of constraints; these constraints are described by Eq. 14-21. Eq. 14 shows the demand balance for consumer i. The demand $\mathrm{D}_{\mathrm{t,i}}$ is determined exogenously and can be satisfied by the electricity withdrawn from the grid ($qw_{\mathrm{t,i}}$), a discharging battery ($qbout_{\mathrm{t,i}}$) or electricity produced by installed solar PV ($is_{\mathrm{i}} * \mathrm{SY}_{\mathrm{t,i}}$). Electricity can also be injected into the grid ($qi_{\mathrm{t,i}}$) or used to charge the battery ($qbin_{\mathrm{t,i}}$). Meeting the electricity demand is a hard constraint. Eq. 15-17 describe the battery balance, where $soc_{\mathrm{t,i}}$ is the state of the battery at time step t, EFC the charge efficiency, EFD the discharge efficiency and LR the leakage rate of the battery. DT is the time step as a fraction of 60 minutes used to convert all numbers to kWhs. Eq. 18-20 constrain the battery in terms of energy stored and instantaneous (dis)charging. $\mathrm{BRD}/\mathrm{BRC}$ stands for the ratio of the maximum instantaneous battery discharge/charge over its maximal energy stored. Eq. 21 indicates that all consumer variables must be non-negative.[45]

$$\mathrm{D}_{\mathrm{t,i}} = qw_{\mathrm{t,i}} + is_{\mathrm{i}} * \mathrm{SY}_{\mathrm{t,i}} + qbout_{\mathrm{t,i}} - qi_{\mathrm{t,i}} - qbin_{\mathrm{t,i}} \quad \forall\, \mathrm{i,t} \tag{14}$$

$$soc_{1,\mathrm{i}} = qbin_{1,\mathrm{i}} * \mathrm{EFC} * \mathrm{DT} - \ (qbout_{1,\mathrm{i}}/\mathrm{EFD}) * \mathrm{DT} + \mathrm{SOC}_0 \ \ \forall\, \mathrm{i} \tag{15}$$

$$soc_{\mathrm{t,i}} = qbin_{\mathrm{t,i}} * \mathrm{EFC} * \mathrm{DT} - \left(qbout_{\mathrm{t,i}}/\mathrm{EFD}\right) * \mathrm{DT} + soc_{\mathrm{t-1,i}} * (1 - \mathrm{LR} * \mathrm{DT}) \quad \forall\, \mathrm{i}, \mathrm{t} \neq 1 \tag{16}$$

$$soc_{\mathrm{T,i}} = \mathrm{SOC}_0 \ \ \forall\, \mathrm{i} \tag{17}$$

$$soc_{\mathrm{t,i}} \leq ib_{\mathrm{i}} \quad \forall\, \mathrm{i,t} \tag{18}$$

$$qbout_{\mathrm{t,i}} \leq ib_{\mathrm{i}} * \mathrm{BRD} \ \ \forall\, \mathrm{i,t} \tag{19}$$

$$qbin_{\mathrm{t,i}} \leq ib_{\mathrm{i}} * \mathrm{BRC} \quad \forall\, \mathrm{i,t} \tag{20}$$

$$qw_{\mathrm{t,i}}, qi_{\mathrm{t,i}}, soc_{\mathrm{t,i}}, qbout_{\mathrm{t,i}}, qbin_{\mathrm{t,i}}, is_{\mathrm{i}}, ib_{\mathrm{i}} \geq 0 \ \ \forall\, \mathrm{i,t} \tag{21}$$

3.3 Solving the bi-level optimisation problem

In order to solve the bi-level problem, it is first reformulated as a Mathematical Problem with Equilibrium Constraints (MPEC); for a full overview of the properties of MPECs see e.g. Gabriel et al. (2012). The reformulation into a single level problem is done by including the Karush-Kuhn-Tucker (KKT) conditions of the linear and thus convex lower-level as constraints to the upper-level problem. A non-linear MPEC results. The non-linearities in Eq. 8 are discretised using the technique described in Momber (2015, p. 102), and the complementarity constraints are transformed into disjunctive constraints using the technique described in Fortuny-Amat and McCarl (1981). A Mixed Integer Linear Program (MILP) results that can be solved by off-the-shelf optimisation software. The reformulation of the bi-level problem can be found in Appendix 0.

[45] No binary variables are introduced to ensure that no electricity is withdrawn/injected and that the battery is not charged/discharged at the same time step. Instead, it is checked ex-post whether these conditions are violated.

4. **Numerical example: setup and data**

In this section, the setup and data of a numerical example are described. The first section briefly introduces the setting. After, four subsections consider four groups of input data. This data is used to calibrate the model.

4.1 Setup

Two consumer types are modelled for simplicity: passive and active consumers, as is also done in Brown and Sappington (2017a, 2017b, 2018) and Schittekatte et al. (2018). The passive consumer does not have the option to invest in solar PV and batteries, unlike an active consumer, who can opt to invest in DER. Passive consumers are uninformed about the possibility to invest in DER. They either do not have the financial means, are strongly risk averse or simply do not have space. Active consumers minimise their costs to meet their electricity demand and may invest in DER to do so. At one extreme, all consumers can be passive, as in the recent past. At the other extreme, all consumers can be active, i.e. install DER when it can reduce their overall electricity cost. Reality presumably lies in the middle. Some consumers will remain passive for a number of reasons. Other consumers could be installing DER even when they do not financially profit from it, but because of other reasons which are harder to monetise, e.g. independence from the grid, sustainability motives etc. In the numerical example, it is assumed that 50% of all consumers are active and 50% are passive.[46]

The different results from the model which are presented in Sections 5, 6 and 7 are compared relative to a baseline scenario. In the baseline scenario, it is assumed that no consumer invests in DERs, i.e. solar PV and battery investment are disabled for active consumers in this scenario. This implies that in the baseline scenario the upper-level regulator is actually indifferent in terms of which distribution network tariff to choose. No tariff choice would distort decisions nor would lead to overall efficiency gains as no consumer can invest in DER and demand elasticity is zero. The historically accepted practice are volumetric charges with net-metering. Therefore these charges are defined as the baseline network tariff. In the recent past, with highly inelastic consumers, it was less an issue to recover grid costs with volumetric charges with net-metering. Limited inefficiencies were introduced as consumers had few options to serve their electricity needs other than from the grid. Also, high-usage and thus

[46] 50 % active consumer might seem quite a lot today. Today many consumers are passive because they are indifferent or vulnerable. A lower proportion of active consumers result in a lower impact of distortive network tariff design on total system costs. However, distortions result in costs shifts from active to passive consumers. In their turn, these cost shifts could again convert more (indifferent) passive consumers into active ones, increasing the impact of the distortion. Also, with dropping costs in DER, rising electricity bills, digitalisation and more climate awareness, a proportion of indifferent passive consumers might turn active.

higher network contributions correlated rather well with richer households, making such practice acceptable.

Under the baseline scenario, the two different types of consumers pay their baseline consumer bill as presented in Subsection 4.3. In the baseline scenario, the total system costs simply equal the consumer bills aggregate over all consumers. In the runs of the model when active consumers are enabled to invest in DER, the relative proportion and absolute values of the bill components can change for both the active and the passive consumers. The change in the consumer bills will be a function of the choice of the network tariff set by the upper-level regulator and the reactions from the lower-level active consumers. In that case, the total system costs consist possibly not only out of the aggregated consumer bills, but also the investment in solar PV and batteries by the active consumers is added.

4.2 Consumer types, demand and solar yield

The consumer demand and solar PV yield profiles are represented using a time series of 48-hours with hourly time steps and are shown in Figure 11 (left). The yield per kWp of solar PV installed is shown in Figure 11 (right).

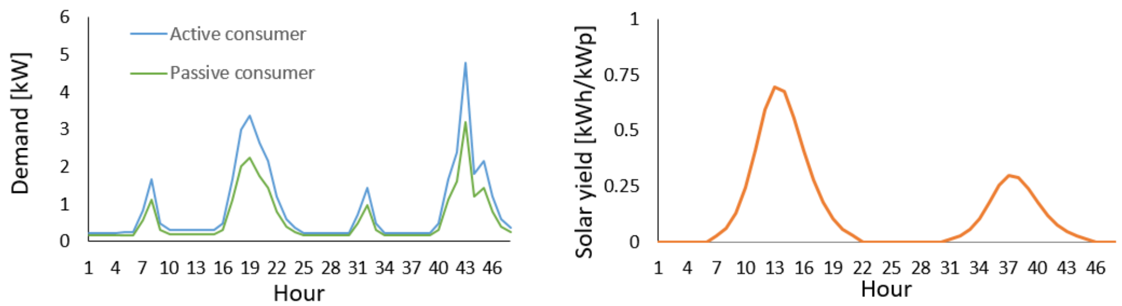


Figure 11: Original 48-hour electricity demand profiles (left) and PV yield profile (right)

Household demand for electricity shows for both modelled days a small peak in the morning and a stronger peak in the evening, the typical 'humped-camel shape' (Faruqui and Graf, 2018). For both consumer types the shape of the demand profile is identical; however, it is scaled differently. As a result, passive consumers have a slightly lower electricity demand than active consumers. The passive consumer has an annual consumption of 5,200 kWh with a peak demand of 3.2 kW and the active consumer a 7,800 kWh annual consumption with a peak demand of 4.8 kW. In Europe, average annual electricity consumption per household ranged from 20,000 kWh (Sweden) to 1,400 kWh (Romania) in 2015. In the same year, the average electricity consumption per household in the USA was about 10,800 kWh (EIA, 2016). The idea behind this difference in the levels of consumption is that active consumers are expected to be more affluent than passive consumers and that affluent consumers have higher electricity needs. This statement is a simplification of reality, but evidence for it is found in the literature. Borenstein (2017) analyses Californian data and finds that the income distribution of solar PV installations is heavily skewed towards the wealthy, but adds that the gap is narrowing with time. It is also found that PV adopters have slightly higher energy consumption levels and peak demand. Borenstein (2016) also confirms that wealthier households consume more electricity, but adds that although this claim is accurate, it is often overstated. Hledik et al. (2016) analyse data from Great Britain and confirm that lower-income consumers are also smaller consumers of electricity, although the correlation appears to be somewhat limited.

The yield per kWp of solar PV installed, as shown in Figure 11 (right), scales up to 1,160 kWh per year. As a reference, this level is similar than the average yield in the territory of France (Šúri et al., 2007). Seasonality is introduced in the PV yield profile by having a daily average PV yield of 40% of either side of the annual mean. The peak demand coincides with the day with the low PV yield. Letting the peak demand day coincide with the day with lower solar irradiation and vice-versa produces two effects. First, a high capacity of PV installed does not necessarily mean that the peak demand can be reduced. Faruqui and Graf (2018) investigate load profiles in Kansas and find that after the installation of PV systems, logically the net energy consumption reduces; nevertheless, the peak demand is virtually left unchanged. Second, if a high capacity of PV is installed, the injection peak of active consumers can become significant.

Additional sensitivity analysis regarding the length of the time series, the profiles of consumer demand and the profiles of solar PV yield is conducted in Appendix C.

4.3 Baseline consumer bills

In Table 7 the baseline consumer electricity bill, paid by the consumers when no consumer installs any DER technology, is shown. However, if active consumers decide to invest in DER, the relative proportion and absolute values of the bill components can change for both the active and the passive consumers. The annual electricity cost for the active and passive consumer equals respectively 1,340 €/year (0.172 €/kWh delivered) and 971 €/year (0.187 €/kWh delivered). This total cost is near the average electricity cost for EU households in 2015, which was estimated at around 0.21€/kWh (Eurostat, 2016). In the USA, the average electricity cost in 2015 was around 0.125€/kWh (EIA, 2016). The consumer bill is based on information from the Market Monitoring report by ACER and CEER (2016). There, the breakdown of the different components of the electricity bill for an average consumer in the EU for the year 2015 is presented. The energy component in the EU in 2015 is estimated at 37%. In absolute terms, this is a cost of 0.077 €/kWh. Further, 26% of the bill consisted of network charges, and 13% are RES and other charges. Finally, an important chunk of the bill (25%)

consists of taxes. A value-added tax (VAT), averaging 15%, must be paid and additional (ecological) taxes, averaging 10%, are raised in some countries. In this work, the VAT is integrated into the three components of the bill. Please note that a typical consumer bill varies from one country to another (e.g. ACER and CEER (2016) for the EU).

Table 7: Consumer bill in the baseline scenario (no investment in DER by active consumers)

		Cost per year	
Bill component	*Recovery*	*Active*	*Passive*
Energy costs	0.08 €/kWh	624 €/year (46 %)	416 €/year (43 %)
Network charges	Default: 0.062 €/kWh In the analysis: least-cost network tariffs	485 €/year (36 %)	324 €/year (33 %)
Other charges	Fixed fee (no interference with the analysis)	231 €/year (17-24 %)	
Total electricity cost		1340 €/year (0.172 €/kWh)	971 €/year (0.187 €/kWh)

The retailer energy price is set at 0.08 €/kWh.[47] Other charges are recovered through a fixed fee and as such do not interfere with the analysis. However, this is not always the case. How to collect such charges, or whether they belong in the electricity bill at all, is beyond the scope of this work, see e.g. the paper of Bohringer et al. (2017) in which the German case is discussed.

The network charges are in the baseline case recovered through (net-metered) volumetric charges equal to 0.062 €/kWh. How to adapt network tariff design when dealing with active consumers is the main contribution of this paper and is discussed in Sections 5, 6 and 7.

4.4 DER investment cost and technical parameters

Two DER technologies are assumed at the disposition of active consumers: solar PV and batteries. A scenario with low PV but also battery investment costs can be expected to materialise soon as pointed out by many studies (Lazard, 2016b, 2016a; MIT Energy Initiative (2016a); RMI, 2015).[48] Regarding solar PV, in the Utility of the Future Study by the MIT Energy Initiative (2016a) it is quoted that PV developers and industry analysts expect the installed cost of utility-scale PV to fall below $1000 per kW before the end of this decade, and that one major US car manufacturer projects that lithium-ion battery cell costs will drop below $100 per kWh by 2022—an order of magnitude less costly than 2010 costs. The levelised cost of energy (LCOE) of solar PV is 0.09 €/kWh[49], slightly higher than the retailer energy price. An important assumption is that no investment subsidy for PV is introduced in this work and no reduced social losses from environmental externalities due to the installation of solar PV are accounted

[47] The retailer energy price is considered flat and modelled exogenously; this assumption is also discussed in Section 7.1. Time-of-use retailer energy prices are introduced in the sensitivity analysis in Appendix C.

[48] For example, Maloney (2018) notes that 20% of Sunrun's customers have chosen to install solar plus storage systems in California in early 2018.

[49] In the model applied, the LCOE of solar PV is a function of the investment cost of the PV panel, lifetime, discount factor, the PV system performance ratio and importantly the solar PV yield profile, which is location dependendent.

for.[50] Batteries are assumed to cost 200 €/kWh with a C-rate of 1, i.e. the battery can fully (dis)charge in one hour. The other DER parameters are shown in Table 8. Technical DER data is in line with Schittekatte et al. (2016).

Table 8: Financial and technical DER data

Parameters PV related	*Value*	*Parameters battery related*	*Value*
Investment cost	1300 €/kWp	Investment cost (C-factor=1)	200 €/kWh
Lifetime PV	20 years	Lifetime battery	10 years
Discount factor PV	5 %	Discount factor battery	5 %
Maximum solar capacity installed	5 kWp	Maximum battery capacity installed	No limit
Price received for electricity injected (% of retailer energy price)	90 %	Efficiency charging & discharging	90 %
		Leakage rate	2 %

4.5 Grid cost structure

Determining the grid cost structure is no easy task. Pollitt (2018) states that if we attribute energy losses to retailers, perhaps 80% or more of distribution network costs are fixed in the medium-run for a given set of connections and probably cannot be reduced significantly within a five to ten-year period. Simshauser (2016) assumes, based on Crawford (2014) and Hanser (2013), that the distribution network has a cost structure which comprises approximately 20% fixed operating costs, 60% sunk capital costs, and 20% variable operating costs. Jenkins and Pérez-Arriaga (2017) provide a more detailed discussion of the different network costs components.

When presenting the results using the numerical example, three different grid cost structures are considered. First, grid costs are assumed to be 100% sunk, a short-term vision, i.e. the grid is over-dimensioned, and the electricity usage of consumers has no effect on the total grid costs. In some countries also policy costs are recovered through the network charges, which from a cost allocation point of view is no different than recovering sunk network costs. Second, half of the grid costs are considered sunk and the other half prospective, i.e. driven by the coincident consumer peak demand. Lastly, the grid costs are assumed to be driven completely by the coincident consumer peak demand. In the very long run grid costs are also variable. The network capacity will adjust to the coincident peak demand need from the consumers. If the coincident peak demand augments, the increase in grid costs could be seen as the cost of reinforcements or additional capacity. If the coincident peak demand is reduced, the decrease in grid costs could be seen as the avoided cost for replacing existing capacity or maintenance. In all cases, short-run marginal costs, e.g. energy losses, are not considered as they typically only contribute to a small proportion of the total cost of a network operator. Different network cost functions could be introduced in future work.

[50] Also this assumption is further discussed in Section 7.1.

The values for the parameters of the grid cost function (Eq. 4), $\mathrm{SunkGridCosts}$ and $\mathrm{IncrGridCosts}$, are derived from the 'baseline network costs' of the modelled consumers (shown in Table 7) and are a function of the proportion of active and passive consumers. With 50 % active and 50 % passive consumers, the (scaled) coincident consumer peak demand equals 4 kW in the baseline scenario, and the average grid costs equal 404 €/consumer.[51] In the first case, grid costs are assumed 100% sunk, the parameters $\mathrm{SunkGridCosts}$ and $\mathrm{IncrGridCosts}$ in Equation 2 are set as equal to € 404 and 0 €/kW respectively. In the second case, 50% of the costs are assumed sunk and 50% perspective, $\mathrm{SunkGridCosts}$ equals € 202 and $\mathrm{IncrGridCosts}$ is set to 50.5 €/kW.[52] In the third case, $\mathrm{SunkGridCosts}$ is zero and $\mathrm{IncrGridCosts}$ are set to 101 €/kW. As a reference, Brown et al. (2015) assume the (annualised) cost to be 75 $ for a kW of incremental household demand. Please note that another implementation constraint would be a correct estimation of the incremental network cost, or the network cost function in general, next to having an imperfect proxy of the network cost driver.

5. **Incorporating an implementation constraint: revisiting the model, results and discussion**

In this section, the model described in Section 3 is used to provide insights into the impact of the implementation constraint, i.e. not having a perfect proxy of the network cost driver. The section consists of two parts. First, the modelling implication is pointed out. Second, the obtained results, using the numerical example as introduced in the previous section, are shown and discussed.

5.1 Revisiting the model

A simple, yet effective change has been made to Eq. 4 to incorporate an imperfect proxy for the network cost driver in the model. This change has as a result that a reduction of the individual peak demand of a consumer of 1 kW results in a reduction of its contribution to the system peak demand by less than 1 kW. Eq. 22 shows the updated version of Eq. 4. DPeak is a parameter and stands for the baseline coincident peak demand, i.e. the coincident peak demand in the case no consumer installs DER, and $CoincidentPeak$ is a variable and stands for the optimised coincident peak demand, i.e. the coincident peak demand after active consumers installed DER when profitable. The parameter WF represents a weighting factor.

$$TotalGridCosts = \mathrm{SunkGridCosts} + \mathrm{IncrGridCosts} * (\mathrm{DPeak} - \mathrm{WF} * (\mathrm{DPeak} - CoincidentPeak)) \qquad (22)$$

The weighting factor can be interpreted as how imperfect the proxy of the network cost driver is. If WF has a low value, the more imperfect the proxy. This would mean that even though some active

[51] 4kW = 0.5*4.8 kW + 0.5*3.2 kW and 404 € = 0.5*485 € + 0.5*324 €

[52] 50.5 €/kW = 0.5*404 €/4kW

consumers adapt their individual peak demand, total grid costs are not affected much. This effect would be witnessed if consumers were being incentivised to lower their demand at a certain time which does not coincide with the time of the system peak. In the extreme, the actions of the consumers have no effect on the total grid costs (WF equals zero). Such a situation resembles the scenario with 100% sunk costs from a cost allocation point of view, although the nature of the grid costs, hard-to-target prospective grid costs versus sunk grid costs, is different. Alternatively, if the proxy for the network cost driver is very accurate, the actions of active consumers will have a stronger effect on the total grid costs. In the extreme, we end up with a fully cost-reflective tariff as implied by Eq. 2 in Section 3 (WF equals 1).

By introducing Eq. 22 also the assumption of identically shaped demand profiles is relaxed. Namely, with Eq. 22 the impact of the optimised coincident peak demand on total grid costs is reduced. A similar effect could be witnessed with heterogeneous demand profiles optimising their individual peak demand under an (individual) capacity-based charge. Passey et al. (2017) find low correlation coefficients in the range of 0.48 to 0.62 between consumer payments under a monthly capacity-based charge and the responsibility for the network peak. The correlation increases to 0.82 if only in months containing the system peaks are included instead of all months.

Finally, please note that the implication of Eq. 22 could also be interpreted from a reliability point of view. Namely, it is difficult to assume that DER at a consumer's premise can be a perfect substitute for the grid. There could be moments when technology fails, leaving the electricity need of consumers unmet. A reliability margin might be built into the grid to accommodate such extreme or unlikely conditions. Pollitt (2018) argues that the impact of DERs on network costs can be overestimated (and over-rewarded) for any network cost reductions. He bases this opinion on the fact that conventional networks may have 99.99% (one hour per year of lost load) or more availability, whereas individual asset availability may struggle to reach 98%. From a modelling point of view this means that even though the optimised peak demand might drive the network investment, the DSO will still make sure that there is spare network capacity available, thus dampening the impact of consumer actions on grid investment.

5.2 Results and discussion

First, a run is done in which we assume that we have a perfect proxy for the network cost drivers (WF equals 1). The results for the least-cost network tariff design are shown in Figure 12 and Table 9. In Table 9, two metrics are calculated for the different grid cost structures. First, the change in total system costs compared to the baseline scenario in which investments in batteries and solar PV are disabled. This metric is a proxy for cost-efficiency. Second, the change in network charges paid by the passive consumers is shown, with as reference the amount of volumetric network charges paid by the passive consumer in the baseline scenario (as shown in Table 7). This metric is a proxy for fairness. The higher the increase in network charges for the passive consumer compared to the past, the more unfair a network tariff is perceived.

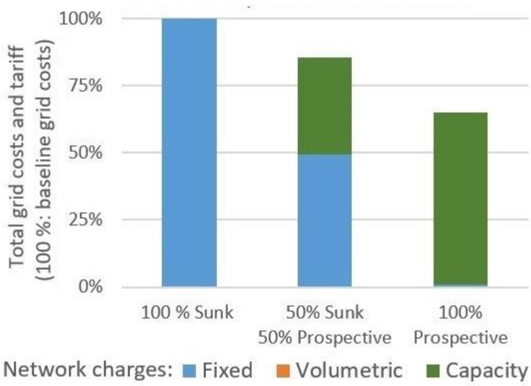


Figure 12: Network tariff components and grid costs compared to the baseline scenario for the three different grid cost structures. Perfect proxy for the network cost drivers.

Table 9: Total system costs and increase network charges per passive consumer compared to the baseline scenario. Perfect proxy for the network cost

50 % active consumers – Results compared to the baseline scenario (=no DER & volumetric network charges)		Perfect implementation cost-reflective charges
Total system costs	100 % Sunk grid costs	0.0 %
	50 % Sunk & 50 % Prospective	-1.4 %
	100 % Prospective grid costs	-6.8 %
Network charges passive consumer	100 % Sunk grid costs	25.0 %
	50 % Sunk & 50 % Prospective	12.6 %
	100 % Prospective grid costs	0.0 %

In Figure 12, the least-cost network tariff consists of a capacity-based charge equal to the incremental grid cost parameter ($\mathrm{IncrGridCosts}$ in Eq. 4) and a fixed charge equal to the sunk grid costs per consumer ($\mathrm{SunkGridCosts}$ in Eq. 4).[53] This corresponds to the theoretical optimal network tariff structure as described by MIT Energy Initiative (2016a).

When grid costs are 100% sunk, the least-cost network tariff design consists solely of a non-distortive uniform fixed charge (Figure 12), and there is no impact on the total system cost (Table 9: Total system costs and increase network charges per passive consumer compared to the baseline scenario. Perfect proxy for the network cost Table 9). Active consumers are indeed not incentivised to install DER: batteries would not reduce the total grid costs, and the LCOE of PV is slightly higher than the retailer energy price. However, due to the high uniform fixed network charge smaller passive consumers see

[53] There can exist an interval around the value of the coefficients of the least-cost network tariff for which the total system costs are the same. In modelling terms this means that there is more than one equilibrium with the same value for the upper-level objective but with not exactly the same network tariff designs and thus values for the lower-level objectives. In this case, one of these equilibria is the theoretical least-cost network tariff, the other equilibria have a network tariff structure which is very similar but the coefficients of the different charges (€/kWh, €/kW and/or €/connection) are slightly higher or lower. The reasoning behind this is that if a capacity-based/volumetric charge is set slightly higher or lower, it might not impact consumer decisions and thus the total system costs. The richer the data (e.g. number of consumer types or the length of the time series), the more sensitive the lower-level response function is to changes and thus the more sensitive the total system costs are to a minor change in the network tariff. When we introduce the fairness constraint and this constraint is binding (see Section 6), the interval around the value of the coefficients of the least-cost network tariff becomes small and generally there will be only one equilibrium.

their network charges significantly increase; some of the network costs, previously allocated to larger consumers through volumetric charges, are shifted to them.

With 100% prospective grid costs, it is efficient to ‘steer’ consumer behaviour with higher cost-reflective capacity-based charges, and each self-interest pursuing active consumer installs a battery of 3.7 kWh. Again, no solar PV is installed as the LCOE of PV is slightly higher than the retailer energy price and solar PV can only weakly help to reduce the network charges. From an active consumer’s point of view, installing more or less DER would result in a higher (individual) total electricity cost. A total system cost reduction of almost 7% results, as shown in Table 9. In this case, the active consumers reduce their grid charges proportionally with the reduction in total system costs and the passive consumers do not see any change in the grid charges paid.

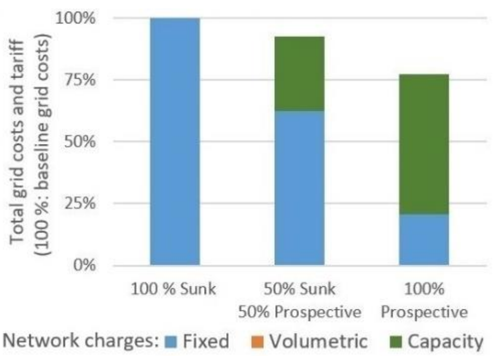


Figure 13: Network tariff components and total grid costs compared to the baseline for the three grid cost structures. Imperfect proxy for the network cost driver assumed (WF=0.75).

Table 10: Total system costs and increase network charges per passive consumer compared to the baseline scenario. Imperfect proxy for the network cost driver assumed

50 % active consumers – Imperfect proxy network cost driver (WF=0.75) Results compared to the baseline scenario (=no DER & volumetric network charges)		Least-cost tariff	Capacity-based charge = incremental grid cost
Total system costs	100 % Sunk grid costs	0.0 %	0.0 %
	50 % Sunk & 50 % Prospective	-0.3 %	-0.1 %
	100 % Prospective grid costs	-4.0 %	-3.7 %
Network charges passive consumer	100 % Sunk grid costs	25.0 %	25.0 %
	50 % Sunk & 50 % Prospective	15.6 %	15.9 %
	100 % Prospective grid costs	7.0 %	10.9 %

Figure 13 shows the least-cost tariff structure when introducing an imperfect proxy for the network cost driver, i.e. the parameter WF in Eq. 22 is lowered from 1 to 0.75. This means that a reduction of the individual peak demand of a consumer of 1 kW results in a reduction of its contribution to the system peak demand (which drives the prospective grid costs) with 0.75 kW instead of 1 kW. Two observations can be made when comparing the network tariff structure with (Table 10) and without (Table 9) an implementation constraint.

First, the results do not change for the case with 100% sunk network costs. There is indeed no value in information about the grid cost driver as the grid costs are assumed to be independent of grid use. Second, when a proportion of the grid costs are prospective, the non-distortive fixed charges are increased at the expense of the ‘steering’ capacity-based charge. This leads to an overall slightly lower grid cost reduction when compared to the case without implementation constraint and less DER installed by the consumer.

The reason for this change in the network tariff when introducing the implementation constraint can be deducted from the results in Table 10. Two result columns are introduced. First, the regulator is free to optimise the network tariff which would lead to the lowest total system cost (first column) - the network tariff shown in Figure 13 results from this run. This can be viewed as the case where the regulator is aware of the implementation difficulties with cost-reflective network charges. After, a run is computed in which the capacity-based charge is set as equal to the incremental grid cost (second column). This would be the situation when the regulator ignores the inaccuracy in the network cost driver proxy. It is evident that by taking into account the imperfect proxy and departing from the theoretical least-cost network tariff, a lower total system cost can be obtained.

The intuition behind these results is the following: if the capacity-based charge is set as equal to the incremental grid costs, batteries are over-incentivised. An individual consumer installs batteries as they are profitable from his individual perspective. However, the grid costs decrease less than the cost of the DER investment. Overall, in that case, total system costs are higher than when active consumers install fewer batteries (2.8 kWh), demonstrating a deadweight loss for society due to distortive tariff design. Further, the grid costs, which did not decrease significantly due to the imperfect proxy of the network cost driver, need to be recovered.

As a consequence, non-cooperative active consumers compete with each other to escape from high grid costs by installing more and more batteries. Active consumers install a battery of 3.7 kWh capacity, instead of one with 2.8 kWh capacity which results in the case the regulator accounts for the inaccuracy in the proxy of the network cost driver in its network tariff design. Higher grid charges for the passive consumers result, not only due to the introduction of uniform fixed network charges but also due to distortive network tariff design, leading to active consumers benefiting from higher reductions in their grid charges than the reduction in total grid costs they are responsible for. This is clearly illustrated by comparing the increase of the network charges of the passive consumer for the 100% prospective grid cost structure. In that case, the grid charges for the passive consumer increase quite significantly (3.9 percentage points) due to the distorted network tariff design. Notably increased grid charges for smaller passive consumers can lead to fairness issues, as discussed in more depth in the next section.

6. **Adding a fairness constraint: revisiting the model, results and discussion**

The previous section has shown that pursuing a least-cost network tariff design can lead to significant distributional effects. In this section, a fairness constraint, in the form of a cap on the increase of grid charges for the smaller passive consumers, is added to the model described in Section 3 and amended in Section 5. The section consists of three parts. First, the modelling implication is pointed out. Second, the results obtained with a fairness constraint, using the same numerical example as introduced in Section 4 and 5, are shown and discussed. Third, results are discussed when jointly applying the fairness and implementation constraint.

6.1 Revisiting the model

In order to assess the least-cost tariff design with a cap on the increase of network charges paid by passive consumers, Eq. 23 is added to the upper-level problem. The index 'i2' stands for the passive consumer type and $\mathrm{BGC}_{'\mathrm{i2}'}$ are the network charges paid by the passive consumer in the baseline scenario. With the parameter $\mathrm{Cap}_{'i2'}$ it can be decided how high the increase in network charges paid by the passive consumer is allowed to be when compared to the network charges paid in the baseline scenario (Table 1). If the cap is set very high, the fairness constraint will not be binding and thus will not influence the least-cost network tariff design. If the cap is set very low, the model can become unfeasible, i.e. there is no network tariff that can lead to cost-recovery for the DSO while taking into account the reactions of the active consumers to the network tariff and at the same time respecting the fairness constraint.

$$vnt * \sum_{\mathrm{t}=1}^{\mathrm{T}} \left(qw_{\mathrm{t},'\mathrm{i2}'} - \mathrm{NM} * qi_{\mathrm{t},'\mathrm{i2}'} \right) * \mathrm{WDT} + cnt * qmax_{'\mathrm{i2}'} + fnt \leq \mathrm{BGC}_{'\mathrm{i2}'} * (1 + \mathrm{Cap}_{'\mathrm{i2}'}) \tag{23}$$

6.2 Results and discussion with a fairness constraint

In this section, the results for the numerical example are discussed. Figure 14 illustrates that the state of the grid determines to what extent the incentives given to active customers via distribution network tariffs result in system benefits and/or whether these benefits are shared with passive consumers. The results are completely different for the three illustrated grid states. Additionally, the resulting least-cost network tariff designs at a 10% fairness cap ($\mathrm{Cap}_{'\mathrm{i2}'}$ = 0.10) are shown for the case in which the grid costs are assumed 100 % sunk and the case in which the grid costs are assumed 50% sunk and 50% prospective costs. In the case grid costs are assumed 100 % prospective, the fairness cap is not binding; thus the results are not impacted.

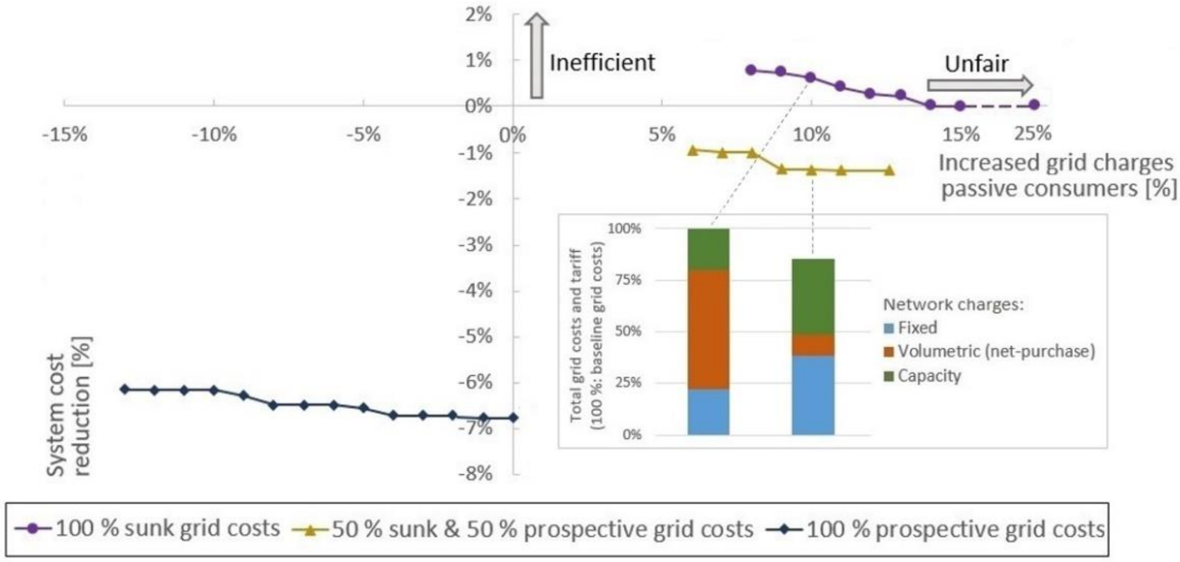


Figure 14: Total system cost increase trade-off with the increase of grid charges of passive consumers for different grid cost structures. Perfect proxy for the grid cost drivers assumed.

The first state of the grid is 100% sunk costs. In this state of the grid, the least-cost network tariff is a fixed charge, which significantly increases the costs for small passive consumers (25% increase in grid charges). However, we can 'sacrifice' some cost-efficiency to lower fairness concerns. Looking at Figure 14, this means moving to the left on the ''100 % sunk grid cost line''. Two opposing forces are working in this case. On the one hand, by lowering the fixed network charges, the fairness issue decreases. But by resorting to other network tariff components which are needed to ensure full grid cost recovery (volumetric charges and/or capacity-based charges as can be seen on the same figure), the network tariff will be distortionary.[54] This implies that active consumers can exploit opportunities that might be beneficial for themselves but which are not necessarily optimal from a system point of view.[55] The private benefits active consumers obtain in this way come at the expense of passive consumers, thus aggravating the fairness issue once again. These two forces can be played out until the moment the model becomes unfeasible, i.e. there is no way anymore to recover all grid costs while limiting the fairness concern. For this example, this occurs at the point when the increase of grid charges for passive consumers is capped at a level lower than 8%. Note that the significant improvement in fairness comes at a relatively small increased total system cost.

[54] Volumetric charges with net-purchase, i.e. only charging for the electricity withdrawn from the network, are opted for by the regulator. Volumetric charges with net-metering lead to a higher system cost and create a fairness issue as they strongly over-incentivise PV adoption.

[55] This happens at the point when the increase of grid charges for passive is capped at a level lower than 14 %. Beyond that point, when further reducing the grid charges for passive consumers, the increase of volumetric and capacity-based charges in the network tariff, which are needed to respect cost-recovery, are large enough to impact the investment decisions of the active consumers. Consequently, the increase in total system costs rises above 0 %.

The second state of the grid is 100% prospective costs. In this case, a cost-reflective tariff can achieve a lot of cost savings thanks to the incentives given to active consumers. These system benefits also lead to a price reduction for passive consumers. It is possible to push the model towards a network tariff structure that sacrifices some of the system benefits for an outcome that is even better for passive consumers, but it is unlikely that this would occur in practice as there is no perceived unfairness in this case.

The third state of the grid is 50-50 sunk and prospective grid costs. In our numerical example, the negative effects we see in the first state of the grid for passive consumers dominate the positive effects we see in the second state of the grid. Even though the system is better off, the passive consumers pay more. This means that the active consumers are winning twice: they are getting all the system benefits and they are pushing some of the costs towards passive consumers. It is possible to engineer a network tariff that somewhat softens the unfairness for passive consumers, but they are always worse off in this case.

6.3 Results and discussion with a fairness and implementation constraint

Figure 15 is even more sobering for passive consumers than the results in the previous section. If we cannot get the cost driver right, we risk passive consumers are worse off in all cases. The results for 100% sunk costs do not change, of course. If all costs are sunk, there is no cost driver, so the inaccuracy of the cost driver does not apply to that case. In the other two cases, the implementation issues with cost-reflective network charges make the system, and also the passive consumers, relatively worse off. In the case of 100% prospective costs, the impact is most significant for passive consumers: they end up mostly losing instead of sharing the benefits with active consumers. In other words, the two issues that we discussed separately in this paper strongly interact with each other.

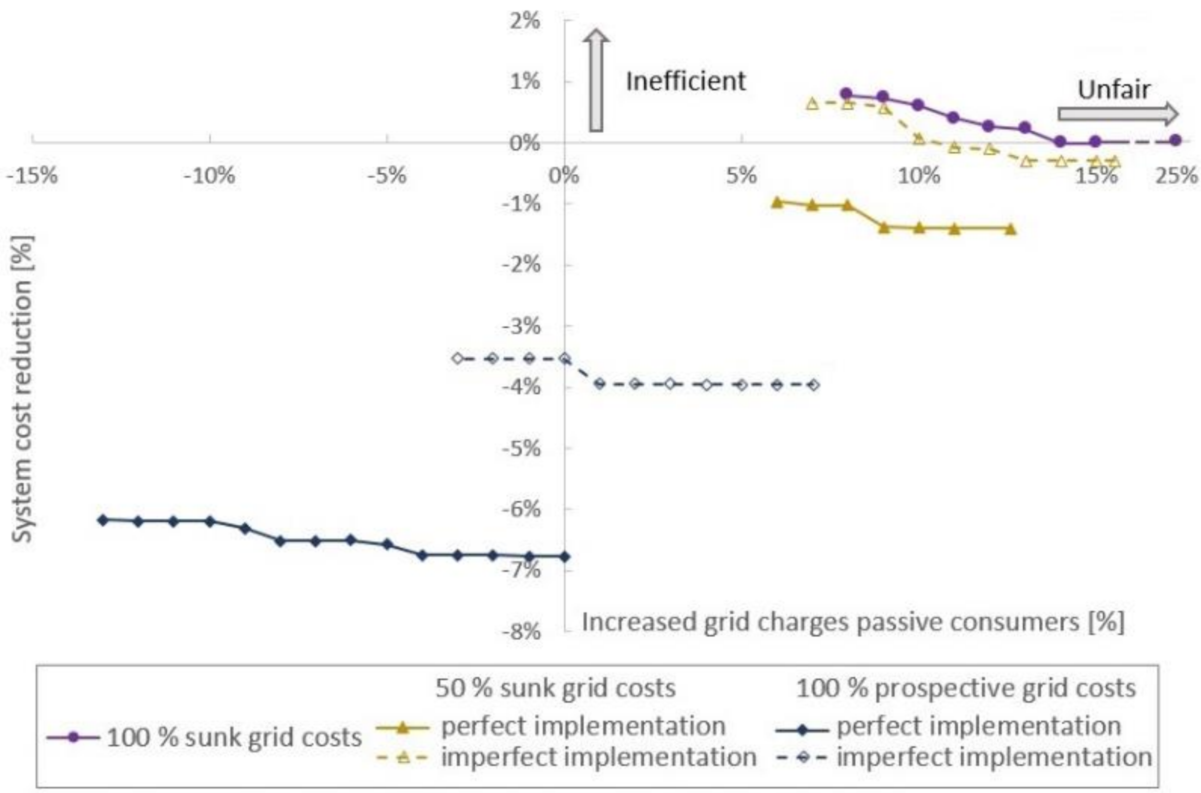


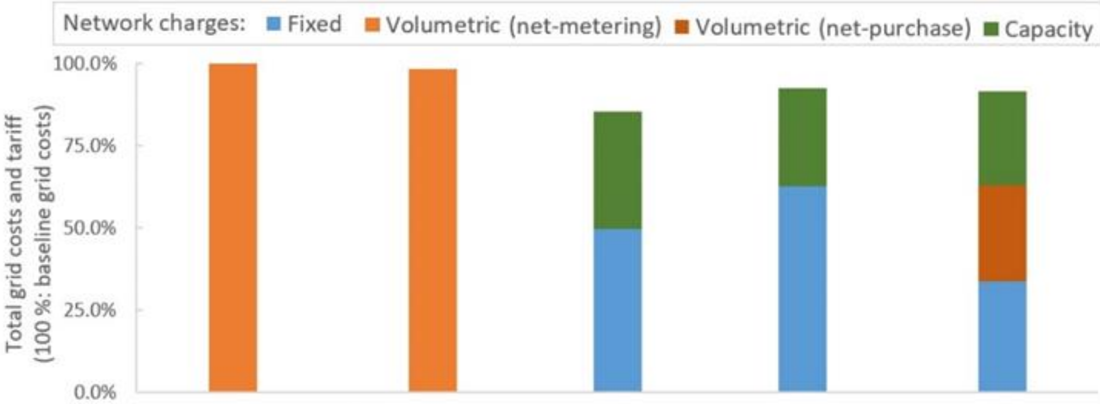
Figure 15: Total system cost increase trade-off with the increase of grid charges of passive consumers for different grid cost structures. Results with and without implementation issues with cost-reflective network tariffs are shown.

7. Discussion results and policy implications

This section consists out of two parts. Firstly, an overview of the results is shown, important assumptions are discussed, and the main findings of the sensitivity analysis are described. The sensitivity analysis can be found in Appendix C. Secondly, the main policy implications are derived.

7.1 Overview of results, discussion assumptions and finding of the sensitivity analysis

Figure 16 shows an overview of the results for the case in which 50 % sunk and 50 % prospective grid costs are assumed. From that figure, it can be seen how the results are gradually impacted by the two considered constraints in terms of the least-cost network tariff design, the total system costs (and its components) and the network charges increase for passive consumers.



50 % sunk &50 % prospective grid costs Results compared to baseline scenario (=no DER & baseline network tariff)	Baseline network tariff with active consumers	Least-cost network tariff with active consumers	Least-cost network tariff with implementation issue	Least-cost network tariff with an implementation issue & fairness constraint
Δ total system costs	**+ 3.4 %**	**- 1.4 %**	**- 0.3 %**	**+ 0.1%**
Δ total grid costs	-1.4 %	- 14.6 %	- 7.5%	- 8.5 %
Δ total energy costs	- 41.6 %	+ 1.7%	+ 0.7 %	- 5.6 %
PV active consumer [kWp]	5	0	0	0.7
Battery active consumer [kWh]	0	2.7	1.8	2.0
Δ network charges passive consumer	**+ 78.0 %**	**+ 12.6 %**	**+ 15.6 %**	**+ 10 %**

Figure 16: Summary of all the results for the case with 50 % sunk and 50 % prospective grid costs assumed.

We do four observations in Figure 16. First, it can be seen that there is a clear case to redesign the historical in place baseline network tariff, volumetric charges with net-metering, as also argued in the introduction of the paper. Active consumers are strongly incentivised to invest in solar PV (5 kWp per active consumer) as by doing so they can avoid paying for energy and grid charges. The overall expenditure on energy costs does indeed reduce strongly (-41.6%), but grid costs remain more or less stable (-1.4 %). Overall a 3.4 % increase in system costs compared to the baseline results; the total costs of PV investment by active consumers is higher than the sum of system benefits in terms of energy and grid. Also, active consumers lower significantly their grid charges but the grid costs do not lower proportionally. Therefore these costs are shifted to the passive consumers (+78 % in grid charges compared to the baseline) and a significant fairness issue results.

The second observation is that when not assuming any implementation constraint or disregarding distributional impacts, Figure 16 shows that the least-cost network tariff replacing volumetric charges with net-metering consists of a fixed charge to recuperate the sunk grid costs and a capacity-based charge to align grid benefits with consumer benefits. It can be seen that when having a perfect proxy for the network cost driver, a system cost reduction can be achieved (-1.4 % compared to the baseline) while the network charges for the passive consumers increase (+12.6 %).[56] Third, in case of not having a perfect proxy, the cost-efficiency decreases and the fairness issue aggravates. Finally, when capping the increase in network charges for the passive consumers a three-part network tariff results. By introducing a volumetric network charge with net-purchase at the expense of the unpopular high network fixed charge some cost-efficiency can be sacrificed for fairness.

In what follows we discuss three important assumptions made in this work and highlight the two main findings of the sensitivity analysis which can be found in Appendix C. A first important assumption made in the numerical example is the fact no positive externalities from solar PV adoption are assumed. If decentralised solar PV adoption would (partly) replace polluting central generation plants, a carbon markup in the energy price and subsidies are not politically feasible; it might be socially beneficial to stimulate PV adoption by allowing for a larger proportion of volumetric network charges (possibly with net-metering). This is also argued for in the work by Brown and Sappington (2017a).[57] However, the fairness issue with overly volumetric network charges combined with active consumers installing solar PV would remain pertinent. A relevant empirical work in this regard is the paper by Borenstein and Bushnell (2018). The authors investigate how some electricity prices in the US might to be too low– such as unpriced pollution externalities– while others cause prices to be too high– such as recovery of fixed costs through volumetric charges.

Second, we assumed perfectly price-inelastic demand. Instead, we allowed active consumers to fulfil their electricity demand by other means than the grid (solar PV and batteries). Demand response (DR) could give consumers the ability to shift their demand in time, just as batteries can. For example, Koliou et al. (2015) analyse a tariff-based DR programme and find that it can result in reduced overall costs both for the DSO and consumers. It is hard to put a price tag on DR actions, but one can imagine that some demand shifting can be done fairly cheap through automatisation. This would mean that by including DR, the attractiveness to invest in batteries might reduce. Also, the negative impact on system cost of a network tariff that overly relies on imperfectly implemented capacity-base charges could be lower. However, this could also mean that the fairness issue would be more significant as it easier for active consumers with automated appliances to 'shift' network charges to passive consumers who do not own such appliances.

[56] Active consumers install a battery (2.7 kWh per active consumer) to lower their grid charges and by doing so they also lower the overall grid costs (-14.6 %). A small increase in energy costs (+1.7 %) results due to energy losses of the battery. The increase in grid charges for the passive consumers compared to the baseline results from the introduction of the uniform fixed network charge in a setting with lower-usage passive consumers.

[57] In that regard, making the parameter NM, which is set to account for net-metering or net-purchase volumetric charges, endogenous and allowing it to be a continuous number might bring new insights.

Lastly, a limitation of the modelling approach is that the retailer energy price a consumer pays is not considered endogenous.[58] One could argue that if consumers install solar PV, this will propagate to the wholesale market and finally energy prices could go down (see e.g. Darghouth et al. (2016)). This is true on the short-run, but in the long run the effect is more ambiguous. For example, Green and Vasilakos (2011) use a long-run market equilibrium model and find that in the long-run equilibrium the average price level does not change much with a significant increase in wind power. However, the volatility of the price would increase. To get an idea of the effect of more volatile energy prices, we added runs with time-of-use (TOU) energy retailer prices in Appendix C. It is found that with TOU energy prices instead of flat energy prices, system cost can decrease more compared to the baseline than in the presented numerical example. With TOU energy prices, batteries cannot only be used by active consumers to lower the peak demand but also to arbitrage energy prices. With TOU energy prices in place, in most scenarios, the proportion of capacity-based network charges in the least-cost network tariff decreases slightly. This occurs because battery investment is additionally incentivised by TOU energy prices. It is also shown that TOU energy prices affect not only battery adoption but can also affect solar PV adoption.

Besides the interaction between network tariff design and TOU energy prices, a second main finding of the sensitivity analysis in Appendix C is that the results are sensitive to how financially attractive solar PV investment is. If we assume that the retailer energy price is higher than the cost to generate electricity from solar PV on rooftops, logically, the total system costs go down with solar PV adoption by the active consumers.[59] However, we find that at the same time the fairness concern becomes more severe. Making the least-cost tariff fairer by increasing volumetric network charges to partially replace unpopular fixed network charges, does not work anymore in the case solar PV is cheaper. This is true because the investment distortion in solar PV investment become more sensitive to these increased volumetric charges. On the contrary, if solar PV is relatively expensive, fairness is less of a concern as the share of (net-purchase) volumetric network charges in the final network tariff can be quite high before these charges induce distortions.

[58] Also, the impact of DER adoption on transmission costs are abstracted from the analysis, see e.g. Denholm et al. (2014) for a complete overview of the system benefits of DER adoption.

[59] In the sensitivity analysis we do this by inserting higher solar PV yield profiles than in the numerical example and keeping the investment cost of solar PV and the retailer energy price constant. Similar results would be obtained by lowering the investment cost of solar PV or increasing the retailer energy price.

7.2 Policy implication: overcoming the limitations of traditional network tariff design options

Our work confirms the challenges faced by regulators today, e.g. in Europe (CEER, 2017a) and the US (Trabish, 2018). Before, distribution network tariffs were mainly a technical discussion between the DSO and the regulator. Today and in the future, there are a whole lot more stakeholders. These stakeholders need impact analysis where the response of consumers to network tariff design and distributional impacts are shown to justify choices.

We found that if the regulator only has the three options available that we consider in this paper, it will be difficult to implement a fair network tariff design. However, in practice, our results regarding fairness might be overestimated as such issues can be improved through other solutions than standard network tariff design. Negative distributional effects could be remedied through specific low-income programmes as described by Wood et al. (2016). Another solution would be not to implement a uniform fixed network charge as in our analysis, but differentiate the fixed network charges per consumer or consumer groups without distorting the use of electricity, e.g. by income, property value, property size, kW connection capacity (Abdelmotteleb et al., 2017; MIT Energy Initiative, 2016; Pollitt, 2018). It might also be possible to improve fairness by introducing some form of taxation for active consumers. However, taxation is also difficult to implement and could conflict with other public policy goals. In the case of high sunk grid costs, under-recovery of the grid costs could be an option as full cost recovery leads to inefficiencies. Not recovered sunk network costs could be recuperated through other means than the electricity bill, an option also discussed in the report by the MIT Energy Initiative (2016). An alternative could be to let taxpayers pay for these costs, as is done for roads in some countries.

On the other hand, our results could underestimate the difficulties with least-cost and fair distribution network tariff in practice. We did assume policy costs not to interfere with the analysis, but the share of these costs in the electricity bill is increasing year by year in most countries, and the way these costs are recuperated from consumers, mostly volumetrically, can seriously distort network tariff design and aggravate efficiency and fairness issues.

An additional takeaway is that we show that it can be reasonable to spread distribution network costs over the different traditional network charge options (volumetric, capacity-based and fixed) if these are the only options available. As such, the identified issues with each of them are dampened, i.e. distortions in solar PV adoption with too high volumetric network charges, distortions in battery adoption with too high capacity-based network charges and fairness issues with too high fixed network charges. Three smaller distortions are desirable over one more significant distortion. Overall, more impact analysis is needed.

8. **Conclusion and future work**

In this paper, we have applied a game-theoretical model to analyse the impact of an implementation and fairness constraint on least-cost distribution network tariff design. The game-theoretical model takes into account decentralised decisions of self-interest pursuing active consumers enabled to invest in solar PV and batteries.

First, we find that both constraints have a significant impact on the least-cost network tariff design. In theory, the least-cost distribution network tariff design has a fixed component that is proportional to the sunk costs, and a capacity component to reflect the costs of grid investments that still have to be made and that can be partly avoided if it is cheaper for active customers to invest in DER. In practice, departing from volumetric charges towards higher fixed charges is often perceived as unfair as their introduction would mean that low-usage passive consumers, who are often also less wealthy consumers, would pay similar charges as high-usage active consumers, who are often richer. Also, in practice, the individual capacity or individual peak is often a relatively weak approximation of the actual cost driver(s) of the network. As a result, a three-part tariff combining fixed, capacity, and volumetric charges may be more suitable, even though in theory, volumetric is not to be considered for a least-cost distribution network tariff design.

Second, we find that there is a strong interaction between the two constraints we analysed. If regulators do not anticipate that their implementation of cost-reflective tariffs will be imperfect, the system costs will increase, and the fairness issues will also aggravate. It is therefore important to have realistic estimations of what we know and do not know about the cost drivers of distribution networks. Limited information is available, suggesting that we need to be careful in setting strong incentives. This is especially true with high shares of active consumers.

Third, the results depend on the state of the grid. If most of the grid investments still have to be made, passive and active consumers can both be made to benefit from cost-reflective tariffs, while this is not the case for passive consumers if the costs are mostly sunk. The standard network tariff design options, i.e. volumetric, capacity, and fixed charges, do not suffice to transfer part of the welfare gains of the active consumers to compensate the passive consumers. Other solutions than standard tariff design would have to be introduced to reach a fairer outcome; examples are specific low-income programmes, differentiated instead of uniform fixed charges, the recuperation of sunk network costs through other means than the electricity bill or the taxation of active customers, which has its own issues.

Regarding future work, it would be interesting to include electric vehicles and heat pumps in the analysis. Accounting for these (mainly) electricity consuming technologies could present new insights. More granular network tariffs could become increasingly important to limit the efficiency loss. Overall, the interaction between network tariff design, retail energy pricing, public policies (e.g. energy efficiency and DER subsidies) and taxation deserves further analysis. Lastly, due to the structure of the model, it is assumed that the regulator has perfect insight into the consumer's reaction on the network tariff design. This is a simplification. In reality, future demand is not known ex-ante and has to be estimated. This anticipation issue could be accounted for by including stochasticity in the consumer reaction. An example is the paper by Weijde and Hobbs (2012) in which a stochastic two-stage optimisation model that captures the multistage nature of the planning of a transmission network under uncertainty is presented. Actually, this planning uncertainty is another implementation issue with improved network tariffs. Adding multiple stages and stochasticity would require an expansion of the presented model.

CHAPTER 4: ON THE INTERACTION BETWEEN DISTRIBUTION NETWORK TARIFF DESIGN AND THE BUSINESS CASE FOR RESIDENTIAL STORAGE

Abstract

Battery adoption by residential consumers, mostly coupled with a new or existing solar PV system, is expected to rise in the near future. In that regards, distribution network tariff design plays an important role. The network tariff design should align the business case of storage with the impact it has on the local grid. We evaluate capacity-based network charges and two types of network charges which stimulate self-consumption: net-purchase and bi-directional volumetric network charges. We show that when grid costs are sunk, all network tariff design options will over-incentivise battery adoption at the expense of overall welfare. In contrast, when many future grid costs are to be made, the considered network tariff design options will mostly under-incentivise battery adoption, and potential welfare gains are missed out. Besides the network tariff design, also time-varying energy prices do improve the business case of storage. However, some unwanted interactions between the network tariff design and time-varying energy prices are possible.

Keywords: Batteries, distributed energy adoption, distribution network tariff design, game-theory, non-cooperative behaviour

This chapter is written without co-authors and serves as a draft for a working paper. The additional finding regarding the interaction between different energy pricing schemes and the evaluated network tariff design might be omitted in the final version of the working paper. The reason for this is that this finding is expected to serve as a starting point for further research after the submission of the thesis. Earlier versions of this chapter were presented at:

- *Workshop storage taskforce SmartEN– Brussels, Belgium, 9 October, 2018*
- *DIW: SET-Nav Modeling Workshop - Two-stage decision making and modelling for energy markets – Berlin, 11 October 2018*
- *Conference on storage business models, organized by EASE and Vlerick Business School – Brussels, Belgium, 30 November 2018*
- *3rd AIEE Energy Symposium –Milan, Italy, December 10-12, 2018*

1. Introduction

Electrical energy storage, mainly in the form of lithium-ion batteries, is becoming a factor in the residential solar market. Schill et al. (2017) state that in Germany in 2015, nearly every second small-scale PV system was installed together with a battery. By the end of 2016, summing up to about 48,000 'prosumage' systems were installed. Maloney (2018) notes that 20% of Sunrun's customers have chosen to install solar plus storage systems in California in early 2018, in parts of Southern California that total is as high as 50% of sales. Greentech Media estimates that battery installations will reach a rate of more than 1300 MW per year by 2022 in the US (GTM Research and Energy Storage Association, 2017). The business case of batteries is mainly a function of two forces. On the one hand, the strongly decreasing investment costs (see e.g. RMI (2015)). On the other hand, the reduction in the electricity bill that can be achieved by battery adoption. In this paper, we focus on the latter. In that regard, rate design, more specifically distribution network tariff design plays an important role. Distribution network charges represent on average around 30 % (incl. VAT) of the final electricity bill in Europe, with a maximum of around 50 % in Norway and a minimum of around 15 % in Italy (ACER and CEER, 2018).

Historically, volumetric distribution network charges (€/kWh) were in place in most jurisdictions around the world. This practice is being challenged in recent years. More specifically, volumetric charges with net-metering, implying that a consumer's network charges are proportional to its net consumption from the grid over a period of time (e.g. month), are deemed inadequate with the massive deployment of solar PV. Consumers with solar PV pay significantly lower network charges but still rely on the distribution grid as much as they did before. In other words, such network charges serve as an implicit subsidy for solar PV which ends up being paid by consumers without solar PV.[60] Therefore, regulators in many countries are thinking to suspend net-metering and move more towards network tariffs which are capacity-based (€/kW) or stimulate self-consumption of the on-site generated electricity (CEER, 2017a; European Commission, 2015b; Hledik, 2014). Such types of distribution network charges are deemed to align better what consumers pay for the network with the costs they cause. Batteries are identified as a key enabling technology to allow the reduction of capacity needs of a consumer or to allow for more self-consumption.

The impact of distribution network tariff design on the business case for residential electricity storage is the topic of this paper. More precisely, it is analysed whether the network tariff design aligns the

[60] See e.g. the blog post by Lucas Davis (March 2018): https://energyathaas.wordpress.com/2018/03/26/why-am-i-paying-65-year-for-your-solar-panels/

business case for residential electricity storage with wider system benefits. We show that depending on the assumed grid cost structure, i.e. whether most grid investments are sunk or many grid investments still have to be made, batteries can be over-or under-incentivised by the design of the distribution network tariff; the network tariff can act as an implicit subsidy or a tax for storage adoption.

Besides the network tariff design, an additional important driver for the business case of residential storage is time-varying energy prices. With time-varying energy prices, a battery can also be used for energy price arbitrage aside from solely reducing grid fees. Ceteris paribus, with time-varying energy prices instead of flat energy prices, the business case for storage will improve. However, a consumer, when deciding about the adoption and operation of storage, will look at the possible reduction in her final electricity bill instead of at each separate cost component (network charges, energy costs and taxes and levies) in isolation. Therefore, there is an interaction between network tariff design and energy price arbitrage. We look briefly at how this interaction can result in energy arbitrage strategies that deviate from the optimal energy arbitrage strategy which would lead to the highest wider system benefits.

The following of the paper is structured as follows. In Section 2, the evaluated distribution network tariff designs are introduced. In Section 3, the methodology is described. Two models are used. A game-theoretical model with which the alignment of incentives of individual consumers and the wider system is evaluated and a central planner model that serves as a benchmark. The full model formulation is not treated in the body of the text but can be found in Appendix A. In Section 4 , the setup and data for the numerical example are described. In the core of the paper, Section 5, results are shown and discussed. The result section is split up into four parts. First, we show the results for the case that all grid costs are assumed sunk. Second, we show the results for the case that the grid costs are driven by the aggregated consumer peak demand. Third, we look at how time-varying energy prices impact the results. Fourth, we show that there exists a theoretically optimal network tariff design, so-called critical peak pricing, which approximates the outcome of the central planner under given assumptions. Lastly, in Section 5 a conclusion is presented, and policy implications are derived.

2. Evaluated distribution network tariff designs

In this section, the three evaluated network tariff designs are introduced. First, we describe capacity-based network charges. After, two types of network charges which stimulate self-consumption are introduced: net-purchase and bi-directional volumetric network charges.

2.1 Capacity-based network charges

With capacity-based network charges, also called (maximum) demand charges in the US, a consumer pays for the grid according to his (individual) monthly or yearly peak capacity usage averaged per e.g. an hour. Simshauser (2016) finds that capacity-based charges resolve issues with volumetric network charges such as rate instability and wealth transfers between solar PV and non-solar PV adopters. The idea behind capacity-based charges is that as the main driver of the network is (peak) network capacity, it makes sense to charge consumers according to their maximum network capacity needs. The problem is however that individual consumer maximum capacity-usage does not always coincide with the main network cost driver, the aggregated peak capacity need over a group of consumers connected to the same network.

In that regard, Simshauser (2016) notes that if the capacity-based charge overstates the value of peak load, it may pull-forward battery storage to an extent that it is not cost-efficient anymore. Similarly, Brown and Sappington (2018) find that capacity-based charges tend to be relatively effective at enhancing welfare when the demand for electricity is relatively sensitive to price and when the peak demands of all consumers occur during the same period. However, welfare gains are a lot more modest when the peak demands of many residential customers do not coincide with the system-wide peak demand for electricity. Finally, Passey et al. (2017) present a method to assess the cost-reflectivity of capacity-based charges visually and test different implementations. They use Australian data and find that standard capacity-based charges to have low cost-reflectivity in terms of aligning customer bills with their contribution to the overall network peak demand. The authors continue by arguing that the potentially significant adverse impacts on the economic efficiency of such tariffs is an issue that does not appear to have received sufficient policy attention. However, more advanced implementations significantly improve the cost-reflectivity. An example are capacity-based charges that are only levied during the months in which the aggregated peak demand occurs.

2.2 Self-consumption incentivising network charges

Besides capacity-based network charges, we also evaluate two distribution network tariff design that stimulates self-consumption.[61] With net-purchase volumetric charges, a consumer pays a €/kWh fee for all electricity withdrawn from the network. Contrarily to the historical practice of volumetric charges with net-metering, the meter does not turn backwards when excess electricity is injected in

[61] Self-consumption is defined as the direct use of PV electricity on the same site where it is produced, with a smaller amount of electricity fed into the grid.

the network. With bi-directional volumetric network charges, a €/kWh network fee is paid for each kWh of electricity withdrawn and injected into the network.[62]

By creating a difference between the value of on-site generated electricity that is self-consumed or injected back into the network, these network tariff design incentivise self-consumption. On one extreme, volumetric network charges with net-metering did not stimulate self-consumption at all, i.e. the grid acts as a free battery, and the price a consumer receives to inject 1 kWh into the grid is always equal (or even greater) than the price a consumer pays to consume 1 kWh from the grid. On the other extreme, volumetric network charges with bi-directional metering, i.e. a consumer has to pay a volumetric network charge to withdraw and a volumetric network charge to inject electricity in the grid, will give the incentive to minimise the exchange of electricity with the grid and thus to maximise self-consumption. The incentive to self-consume under volumetric charges with net-purchase lies in the middle.

Different self-consumption policies have been implemented in different countries. Luthander et al. (2015) describes that for example Italy had a self-consumption premium and that also China has recently introduced a similar self-consumption subsidy. The authors add that also in Germany there was a bonus for self-consumed electricity between 2000 and 2012. However, since 2012 the price a consumer received to inject one kWh of electricity into the grid fell below the final price to consume one kWh of electricity (energy cost, network charges plus taxes and levies). As such, self-consumption has become profitable even without the extra incentive and the bonus has therefore disappeared. Similarly, Green and Staffell (2017) explain that an electricity tariff is in place in the UK which triples the value of stored energy due to the arbitrage value of avoiding exports and storing electricity until it is consumed.

3. **Methodology**

Two models are used to do the analysis: a game-theoretical model and a central planner model. First, we describe the game-theoretical model. After, the central planner model is briefly described. The game-theoretical model is used to capture the interaction between the distribution network tariff design, decentralised decision making of self-interest pursuing active consumers investing in solar PV and batteries, and their aggregated effect on the network costs. The model was first introduced in Schittekatte and Meeus (2018). In Schittekatte and Meeus (2018) the model was used to analyse the

[62] We assume in this analysis that the fee to withdrawn has the same magnitude as the fee to inject.

trade-off between cost-reflective and fair distribution network tariff design. The central planner model serves as a first-best benchmark. The full formulation of both models can be found in Appendix A.

3.1 Game-theoretical model

The game-theoretical model has a bi-level structure. A regulator is represented in the upper-level. The regulator decides upon the distribution network tariff in place anticipating the reactions of the consumers represented in the lower-level. The objective of the regulator is to minimise the total system cost under the condition that the total network costs equal the network charges collected from the consumers. The total system costs consist of four components: total grid costs, total retailer energy costs, total DER investment costs and other costs.[63] The relative share of the different components of the total system costs are a function of the incentives of the consumers, i.e. the mix of the energy sourced from the retailer and delivered by the grid and the energy delivered directly from installed DER at the consumer-side.

The total grid costs can consist of two parts: sunk grid costs and prospective grid costs. Sunk grid costs are the costs of grid investments made in the past to be able to cope with electricity demand in the future and these costs are unaffected by the utilisation of the network. Prospective grid costs are variable (in the long-run) and a function of the maximum coincident network utilisation of all consumers. The higher the coincident peak, the higher the network costs to be recovered. Abdelmotteleb et al. (2017), Pérez-Arriaga et al. (2017) and Simshauser (2016) describe that the coincident peak demand (or exceptionally the injection if higher) is generally considered as the main cost driver of a distribution network. Next to the coincident peak demand, other network cost drivers can be identified, such as thermal losses and the investment cost to replace electronic components (e.g. protection) to deal with bi-directional flows due to high concentrations in PV adoption (see e.g. MIT Energy Initiative (2015) and Cohen et al. (2016)). These other network cost drivers are not included in the current analysis.

Consumers react to the electricity bill as a whole, but the accounting of the cost components is separate as we consider an unbundled setting. Besides the endogenously considered network charges, the consumers buy electricity, the commodity, from a retailer who bought this energy in the wholesale market and sells it to downstream consumers for an exogenous price. Finally, next to the retailer energy price and the network charges, a consumer pays taxes and levies; the level of these costs is considered invariant, and the way these are collected does not interfere with the analysis. Modelled

[63] Other costs represent taxes and levies recovered from consumers; it is assumed that the total level of these costs is invariant.

consumers can be passive or active. Passive consumers are assumed not to react to prices; active consumers pursue their own self-interest, i.e. their objective is to minimise the cost to satisfy their electricity demand. They have the option to invest in two technologies, solar PV and batteries, to lower their dependence on grid supplied electricity.

The incentives of the active consumers will not always align with system benefits and can have negative distributional consequences. An intuitive example is what happens with volumetric charges with net-metering in place. In that case, an active consumer will be incentivised to install solar PV; the investment cost of solar PV is compared to the avoided retailer energy costs ánd network charges. From a system perspective, the total retailer energy costs will go down as consumers buy less energy from the retailer, the total DER investment costs will go up due to investment in solar PV and the total grid costs will more or less stay the same as stand-alone solar PV does not affect the grid costs much. High PV generation and the aggregated consumer peak demand often do not coincide. As a result, the reduction in grid charges for consumers is higher than the avoided grid cost. Overall, the total system costs might even go up due to the solar PV adoption compared to a situation in which no consumer installs solar PV.[64] In addition, the network charges (in €/kWh) need to increase to allow full grid cost recovery. As a result of this increase, mostly passive consumers, which did not install solar PV, will see their electricity bill increase. Similarly, in this paper, we focus on battery adoption and do this analysis for capacity-based charges, net-purchase volumetric charges, bi-directional volumetric charges in Sections 5.1 to 5.3 and for (time-varying) peak-coincident network charges in Section 5.4.

Mathematically speaking the model is formulated as a Mathematical Program with Equilibrium Constraints (MPEC). An equilibrium is obtained if all grid costs are recovered and none of the consumers has an incentive to adapt their electricity withdrawal and injection pattern from the grid by e.g. by installing more solar panels or using installed batteries in an alternate fashion. Different methods exist to solve the model. In this case, the model is reformulated as a Mixed Integer Linear Programme (MILP) which can be solved using commercial off-the-shelf optimisation software. For a complete treatment of different solution methods see Gabriel et al. (2012).

3.2 Central planner model

Besides the game-theoretical model, a centralised planner model is used as a benchmark. The difference with the game-theoretical model is that there is no distribution network tariff formulated in the central planner model; the consumers do not need to be coordinated. Instead of consumers

[64] Disregarding the environmental benefits of the adoption of solar PV.

acting in their own interest, the central planner decides unilaterally about their actions. [65] The central planner model is formulated as a linear programme (LP). By comparing the results for the evaluated network tariff designs with the game-theoretical model and this benchmark, we can show how much storage is under- or over incentivised due to imperfect distribution network tariff design. Also, the impact on system cost due to the imperfect network tariff design can be estimated.

4. **Numerical example**

In this section, the numerical example is described. The section is split up into four subsections which each consider a different group of input data. This data is used to calibrate the model. It should be noted that the demand and solar PV profiles presented in subsection 4.1, the baseline consumer bill presented in subsection 4.2 and the grid costs as described in subsection 4.3 are the same as used in Schittekatte and Meeus (2018). Results for additional consumer profiles can be found in Appendix D.

4.1 Consumer types, demand and solar yield

Two consumer types are modelled for simplicity: passive and active consumers, as is also done in Brown and Sappington (2017a, 2017b, 2018) and Schittekatte et al. (2018). The passive consumer does not have the option to invest in solar PV and batteries, unlike an active consumer, who can opt to invest in DER. Passive consumers do not have the financial means, are strongly risk averse or are uninformed about the possibility to invest in DER. Active consumers minimise their costs to meet their electricity demand and may invest in DER to do so. At one extreme, all consumers can be passive, as in the recent past. At the other extreme, all consumers can be active, i.e. install DER when it can reduce their overall electricity cost. Reality presumably lies in the middle. Some consumers will remain passive for a number of reasons. Other consumers could be installing DER even when they do not financially profit from it, but because of other reasons which are harder to monetise, e.g. independence from the grid, sustainability motives etc. In the numerical example, it is assumed that 50% of all consumers are active and 50% are passive.[66] The consumer demand and solar PV yield profiles are represented using a time series of 48-hours with hourly time steps and are shown in Figure 17 (left). The yield per kWp of solar PV installed is shown in Figure 17 (right).

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[65] Please note that no economies of scale in terms of battery investment are considered, e.g. a battery of 250 kWh energy capacity is cheaper than 25 batteries of 10 kWh. If that would be the case, an additional advantage of the central planner approach would be to invest in a couple of large batteries instead of a multitude of smaller batteries per household as also discussed in Schill et al. (2017).

[66] 50 % active consumer might seem quite a lot today. Today many consumers are passive because they are indifferent or vulnerable. A lower proportion of active consumers result in a lower impact of distortive network tariff design on total system costs. However, distortions result in costs shifts from active to passive consumers. In their turn, these cost shifts could again convert more (indifferent) passive consumers into active ones, increasing the impact of the distortion. Also, with dropping costs in DER, rising electricity bills, digitalisation and more climate awareness, a proportion of indifferent passive consumers might turn active.

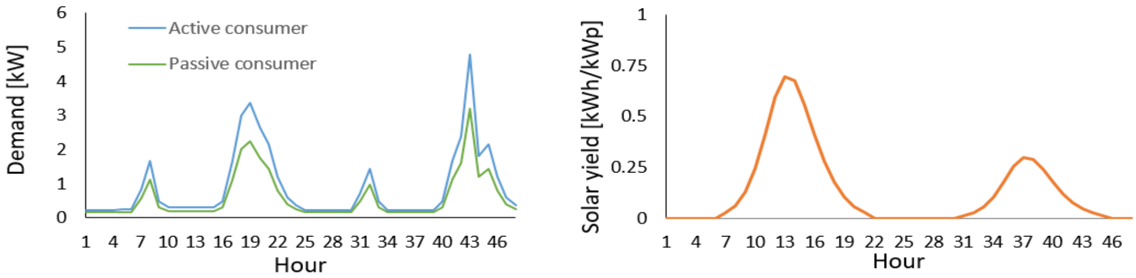

Figure 17: Original 48-hour electricity demand profiles (left) and PV yield profile (right)

The household demand for electricity shows for both modelled days a small peak in the morning and a stronger peak in the evening, the typical 'humped-camel shape' (Faruqui and Graf, 2018). For both consumer types the shape of the demand profile is identical; however, it is scaled differently. As a result, passive consumers have a slightly lower electricity demand than active consumers. The passive consumer has an annual consumption of 5,200 kWh with a peak demand of 3.2 kW and the active consumer a 7,800 kWh annual consumption with a peak demand of 4.8 kW. In Europe, average annual electricity consumption per household ranged from 20,000 kWh (Sweden) to 1,400 kWh (Romania) in 2015. In the same year, the average electricity consumption per household in the USA was about 10,800 kWh (EIA, 2016). The idea behind this difference in the levels of consumption is that active consumers are expected to be more affluent than passive consumers and that affluent consumers have higher electricity needs. This statement is a simplification of reality, but evidence for it is found in the literature (e.g. Borenstein (2017) and Hledik et al. (2016)).

The yield per kWp of solar PV installed, as shown in Figure 17 (right), scales up to 1,160 kWh per year. As a reference, this level is similar to the average yield in the territory of France (Šúri et al., 2007). Seasonality is introduced in the PV yield profile by having a daily average PV yield of 40% of either side of the annual mean. The peak demand coincides with the day with the low PV yield. Letting the peak demand day coincide with the day with lower solar irradiation and vice-versa produces two effects. First, a high capacity of PV installed does not necessarily mean that the peak demand can be reduced. Faruqui and Graf (2018) investigate load profiles in Kansas and find that after the installation of PV systems, logically the net energy consumption reduces; nevertheless, the peak demand is virtually left unchanged. Second, if a high capacity of PV is installed, the injection peak of active consumers can become significant.

4.2 Baseline consumer bills

In Table 11 the baseline consumer electricity bill, paid by the consumers when no consumer installs any DER technology, is shown. However, if active consumers decide to invest in DER, the relative proportion and absolute values of the bill components can change for both the active and the passive consumers. The annual electricity cost for the active and passive consumer equals respectively 1,340 €/year (0.172 €/kWh delivered) and 971 €/year (0.187 €/kWh delivered). This total cost is near the average electricity cost for EU households in 2015, which was estimated at around 0.21€/kWh (Eurostat, 2016). In the USA, the average electricity cost in 2015 was around 0.125€/kWh (EIA, 2016). The consumer bill is based on information from the Market Monitoring report by ACER and CEER (2016). There, the breakdown of the different components of the electricity bill for an average consumer in the EU for the year 2015 is presented. The energy component in the EU in 2015 is estimated at 37%. In absolute terms, this is a cost of 0.077 €/kWh. Further, 26% of the bill consisted of network charges, and 13% are RES and other charges. Finally, an important chunk of the bill (25%) consists of taxes. A value-added tax (VAT), averaging 15%, must be paid and additional (ecological) taxes, averaging 10%, are raised in some countries. In this work, the VAT is integrated into the three components of the bill. Please note that a typical consumer bill varies from one country to another (e.g. ACER and CEER (2016) for the EU).

Table 11: Consumer bill in the baseline scenario (no investment in DER by active consumers)

		Cost per year	
Bill component	*Recovery*	*Active*	*Passive*
Energy costs	0.08 €/kWh	624 €/year (46 %)	416 €/year (43 %)
Network charges	Default: 0.062 €/kWh In the analysis: least-cost network tariffs	485 €/year (36 %)	324 €/year (33 %)
Other charges	Fixed fee (no interference with the analysis)	231 €/year (17-24 %)	
Total electricity cost		1340 €/year (0.172 €/kWh)	971 €/year (0.187 €/kWh)

In the result sections 5.1 and 5.2, the retailer energy price is set at a constant rate of 0.08 €/kWh in order to isolate the impact of distribution network tariff design. In Section 5.3, two time-of-use (TOU) energy pricing schemes are introduced. To be able to compare results among the three energy price profiles, the TOU energy price schemes are scaled to make sure that in the baseline scenario (no DER) the weighted average energy price per consumer type is equal over the different energy price profiles. This means that the average TOU energy price will be slightly lower than 0.08 €/kWh. This is because consumers have a higher demand during the times that the energy prices are relatively higher for these profiles. Other charges are recovered through a fixed fee and as such do not interfere with the analysis. However, this is not always the case. How to collect such charges, or whether they belong in the electricity bill at all, is beyond the scope of this work, see e.g. the paper of Bohringer et al. (2017) in which the German case is discussed. The network charges are in the baseline case recovered through (net-metered) volumetric charges equal to 0.062 €/kWh. In the results presented in Section 5, different network tariff designs are evaluated.

4.3 Grid cost structure

The values for the parameters of the grid cost function (Eq. A.9) are derived from the 'baseline network costs' of the modelled consumers (shown in Table 11) and are a function of the proportion of active and passive consumers. With 50 % active and 50 % passive consumers, the (scaled) coincident consumer peak demand equals 4 kW in the baseline scenario, and the average grid costs equal 404 €/consumer.[67]

In Section 5.1 grid costs are assumed 100% sunk. In Section 5.2-5.4, all grid costs are assumed to be driven by consumers. In that case, the incremental grid cost is set to 101 €/kW. As a reference, Brown et al. (2015) assume the (annualised) cost to be 75$/kW.

4.4 DER investment cost and technical parameters

Two DER technologies are assumed at the disposition of active consumers: solar PV and batteries. A scenario with low PV but also battery investment costs can be expected to materialise soon as pointed out by many studies (Lazard, 2016b, 2016a; MIT Energy Initiative (2016a); RMI, 2015).

The investment cost of solar PV is set equal to 1250 €/kWp. Under flat energy prices, this means that the levelised cost of energy (LCOE) of solar PV is 0.086 €/kWh.[68] Excluding grid charges, an active consumer is assumed to receive 98 % of the retailer energy price when injecting solar energy.[69] An important assumption is that no investment subsidy for PV is introduced in this work and no reduced social losses from environmental externalities due to the installation of solar PV are accounted for. Table 12 shows the other DER parameters. Technical DER data is in line with Schittekatte et al. (2016).

Table 12: Financial and technical DER data

Parameters PV related	*Value*	*Parameters battery related*	*Value*
Lifetime PV	20 years	Lifetime battery	10 years
Discount factor PV	5 %	Discount factor battery	5 %
Maximum solar capacity installed	5 kWp	Maximum battery capacity installed	No limit
Price received for electricity injected (% of retailer energy price)	98 %	Efficiency charging & discharging	90 %
		Leakage rate	2 %

Sensitivity is done regarding the batteries investment costs. Investment costs between 350 €/kWh and 100 €/kWh with steps of 50 €/kWh are tested for. All batteries are assumed to have a C-rate of 1, i.e.

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67 4kW = 0.5*4.8 kW + 0.5*3.2 kW and 404 € = 0.5*485 € + 0.5*324 €

68 In the model applied, the LCOE of solar PV is a function of the investment cost of the PV panel, lifetime, discount factor, the PV system performance ratio and importantly the solar PV yield profile, which is location dependendent.

69 This percentage is deliberatly not set equal to 100 % but just below. The reason is that if it would be 100 %, excluding the impact of the network tariff design, an active consumer would be indifferent in self-consuming or injecting the solar PV energy. This could lead to modelling issues. Setting the selling price equal to 98 % instead of 100 % of buying price has no significant effect on the results.

the battery can fully (dis)charge in one hour. Schmidt et al. (2017) find that regardless of electricity storage technology, capital costs are on a trajectory towards US$ 340± 60kWh^{-1} for installed stationary systems and US$175±25kWh^{-1} for battery packs by 2027-2040. Hledik et al. (2018) review many studies and are more bullish. They state that the investment cost of residential storage could be declined to 250 $/kWh by 2025.

As mentioned before, what matters for the business case of residential electricity storage is how the battery investment costs measure up against the reduction in the electricity bill that can be made by investing in batteries. The point of this work is not to obtain an estimate about at what exact investment costs residential storage becomes financially viable. Instead, the aim is to analyse the interactions between the business case for storage and the distribution network tariff design. As an alternative to ranging over different values for battery investment costs, the results could be tested for different magnitudes of the grid costs recuperated through the electricity bill.

5. **Results**

In this section, we show and discuss the results obtained with the numerical example. We show the results for the three considered network tariff structures: capacity-based charges, net-purchase volumetric network charges and bi-directional volumetric network charges. More specifically, per network tariff design we show the capacity of storage adopted by the active consumers compared to the benchmark. Also, we compare the total system costs, a proxy for overall cost-efficiency of the network tariff design.

The section is split up into four parts. First, we show the results for the case that all grid costs are assumed sunk. Second, we show the results for the case that the grid costs are driven by the aggregated consumer peak demand. Third, we look at how time-varying energy prices impact the results. Fourth, we show that there exists a theoretically optimal network tariff design, so-called critical peak pricing, which approximates the outcome of the central planner under the given assumptions.

5.1 Sunk grid costs

First, grid costs are assumed to be 100% sunk, a short-term vision, i.e. the grid is over-dimensioned, and the electricity usage of consumers has no effect on the total grid costs. In some countries, also policy costs are recovered through the network charges, which from a cost allocation point of view is no different than recovering sunk network costs. In Table 13, the capacity of the battery installed per active consumer is shown for the different distribution network tariff designs. Sensitivity analysis regarding the investment costs of the batteries is done. The benchmark network tariff design is the central planner. Also fixed network charges (€/consumer) give the same results as the central planner. This is true as it is assumed that all grid costs are sunk, no consumers go off-grid completely and that all externalities (e.g. CO2 emissions) are priced correctly in the other components of the electricity bill.

The results are split up in three parts to single out the interaction between investment in solar PV and batteries by active consumers. First, it is assumed that there is no possibility for the active consumer to invest in solar PV. Second, the active consumer is free to install solar PV up to 5 kWp if this investment lowers its costs to fulfil its electricity needs. Third, it is assumed that the active consumer always installs a 5 kWp solar PV installation at its premises.[70]

Table 13: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed sunk.

Distribution network tariff design		Benchmark – central planner/ fixed charges [€]	Capacity-based [€/kW]	Volumetric Net-purchase [€/kWh]	Volumetric Bi-directional [€/kWh]
Investment cost batteries		Battery installed per active consumer [kWh] / PV in brackets [kWp]			
No PV installed, only batteries can be invested in by the active consumers	350 €/kWh	0 (0)	3.7 (0)	0 (0)	0 (0)
	300 €/kWh	0 (0)	3.7 (0)	0 (0)	0 (0)
	250 €/kWh	0 (0)	3.7 (0)	0 (0)	0 (0)
	200 €/kWh	0 (0)	3.7 (0)	0 (0)	0 (0)
	150 €/kWh	0 (0)	4.7 (0)	0 (0)	0 (0)
	100 €/kWh	0 (0)	6.8 (0)	0 (0)	0 (0)
Batteries and PV can be installed in by the active consumers	350 €/kWh	0 (0)	3.4 (3.2)	0 (5)	0 (0.7)
	300 €/kWh	0 (0)	3.6 (1.4)	0 (5)	0 (0.7)
	250 €/kWh	0 (0)	3.6 (0.5)	0 (5)	0 (0.7)
	200 €/kWh	0 (0)	3.7 (0.4)	0 (5)	0 (0.7)
	150 €/kWh	0 (0)	6.9 (3.7)	0 (5)	0.6 (0.7)
	100 €/kWh	0 (0)	9.6 (4.8)	4.9 (5)	2.2 (1.4)
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	0 (5)	3.2 (5)	0 (5)	0 (5)
	300 €/kWh	0 (5)	3.2 (5)	0 (5)	0 (5)
	250 €/kWh	0 (5)	3.2 (5)	0 (5)	4.9 (5)
	200 €/kWh	0 (5)	6.4 (5)	0 (5)	4.9 (5)
	150 €/kWh	0 (5)	6.5 (5)	0 (5)	13.3 (5)
	100 €/kWh	0 (5)	9.7 (5)	4.9 (5)	13.3 (5)

[70] In modelling terms, this means that first for the active consumers the maximum capacity of solar PV installed is set equal to 0 kWp. Then, the maximum capacity of solar PV is set to 5kWp and the minimum capacity of solar PV is set to 0 kWp. Lastly, both the maximum and the minimum capacity of solar PV are set to 5kWp. For the passive consumers, the minimum and maximum capacity of solar PV (and batteries) are always set to zero.

Figure 18 shows the impact on the total system costs of the different distribution network tariff designs. Again the results are split up for the three cases of solar PV investment and the results are shown relative to the benchmark.

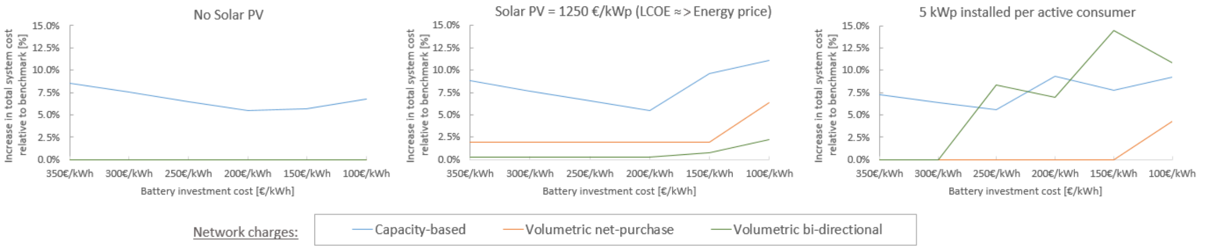

Figure 18: Increase in total system costs for the three network tariff structures when compared with the benchmark. Sensitivity for three different assumptions regarding solar PV adoption and the investment cost of storage.

Three observations can be made from Table 13 and Figure 18. First, capacity-based network charges over-incentivise battery adoption for all runs. Under capacity-based charges, active consumers can lower their individual peak demand by investing in a battery. By lowering their peak demand, they reduce their individual grid charges to be paid. But as we assume that grid costs are sunk, the total grid costs do not reduce. Therefore, when looking at the overall system cost in Figure 18, an increase results due to the investment in batteries by active consumers and accompanied energy losses in the battery. The reductions in grid charges by the active consumers are simply transferred to the passive consumers who see their electricity bill increase, and the investment cost in batteries by active consumers adds to the total system costs. The blue line in the left graph in Figure 18, which represents the cost of the distortion under the given assumptions, has a U-shape. This can be explained by the fact that the cost of the distortion is a function of the capacity of batteries adopted, the losses in the batteries and the investment costs of batteries. Logically, the cheaper batteries are, the higher the capacity of the batteries installed and the higher the losses are but, the lower the cost per kWh of battery installed. The results for when active consumers can invest in both batteries and solar PV in Table 13 show that there are some synergies between solar PV and battery investment under capacity-based network charges; higher capacities of solar PV are installed than under the benchmark network tariff, and the capacity of the batteries generally increases when compared to the case when no solar PV investment is enabled.

The second observation is that no investment in batteries is made under the network tariff designs which incentivise self-consumption when no solar PV investment is enabled or when batteries are relatively expensive. It makes sense that under these network tariff designs, no batteries are invested in when no solar PV is enabled. In that case, the only other potential revenue from a battery investment would be arbitraging the energy price, but the energy price is assumed constant. This assumption is relaxed in Section 5.3. The left graph in Figure 18 shows that these two tariff structures have the same performance as the benchmark, i.e. they do not cause any distortions. The middle graph in Figure 18 shows that under net-purchase volumetric charges there is a constant minor distortion, excluding the case when the battery investment costs are 100 €/kWh. This can be explained by the fact that the active consumers each invest in 5 kWp while under the benchmark in no solar PV is invested; net-purchase volumetric charges over-incentivise solar PV adoption in this case.[71] The cost of the distortion is rather small as the LCOE of solar PV is just slightly higher than the energy price. A similar but less significant result is found for volumetric charges with bi-directional metering as less solar PV investment is done by the active consumers.

Third, when active consumers have solar PV installed, and batteries are relatively cheap, batteries with a significant capacity are invested in under the network tariff designs that strongly incentivises self-consumption. In that case, it makes sense for an active consumer to invest in a (relatively cheap) battery to avoid paying network charges by increasing self-consumption. We split this observation up into two. First, when the active consumer can choose to invest in solar PV, it can be seen in Table 13 that under net-purchase volumetric charges the over-investment in solar PV can suddenly also trigger a significant over-investment in batteries. This happens when the battery investment costs drop to a low level. Again, this battery investment does not lower the grid costs and slightly increase the retailer energy costs due to losses. Therefore, the orange line the middle graph in Figure 18 shows a strong increase at that point. Second, when assumed that 5 kWp solar PV is already installed per active consumer, batteries are most over-incentivised under bi-directional volumetric charges. As a result, the self-consumption rate increases from 32.4 % without batteries to 59.0 % with batteries of 250 €/kWh to finally 80.8 % when the cost of batteries reaches 150 €/kWh.[72] This means that if the cost of batteries drops to that low level (alternatively, if the grid charges are very high), it is optimal for an active consumer to install a battery in order to strongly reduce the injection of any electricity generated by its solar PV panels into the network. Figure 18 (right) shows that this distortion has a high cost at relative cheap battery prices. The cost of the distortions becomes even higher than under capacity-based charges.

[71] 1/ This over-incentive is much less strong than under volumetric network charges with net-metering and a function of the coincidence of the solar PV generation and the demand of the consumer. 2/ This distortion vanishes in the right graph in Figure 18 as in that case also 5 kWp is assumed to be installed by the active consumers under the benchmark network tariff, thus there is no difference in solar PV investment anymore between the benchmark and net-purchase volumetric charges.

[72] The self-consumption rate (SCR) is calculated as in Eq. 8 in Quoilin et al. (2016): the total solar electricity generated plus the total battery electricity output minus the total electricity injected in the grid and the total battery electricity input over the total solar electricity generated. $SCR_i = \frac{\sum_t^{\mathrm{T}}(is_i * \mathrm{SY}_{\mathrm{t,i}} - qi_{t,i} + qbout_{t,i} - qbin_{t,i})}{\sum_t^{\mathrm{T}}(is_i * \mathrm{SY}_{\mathrm{t,i}})}$. In the same paper, it is stated that self-consumption rates without batteries vary between 30% and 37%, thus agreeing with the value in this example.

5.2 Grid costs as a function of the aggregated consumer peak demand

In this subsection, the other extreme in terms of grid cost scenario is examined. Instead of assuming the grid costs to be sunk, they are assumed to be fully driven by the aggregated consumer peak demand. The aggregated consumer peak demand, also called coincident peak demand, is commonly considered to be the main cost driver of the network (Abdelmotteleb et al., 2017; Baldick, 2018; Pérez-Arriaga et al., 2017). The assumption that no grid costs are sunk could be interpreted as a context in which the network is being built up or a fully amortised network is operating near its limits and needs to be expanded to accommodate strong load-growth.

In Table 14, the capacity of the batteries installed per active consumer is shown for the different distribution network tariff designs. Again, sensitivity analysis regarding the investment costs of the batteries is conducted. The benchmark network tariff design is again the central planner. In this case, fixed network charges do not replicate the outcome of the central planner anymore. Namely, with fixed network charges, active consumers are not incentivised to adjust their electricity withdrawal or injection patterns and thus to limit the incurred network cost. A fully informed central planner who can decide unilaterally on behalf of the consumers on how many batteries to install and how to operate them in order to obtain the lowest system costs is the first best outcome. In reality, however, there is no central planner. Instead, consumer decisions are driven by price signals, in this case network tariffs.

Again the results are split up in three parts to single out the interaction between investment in solar PV and batteries by active consumers. Similarly, first, it is assumed that there is no possibility for the active consumer to invest in solar PV. Second, the active consumer is free to install solar PV up to 5 kWp if this investment lowers its costs to fulfil its electricity needs. Third, it is assumed that the active consumer has a 5 kWp installation at its premises.

Table 14: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated consumer peak demand.

Distribution network tariff design		Benchmark – central planner	Capacity-based [€/kW]	Volumetric Net-purchase [€/kWh]	Volumetric Bi-directional [€/kWh]
Investment cost batteries		Battery installed per active consumer [kWh] / PV in brackets [kWp]			
No PV installed, only batteries can be invested in by the active consumers	350 €/kWh	4.4 (0)	2.7 (0)	0 (0)	0 (0)
	300 €/kWh	4.4 (0)	2.7 (0)	0 (0)	0 (0)
	250 €/kWh	5.5 (0)	3.3 (0)	0 (0)	0 (0)
	200 €/kWh	6.2 (0)	3.7 (0)	0 (0)	0 (0)
	150 €/kWh	6.2 (0)	3.7 (0)	0 (0)	0 (0)
	100 €/kWh	6.2 (0)	3.7 (0)	0 (0)	0 (0)

Batteries and PV can be installed in by the active consumers	350 €/kWh	4.4 (0)	2.7 (0)	0 (5)	0 (0.7)
	300 €/kWh	4.4 (0)	2.7 (0)	0 (5)	0 (0.7)
	250 €/kWh	5.5 (0)	3.3 (0)	0 (5)	0 (0.7)
	200 €/kWh	6.2 (0)	3.7 (0)	0 (5)	0 (0.7)
	150 €/kWh	6.2 (0)	3.7 (0)	0 (5)	0.6 (0.7)
	100 €/kWh	6.2 (0)	3.7 (0)	4.7 (5)	2.2 (0.7)
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	4.6 (5)	2.8 (5)	0 (5)	0 (5)
	300 €/kWh	4.8 (5)	2.8 (5)	0 (5)	0 (5)
	250 €/kWh	5.1 (5)	3.0 (5)	0 (5)	0 (5)
	200 €/kWh	5.7 (5)	3.1 (5)	0 (5)	4.9 (5)
	150 €/kWh	5.7 (5)	3.2 (5)	0 (5)	4.9 (5)
	100 €/kWh	7.3 (5)	4.2 (5)	4.7 (5)	13.3 (5)

Figure 19 shows the impact on the total system costs for the different distribution network tariff designs. Again, the results are split up for the three cases of solar PV investment, and the results are shown relative to the benchmark.

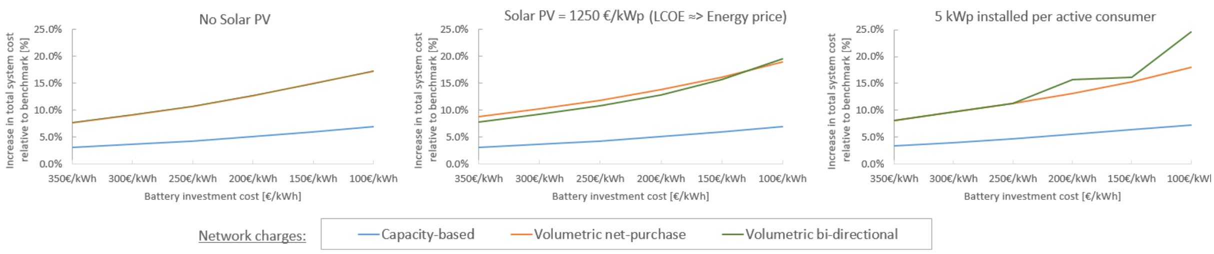

Figure 19: Increase in total system costs for the three network tariff structures when compared with a central planner. Sensitivity for three different assumptions regarding solar PV adoption and the investment cost of storage.

Four observations are derived from Table 14 and Figure 19. First, under capacity-based charges, batteries are always under-incentivised when all grid costs are driven by the aggregated peak demand. More striking, when comparing these results with the results in Table 13, it can be seen that batteries with a lower capacity are installed than in the case grid costs are assumed sunk even though they are more useful from a system perspective. This can be explained as follows. Under the grid cost assumption, each investment in batteries by active consumers increases the value of additional investment in batteries until a certain point of saturation. This happens as, by each investment in batteries, the network tariff needs to increase in order to recuperate all network costs which remain the same. Thus, the business case of batteries (and solar PV) improves with increasing DER adoption. Saturation occurs when it becomes very costly to lower individual network charges, e.g. further reduce the individual peak demand when it is already significantly lowered due to a certain investment in batteries. This ‘’race-to-the-bottom’’ effect or non-cooperative behaviour is captured by the modelling formulation.[73] On the other hand, if grid costs are assumed to be driven by the aggregated peak demand and the network tariff in place adequately targets the network cost driver, an investment in batteries by active consumers can decrease the value of additional investment in DER. This effect is however ambiguous. Namely, each additional investment in batteries can lower the total grid costs. But at the same time, the grid charges paid by the active consumers will decrease as well. If the decrease in grid charges paid by the active consumer due to the adoption of batteries is lower in magnitude than the decrease in the total grid costs caused by their investment in batteries, all grid costs can be recuperated with a lower network tariff. In that case, an investment in batteries will decrease (''cannibalise'') the incentive to install additional battery capacity.[74] On the other hand, if the decrease in grid charges paid by the active consumer due to the adoption of batteries is higher than the magnitude of the decrease their investment caused on the total grid costs, the network tariff needs to increase to recuperate all grid costs. In this case, the same but weakened ''race-to-the-bottom'' effect as under the sunk grid assumption occurs.

The second observation is that not only batteries are under-invested in; active consumers also do not operate batteries in a way that their operation would lead to the lowest grid costs possible given the installed battery capacity. This is illustrated in the example shown in Figure 20; the results are shown for the run in which we assume that 5 kWp solar PV is installed by the consumer and batteries cost 100 €/kWh. It is clear that under capacity-based charges, the active consumers flatten their profile in order to lower the grid charges to be paid (2nd row - left graph). However, it is the aggregated demand profile of both active and passive consumers that drives the grid costs. The aggregated profile is also shown in Figure 20 (2nd row –right graph). It could be said that active consumers operating their battery under capacity-based charges are uninformed about the aggregated demand.[75] As such, the reduction of the aggregated peak demand is limited. Under the central planner approach, the active consumers significantly lower their demand at the time that the passive consumers have their peak. As a result, the aggregated peak, the one that really matters, is minimised.

In this numerical example, only two consumer groups are modelled: active and passive consumer. Each consumer group is represented by one profile, and the profiles are coincident. In reality, many individual profiles exist, and these will not all be coincident. The assumption of coincident profiles can

[73] Its significance is mostly a function of the proportion of active consumers and the attractiveness of DER investments relative to the network tariff structure and the magnitude of its coefficients.
[74] Similarly, as each investment in solar PV lowers the price of energy around noon and thus decreases the incentive to install more solar PV as described in Hirth (2013).
[75] Capacity-based network charges would have the same outcome as the central planner in the case that all consumers are active and they all have exactly the same electricity demand profile. This is also verified with the model.

be interpreted as capacity-based charges which are very carefully implemented, e.g. the capacity is only considered during certain months or even only during moments of the days within these months that the local system peak is expected to take place. More discussion on the implementation of capacity-based charges can be found in Passey et al. (2017) and Hledik (2014). In Appendix D, results are shown for three non-coincident consumer profiles. The results show that all observations remain the same for that setup, except for the fact that the performance of capacity-based network charges in terms of the reduction of system costs is overestimated with coincident consumer profiles. This overestimation mainly occurs when batteries are expensive and thus smaller battery capacities are installed. If higher battery capacities are installed, the individual peaks will be flattened over multiple time-steps thus possibly also during the time steps other consumers have their peak demand. As a result, also the aggregated consumer peak will decrease to a certain extent.

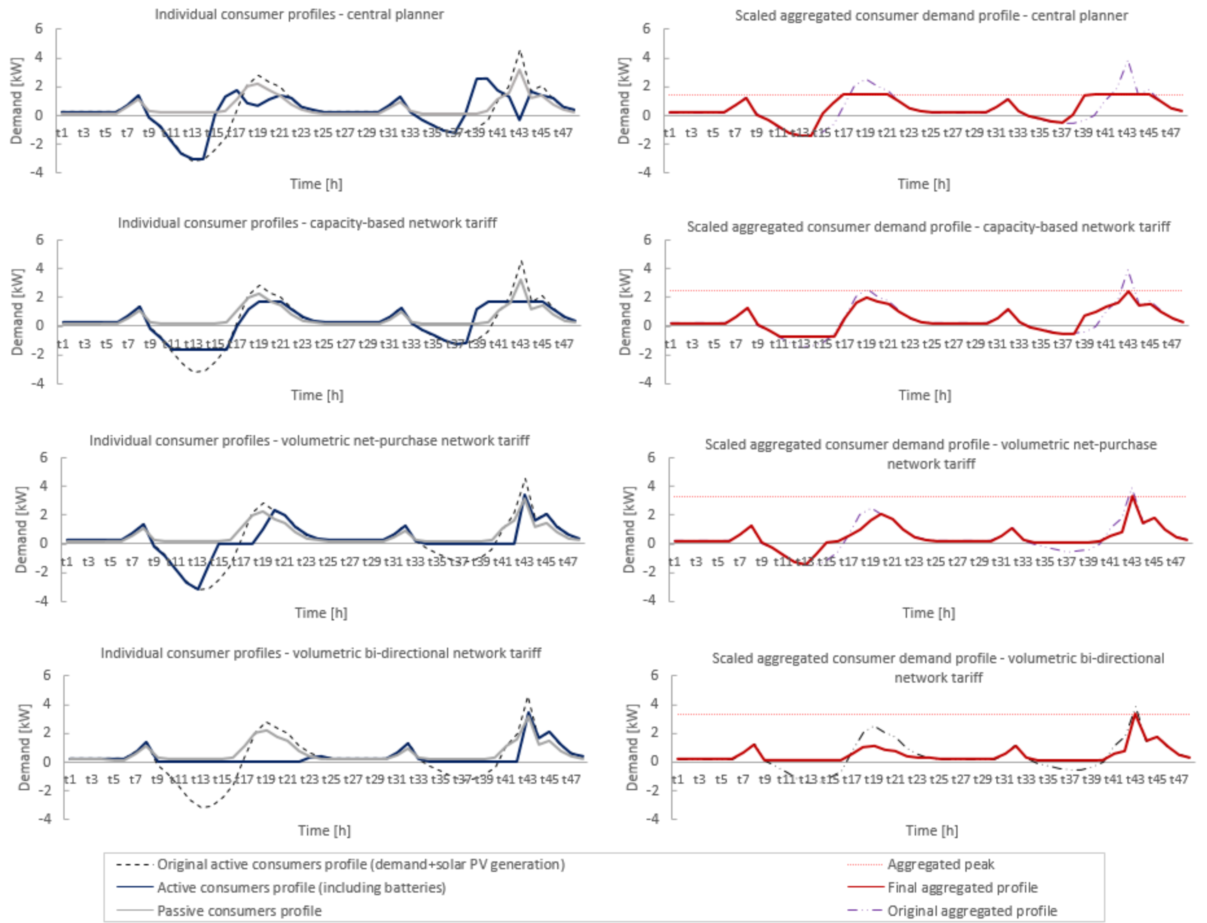

Figure 20: Reactions of active consumers to the different network tariff design and their impact on the aggregated load profile and peak. Assumption: 5 kWp solar PV already installed by the active consumer and battery investment cost of 100 €/kWh.

The third observation is that the two network tariff designs that incentivise self-consumption do not lead to investment in batteries if there is no solar PV installed by the active consumer or when there is solar PV installed, but batteries are relatively expensive. In other words, these network tariff designs block the business case of storage when not coupled with electricity generation behind the meter. Figure 19 shows that because of the fact that no batteries are installed, the system costs are significantly higher than in the central planner case.

Similar as in the case grid costs are assumed sunk, the fourth observation is that the two network tariff designs that incentivise self-consumption are shown to lead to significant investment in batteries if there is solar PV installed by the active consumer and batteries are relatively cheap. However, the investment in batteries does not result in a lower system cost as can be seen from Figure 19. Instead, the opposite occurs. The system cost increases relative to the benchmark. Figure 20 illustrates what happens. Indeed, the active consumers use the battery to increase self-consumption; under volumetric network charges with net-purchase 57.8 % of the electricity generated by solar PV is self-consumed for this example. This percentage increases further for bi-directional volumetric charges as also can be deducted from Figure 20, the self-consumption rate attained is 80.8 %.[76] However, the batteries are not operated in a way that their functioning leads to a lower aggregated peak demand. Instead, the batteries are used to store as much as self-produced electricity as possible until it is fully charged. After, the battery is used to fulfil the demand of the active consumers instead of grid supplied electricity. The discharging goes on until a point in time that the batteries are fully discharged. Looking at Figure 20, for this example, the batteries are fully discharged just before the time steps when aggregated peak demand is near its maximum. As a result, the aggregated peak demand decreases only very slightly.

Figure 21 summarises observations 1, 2 and 4 and further clarifies what happens regarding the total system cost for the example shown in Figure 20. The first vertical bar represents the baseline scenario, the case that no active consumer invests in DER. The proportions of the grid costs, energy retailer costs and taxes and levies are those as shown in Table 11. The next vertical bar represents the most optimal trade-off between the grid costs, retailer energy costs, solar PV and batteries for the given parameter settings. This optimal trade-off is the result of the central planner. This mix lowers the sum of the interacting components of the electricity bill to a total system cost which is 14 percentage points lower than the baseline.[77] In the example, capacity-based charges, also lead to a mix which lowers the total system costs relative to the baseline, however, not as much as the central planner. Mainly due to an under-incentive to invest in batteries and sub-optimal operational signals, the grid costs are not

[76] The self-consumption rates under the central planner and capacity-based charges are respectively 40.6 % and 43.4% for this example.

[77] Taxes and levies are assumed to be invariable and recovered through a fixed charge which does not distort the decisions of consumers.

decreased as much as would be optimal, as discussed in observations 1 and 2. Volumetric network tariffs with net-purchase lead to a total system cost with around the same value as the baseline, even though the composition of the different components is very different. Some batteries are installed, less than optimal, and they are not operated in a way that the grid costs are decreased. Interestingly, for this example, volumetric charges with bi-directional charges lead to a system which is more expensive than the baseline case without any DER investment. An overinvestment in batteries by the active consumers occurs. The active consumers are incentivised to increase self-consumption to a level which is not cost-efficient from a system point of view under the given assumptions.

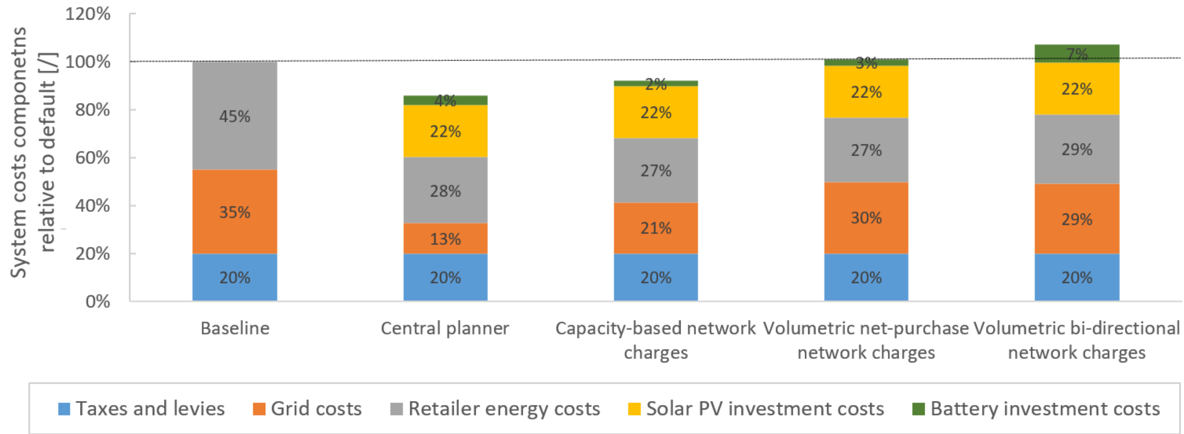

Figure 21: System costs and its components for the different network tariff designs. Assumption: 5 kWp solar PV already installed by the active consumer and battery investment cost of 100 €/kWh.

5.3 The impact of time-varying energy prices

In the previous two sections, the focus was laid on the design of the distribution network tariff design. It was shown that the network tariff design has an impact on the business case for storage and whether the business case is aligned with overall system benefits. To single out the impact of distribution network tariff design, we assumed that the energy price was constant in time. However, besides network tariff design, another important driver for battery adoption are time-varying energy prices; households can arbitrage energy prices with batteries. Different papers, e.g. Ren et al. (2016) and Erdinc et al. (2015), show with case studies that a battery system creates greater savings for a household if energy prices are time-varying instead of flat.

In this section, we introduce two TOU energy pricing schemes besides the flat retailer energy prices. In the previous sections, a constant retailer energy price of 0.08 €/kWh is assumed. Figure 22 shows the two newly introduced options. The TOU1 profile is 'solar PV friendly' as during hours that solar PV is producing, an energy price is charged which is slightly higher than the flat energy charge. The TOU2 profile charges relatively high prices during the evening when consumer demand is expected to peak and charges a relatively low price during the hours that solar PV is producing a lot. The TOU2 profile is less ‘solar PV friendly’ but might induce battery investment due to significant relative changes in the energy price between the different periods. These daily energy price patterns are used as representative for the year. To be able to compare results among the three energy price profiles, the TOU1 and TOU2 profile are scaled to make sure that in the baseline scenario (no DER) the weighted average energy price per consumer type is equal over the different energy price profiles. Also, for the runs for which the PV investment is forced, the difference in avoided energy costs due to solar PV adoption with the different TOU energy price schemes are corrected for to be able to compare the results with flat retailer energy prices.

Please note that energy prices remain considered exogenous, i.e. more solar PV or battery adoption has no impact on the retailer energy prices. These results should therefore be interpreted carefully. They can be interpreted in the context of a specific area with high DER penetration which is part of a very large power system over which as a whole the DER penetration is a lot more modest. This assumption can be relaxed in future work.

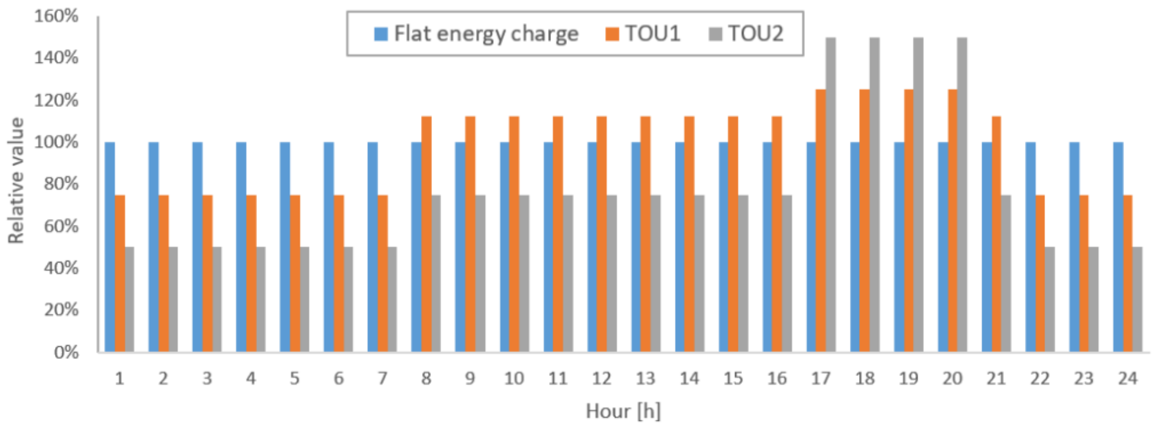

Figure 22: Three energy price schemes.

In Table 15, the results for the battery capacity installed per active consumer are shown for the different battery investment costs, distribution network tariff designs and energy price schemes. We assume that all grid costs are driven by the aggregated peak demand. We do three observations. First, when comparing the results in Table 15 with the results in Table 14, it can be seen that indeed the battery capacity installed by the active consumers remains the same or in most cases increases under the TOU energy prices when compared to flat energy prices. This statement holds for the benchmark and the three evaluated distribution network tariff designs. Second, when comparing the two TOU energy price schemes, the TOU2 energy price scheme results in the highest increase in battery capacity installed for this numerical example. Third, interestingly, still no batteries are installed under the network tariffs that incentivise self-consumption if not combined with the adoption of solar PV. Even though with time-varying energy prices there is the additional opportunity to arbitrage the energy prices.

Table 15: Battery and solar PV investment per active consumer for the different network tariff designs and energy pricing schemes under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated peak demand.

Distribution network tariff design		Benchmark – central planner		Capacity-based [€/kW]		Volumetric Net-purchase [€/kWh]		Volumetric Bi-directional [€/kWh]	
Energy price		TOU1	TOU2	TOU1	TOU2	TOU1	TOU2	TOU1	TOU2
Investment cost batteries		Battery installed per active consumer [kWh] / PV in brackets [kWp]							
No PV installed, only batteries can be invested in by the active consumers	350 €/kWh	4.6 (0)	6.1 (0)	2.8 (0)	3.7 (0)	0 (0)	0 (0)	0 (0)	0 (0)0
	300 €/kWh	5.5 (0)	6.2 (0)	3.3 (0)	3.7 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	250 €/kWh	6.2 (0)	7.4 (0)	3.7 (0)	4.5 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	200 €/kWh	6.2 (0)	11.0 (0)	3.7 (0)	6.6 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	150 €/kWh	6.8 (0)	12.4 (0)	4.6 (0)	7.4 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	100 €/kWh	6.8 (0)	13.5 (0)	6.1 (0)	8.1 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Batteries and PV can be installed in by the active consumers	350 €/kWh	4.7 (0.8)	6.1 (0)	2.8 (0.8)	3.7 (0)	0 (5)	0 (1.2)	0 (0.7)	0 (0.5)
	300 €/kWh	5.5 (0.7)	6.2 (0)	3.3 (0.7)	3.7 (0)	0 (5)	0 (1.2)	0 (0.7)	0 (0.5)
	250 €/kWh	6.1 (0.4)	7.4 (0)	3.6 (0.4)	4.5 (0)	0 (5)	0.3 (1.2)	0 (0.7)	0.1 (0.5)
	200 €/kWh	6.2 (0)	11.0 (0)	3.7 (0)	6.6 (0)	0 (5)	3.8 (4.1)	0.0 (0.7)	0.6 (0.7)
	150 €/kWh	7.6 (0)	12.4 (0)	4.6 (0)	7.4 (0)	0.3 (5)	4.9 (5)	1.7 (1.2)	7.4 (3.1)
	100 €/kWh	10.1(0.5)	13.5 (0)	6.1 (0.5)	8.1 (0)	4.9 (5)	9.4 (4.3)	11.8(4.5)	9.8 (3.9)
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	4.8 (5)	5.7 (5)	2.8 (5)	3.1 (5)	0 (5)	0 (5)	0 (5)	4.9 (5)
	300 €/kWh	5.2 (5)	5.7 (5)	3.0 (5)	3.1 (5)	0 (5)	0 (5)	0 (5)	4.9 (5)
	250 €/kWh	5.7 (5)	7.3 (5)	3.1 (5)	3.7 (5)	0 (5)	4.7 (5)	4.9 (5)	6.1 (5)
	200 €/kWh	5.7 (5)	10.3 (5)	3.2 (5)	6.0 (5)	0 (5)	4.9 (5)	4.9 (5)	8.9 (5)
	150 €/kWh	7.3 (5)	11.9 (5)	3.9 (5)	6.5 (5)	0.3 (5)	4.9 (5)	4.9 (5)	13.3 (5)
	100 €/kWh	10.3 (5)	15.0 (5)	6.0 (5)	10.2 (5)	4.9 (5)	8.9 (5)	13.3 (5)	13.3 (5)

By including TOU energy prices, not only the grid costs can be decreased due to battery adoption but also the retailer energy costs can be lowered due to gains from arbitrage. For this numerical example, Table 16 shows whether this increased battery capacity installed also leads to a lower total system cost. The relative difference in system costs between flat energy prices and the two TOU energy price schemes are shown for different distribution network tariff designs and investment cost of batteries.

Table 16: Relative difference in system costs between flat energy prices and TOU energy prices for different distribution network tariff designs and investment cost of batteries.

Distribution network tariff design		Benchmark – central planner		Capacity-based [€/kW]		Volumetric Net-purchase [€/kWh]		Volumetric Bi-directional [€/kWh]	
Energy price		TOU1	TOU2	TOU1	TOU2	TOU1	TOU2	TOU1	TOU2
Investment cost batteries		Difference in total system costs compared to a flat energy price [%]							
No PV installed, only batteries can be invested in by the	350 €/kWh	-1.5%	-5.4%	-0.9%	-3.2%	0.0%	0.0%	0.0%	0.0%
	300 €/kWh	-1.8%	-6.0%	-1.0%	-3.5%	0.0%	0.0%	0.0%	0.0%
	250 €/kWh	-2.2%	-6.5%	-1.3%	-3.8%	0.0%	0.0%	0.0%	0.0%
	200 €/kWh	-2.4%	-7.5%	-1.3%	-4.3%	0.0%	0.0%	0.0%	0.0%
	150 €/kWh	-2.5%	-9.4%	-1.4%	-5.3%	0.0%	0.0%	0.0%	0.0%

active consumers	100 €/kWh	-2.7%	-11.9%	-1.9%	-6.7%	0.0%	0.0%	0.0%	0.0%
Batteries and PV can be installed in by the active consumers	350 €/kWh	-1.6%	-5.4%	-0.9%	-3.2%	-0.5%	-0.2%	-0.1%	**0.3%**
	300 €/kWh	-1.8%	-6.0%	-1.0%	-3.5%	-0.5%	-0.2%	-0.1%	**0.3%**
	250 €/kWh	-2.2%	-6.5%	-1.3%	-3.8%	-0.5%	**0.3%**	-0.1%	**0.4%**
	200 €/kWh	-2.4%	-7.5%	-1.3%	-4.3%	-0.5%	**5.3%**	-0.1%	**0.8%**
	150 €/kWh	-2.5%	-9.4%	-1.4%	-5.3%	-0.2%	**0.6%**	**1.0%**	-0.7%
	100 €/kWh	-3.3%	-11.9%	-1.9%	-6.7%	-2.0%	-3.4%	**5.1%**	0.6%
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	-1.5%	-5.0%	-0.9%	-3.0%	0.0%	0.0%	0.0%	**5.0%**
	300 €/kWh	-1.6%	-5.4%	-0.9%	-3.0%	0.0%	0.0%	0.0%	**3.6%**
	250 €/kWh	-1.8%	-5.7%	-0.9%	-3.2%	0.0%	-0.4%	**3.1%**	**2.2%**
	200 €/kWh	-1.9%	-6.9%	-1.0%	-3.8%	0.0%	-2.1%	-0.5%	-9.7%
	150 €/kWh	-2.1%	-8.7%	-1.0%	-4.8%	**0.3%**	-3.5%	-0.5%	3.2%
	100 €/kWh	-3.1%	-11.1%	-1.5%	-6.2%	-1.5%	-12.8%	-0.1%	-5.4%

Three observations are made from Table 16. The first observation is that for the benchmark, the central planner, the system costs always decrease when introducing TOU energy prices. With TOU energy prices instead of flat energy prices, there is an additional revenue stream for the battery which can also induce a decrease of the total system costs. In the central planner case, there are no distortive effects between network tariffs and energy prices. The higher investment in batteries is justified from a system point of view and leads to lower total system costs. Figure 23 shows this in detail for four runs of the model. It can be seen that in all four cases, under the central planner there are higher DER costs when TOU prices are put in place due to more investment in batteries but that these higher DER costs are compensated by a stronger decrease in energy costs and grid costs. Thus overall, the system costs go down.

The second observation is that the system costs are always most decreased under the benchmark, with two exceptions. These two exceptions are underlined in Table 16. Excluding these two exceptions, the fact that the system costs decrease most under the benchmark implies that the evaluated network tariff designs distort energy price arbitrage. The two exceptions for which the system costs decrease more than the benchmark happens for the network tariffs which incentivise self-consumption. In these two cases, the TOU energy prices scheme alleviates part of the distortions introduced by the network tariff design. There is thus a positive synergy between TOU energy price scheme and the network tariff design when compared to the case that energy prices are flat.[78] The lower-right graph in Figure 23 shows the case where under net-purchase volumetric network charges, the system costs decrease more than under the central planner. It can be seen that DER costs increase but that a strong decrease in energy costs (due to arbitrage) results which also lowers the grid costs. This happens because the

[78] The synergy is a function of the coincidence between the TOU energy price profile, the consumer demand profiles, the solar PV profiles and the battery investment cost.

periods in which the energy price is high, coincides with the periods of a high aggregated demand. As a result, less energy is bought at the time steps around the system peak demand.

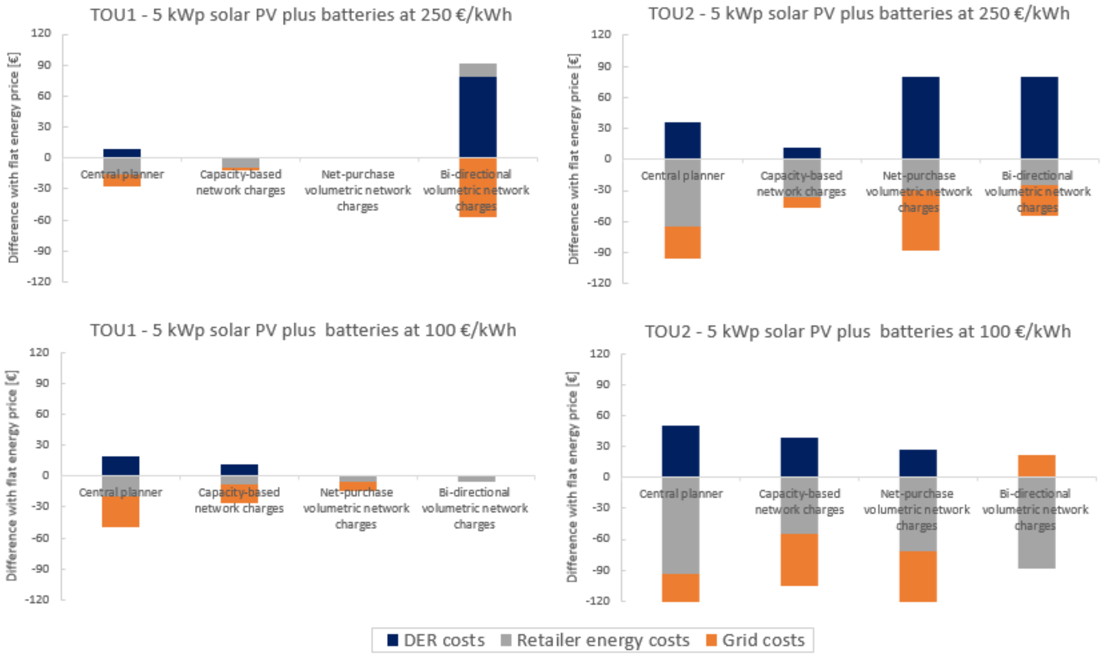

Figure 23: Absolute difference in the different system costs components when comparing a flat energy price with the two time-of-use energy price schemes under different battery investment cost scenarios.

The third observation is that the system costs can also increase with time-varying energy prices instead of flat energy prices. Unfortunately, the positive synergy between time-varying energy prices and network tariffs as discussed in the previous observations seems to be not intentional but a pure coincidence. It is rather counterintuitive that with the introduction of TOU prices total system costs increase. One would thus expect that time-varying energy prices will always lead to an overall system cost reduction. Namely, with exogenous time-varying energy prices, an additional revenue source is added for batteries which can generate a decrease in energy costs for active consumers without having a direct adverse effect on passive consumers. Instead, it is shown that time-varying energy prices can also aggravate the distortion created by the network tariff design. The upper-right graph in Figure 23 shows a case where this happens both for net-purchase and bi-directional volumetric network charges. It can be seen that time-varying energy prices lead to a decrease in energy costs but that this decrease is significantly smaller than the increase in DER costs and grid costs. The grid costs increase because of the creation of new aggregated demand or injection peaks at times the energy price is very low or high respectively.

It should be added that a disclaimer applies to the results discussed in this last observation. The creation of new peaks, driven by changes in the demand profiles of active consumers, only will have a strong effect on the overall grid costs if the proportion of active consumers is high and their demand profiles are rather homogeneous. Overall, with self-consumption incentivising network tariffs in place, the impact on total system cost of time-varying energy prices when replacing flat energy prices is ambiguous. Chaotic interactions between the network tariff design and energy prices can bring forward results which are hard to anticipate. Also, because of the fact that the energy prices are not endogenous in the model, it cannot be assessed whether the arbitrage actions of the active consumers would affect the energy price in a way that the energy costs are further decreased (or exceptionally increase). Therefore, it cannot be excluded that overall a system costs decrease would result relative to the case that energy prices are flat. An extension of the modelling approach is needed. Whatsoever, what is clear from these results, is that imperfect network tariff design obstructs optimal energy arbitrage strategies. A consumer, when deciding about the adoption and operation of storage will look at the possible reduction in her final electricity bill, instead of at each separate cost component (network charges, energy costs and taxes and levies) in isolation. As a result, the interaction between network charges and energy prices has an impact on the business case of storage but also on the potential welfare gains from introducing time-varying instead of flat energy prices to residential consumers.

5.4 Peak-coincident network prices: approximating the central planner outcome

In the previous subsection, it is shown that none of the evaluated distribution network tariffs can replicate the outcome of the central planner. However, the evaluated network tariff designs are rather simple. In the literature, it is discussed that so-called critical peak-pricing or coincident peak-pricing can reproduce ideal incentive properties for consumers (see e.g. Abdelmotteleb et al. (2017), Baldick (2018) and Pérez-Arriaga et al. (2017)). In this work, we test what happens if we allow the upper-level regulator to set such time-varying network charges. These network charges can be quite easily integrated into the model. The grid cost recovery described by Eq. A.9 in Appendix A becomes Eq. 1 below where cpp_t stands for the (time-varying) network charge in €/kWh. fnt represents the uniform fixed network charge which might complement the time-varying network charge.

$$TotalGridcosts = \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * cpp_t * (qw_{t,i} - qi_{t,i}) * \mathrm{WDT} + fnt \qquad (1)$$

cpp_t is a free variable. In the case of high solar PV penetration combined with low levels self-consumption, it might even be optimal to have negative network prices. The equation representing grid charges in the objective function of the lower level consumers (Eq. A.11 in Appendix A), becomes:

$$GridCharges_i = \sum_{t=1}^{\mathrm{T}} (qw_{t,i} - qi_{t,i}) * cpp_t * \mathrm{WDT} + fnt \qquad (2)$$

In this case, the regulator has to decide how to set the time-varying network charges in order to minimise the total system costs. Regarding the solution method, it is in this case extremely important that the bilinear products in the upper-level cost recovery constraint (Eq. 1) are efficiently linearised using the strong duality theorem instead of being discretised are for example done in Momber (2015, p. 102) and Schittekatte and Meeus (2018). The strong duality theorem says that if a problem is convex, the objective functions of the primal and dual problems have the same value at the optimum (Castillo et al., 2001). Another application of the strong duality theorem to linearize a bilinear term in an MPEC problem can be found for example in Ruiz and Conejo (2009).

The reason why the linearization using strong duality is helpful in this case is due to the fact that the time-varying network charges are by definition a function of the time-step while this is not the case for the previously modelled capacity based-charges, volumetric net-purchase and volumetric bi-directional charges. Therefore, when using the discretisation technique, the number of binaries needed to discretise the bilinear products with time-varying network charges are multiplied by the number of time-steps when compared to the number of binaries needed with non-time varying network charges. The introduction of such a high number of binaries slows down the model significantly and can even lead to not finding any solution while there is one.

Figure 24 shows the resulting peak-coincident network charges for the numerical example with the three energy prices schemes. The results are shown for the case we assume that the active consumers have 5 kWp solar PV installed and the battery investment costs are 250 and 100 €/kWh.

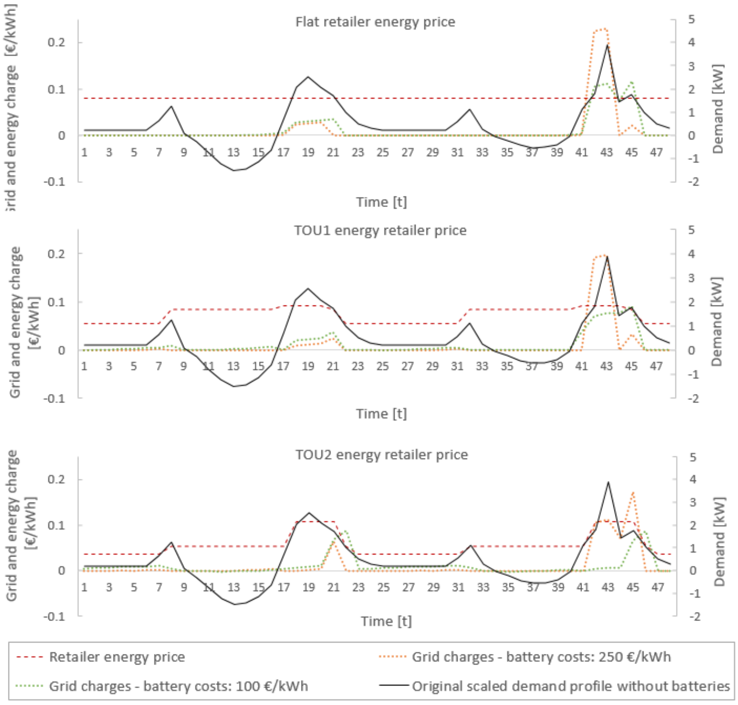

Figure 24: Examples of peak-coincident network prices for the case 5 kWp is installed by the active consumers. Sensitivity for the battery investment costs of 250 and 100 €/kWh.

As expected, it can be seen from Figure 24 that this more advanced network tariff exhibits peak prices at the time steps that the aggregated demand peaks and that network prices are equal to zero when the aggregated demand is rather low.[79] Additionally, it is shown that the network charges are a function of the investment cost of the batteries and the energy price scheme in place. Overall, the lower the battery investment cost, the wider but, the less steep the network peak prices. The width has to do with the fact that if batteries are cheaper and thus higher capacities are adopted, the number of time steps increases in which the aggregated demand reaches its maximum. During all these time steps a network price signal is needed. The decreasing steepness of the peak has to do with the fact that with cheaper batteries a less strong incentive is needed to reaches the optimal outcome.[80] If the peak price would be steeper, too many batteries could be invested in and vice-versa. Further, it can be seen that the network charges adjust with the energy prices scheme in place in order to send an adequate aggregated price signal to the consumers.

For this numerical example, the outcome obtained by these peak-coincident network charges in terms of battery investment and the total system cost is exactly the same or less than 1 % higher than under the central planner.[81] Overall, these results suggest that a more advanced network tariffs as formulated in this paper can approximate the outcome of a first-best outcome closely. A formal proof of how close the approximation is as a function of the parameters is out of the scope of this paper.

Even though these results for peak-coincident network charges are very promising, it should be understated that they hinge upon the assumption that the upper-level regulator has full information about which consumers are active and how these active consumers will respond to a certain network price signal. In reality, there persists an information asymmetry between the regulator and the actions of consumers. It goes without saying that this asymmetry complicates implementation of this optimal network tariff design.

[79] The peak-coincident network charges shown in Figure 24 are obtained using a two-step process. First, the MPEC is solved. After solving the MPEC, the lowest possible system costs (the objective of the upper-level) is known. However, the network charges computed are not unique. Namely, the upper-level regulator can arbitrarily increase the time-varying network charge at time-steps that the elasticity of the consumers is very low without changing the obtained value of the objective function. However, these arbitrary choices for the upper-level do have a distributional impact for the lower level consumers. Therefore, a second solution step was added. The MPEC remains exactly the same except for one constraint and the objective function. One constraint is added which states that the total system cost is forced to be equal to the minimal total system cost obtained in step one. The objective function of the upper-level changed to a minimisation the sum of the coefficients of the network charges. As such, a unique solution is obtained for the network charges without room for arbitrary choices of the upper-level regulator.

[80] The total costs spend on batteries by the active consumer under-time varying prices, which equals the product of the battery capacity installed with the investment cost, decreases with decreasing battery costs.

[81] There are two exceptions, for the scenario when battery costs are 150€/kWh and 100 €/kWh and no investment in solar PV is assumed under TOU2 energy prices, the difference in total system costs is 2.2 and 4.0% respectively. Also, the installed battery capacities differ slightly.

6. **Conclusion and policy implications**

We use a game-theoretical model to analyse whether different distribution network tariff designs align the business case of residential electricity storage, in the form of batteries, with overall wider system benefits. Three different network tariff designs are evaluated: capacity-based charges, net-purchase volumetric network charges and bi-directional volumetric network charges. Capacity-based network tariffs incentivise consumers to lower their individual peak demand. The two other network tariff designs result in a difference between the value of on-site generated electricity that is self-consumed and electricity that is directly injected back into the network. As such, these network tariff design incentivise self-consumption. We compare the outcome of the game-theoretical model for the different network tariff designs with a first-best central planner solution. Besides network tariff design, another important driver for battery adoption is time-varying retailer energy prices. Therefore, also the impact of time-varying energy prices on battery adoption and the interaction with distribution network tariff design is investigated.

We found that the business case of batteries and overall system benefits are not always aligned. In one extreme, the case that most grid costs are sunk and little future grid investment is expected, the evaluated network tariffs mostly over-incentivize battery adoption. In this case, network costs are simply transferred from active to passive consumers, and each investment in batteries by active consumers increases the (private) value of additional investment in batteries. From a grid perspective, there is little need for batteries and the main exercise is to find an as little as possible distortive network tariff design which remains acceptable in terms of distributional impacts. Examples can be found in e.g. Pérez-Arriaga et al. (2017), Pollitt (2018) and Wolak (2018): differentiated fixed network charges or not recovering all sunk grid costs through the electricity bill. Schittekatte and Meeus (2018) show that spreading the grid costs over capacity-based charges, volumetric charges and fixed charges can also mitigate the induced distortions.

After, the other extreme is investigated; the situation when still many grid investments have to be made, and the future grid costs are driven by the growing aggregated peak demand of consumers. It is shown that in that situation the tested network tariff designs will not only give an inadequate investment signal to the consumers, also will the consumers operate their installed batteries sub-optimally from a grid point of view. If consumer electricity demand profiles are rather homogeneous, batteries are under-invested by capacity-based charges. If consumer electricity demand profiles are heterogeneous, consumers will lower their individual demand which will have little effect on the system peak demand; a similar dynamic as in the sunk grid cost scenario occurs. With a network tariff design that encourages self-consumption, the business case of storage is unrightfully negatively impacted when the batteries are not coupled with onsite generation such as solar PV. Oppositely, when active consumers combine solar PV with cheap batteries or grid costs are high, an over-investment in batteries can result under the network tariff designs that encourage self-consumption. The batteries are fully charged with self-generated solar PV to increase self-consumption, but it can happen that by the time the system peak demand occurs, the batteries are already fully discharged again. In that case, a high capacity of batteries is installed, but they do not contribute to overall grid costs savings. It should be noted that energy losses in the distribution network or the cost of bi-directional flows are omitted in the presented analysis.[82] When self-consumption increases, there is less electricity exchange between the active consumers and the grid and bi-directional flows are reduced. More elaborated grid costs functions could be experimented with in future work.

Time-of-use energy prices instead of flat energy prices are shown to improve the business case for residential storage for all evaluated network tariff designs. With time-of-use energy prices, the active consumers can use their batteries to arbitrage energy prices on top of lowering their network charges. The introduction of time-of-use energy prices seems in most cases also beneficial from a system point of view. However, far from all potential efficiency gains are exploited due to unwanted interaction between the network tariff design and retailer energy prices; imperfect network tariff designs obstruct the optimal energy arbitrage strategies. This mechanism shows that distribution network tariff design and retailer energy price schemes should not be evaluated in isolation. Both interact as a consumer reacts to their aggregate. Even more difficulties can be expected when accounting for taxes and levies in the electricity bill which are left out in this analysis.

Overall, in a high future grid cost scenario, a more advanced network tariff design is needed to correctly align the business case of residential storage and wider system benefits. Without a more advanced network tariff design, it is not possible to fully unlock flexibility from the consumers-side and efficiently coordinate grid charges and energy prices signals. It is shown that peak-coincident network prices, which exhibit strong peak prices at times when there are system demand peaks, give optimal or near-optimal results. Baldick (2018) explains that such types of tariffs are already used for transmission grid prices in for example ERCOT and Great-Britain. However, such distribution network tariff is hard to implement as they should have a very fine locational and temporal granularity. Peak prices could differ from one feeder to another and would have to be announced ex-ante or accounted for ex-post. If they

[82] As a reference, Costa-Campi et al. (2018) describe that energy losses in Spain in 2012 represented 8.9% of the total energy injected into the grid.

are announced ex-ante, it could happen that the expected peak differs from the realized peak. If they are accounted for ex-post, consumers' bills could become unpredictable. Also, to estimate the magnitude of the coefficients of the peak charges is a hard job. Possibly time-of-use (TOU) network charges could be a good compromise between efficiency and implementation difficulty.

Finally, other mechanisms could complement network tariff design to unlock consumer flexibility in terms of batteries adoption and operation. Examples are flexibility markets for system services (also referred to as markets for ancillary services) in which the DSO and/or TSO are the buyers of these services as described in Hadush and Meeus (2018). Both local congestion management or system balancing services can be procured. In these markets, aggregators can bundle DER resources. However, similar as with the introduction of time-of-use energy prices, it can also be expected that there will be an interaction between the network tariff design and the markets for the delivery of such services. This interaction deserves further attention when designing flexibility markets.

It should be added that an important driver for the business case of residential electricity storage is left out the analysis, namely resilience. In areas where the electricity supply from the central grid is not very reliable, this can be an important driver. This driver is however hard to quantify. Also, by including an endogenous energy market in the model, more insight can be gained about how the interaction of time-varying energy prices and network tariffs impacts welfare. Govaerts et al. (2019) apply a similar model to analyse the spill-over effects of different distribution network tariffs across multiple countries.

Finally, the game-theoretical applied in this work is highly stylised. For example, battery degradation is not taken into account. Battery degradation has shown to be an important cost for batteries which can also impact the operational strategy (Sidhu et al., 2018; Thompson, 2018; Uddin et al., 2017). Also, a constant C-rate (max. output over max. energy capacity) of the battery has been assumed. Different C-rates could lead to different business cases and uses for the battery as also shown in Schittekatte et al. (2016) and Schill et al. (2017). Besides battery storage, demand-side management (DSM) and smart charging of an electric vehicle is another way to do peak shaving, increase self-consumption or arbitrage energy prices. For example, Erdinc et al. (2015) show how the optimal sizing of batteries is impacted when considering the demand response possibilities and Hoarau and Perez (2018) discuss the impact of smart EV charging on battery adoption. These points offer possibilities to extend the presented analysis

CONCLUSIONS

This final section consists of two main parts. First, the conclusions of the thesis are summarised per chapter, excluding the first introductory chapter. Second, future work is discussed. Future work is split up into three parts: research options within the modelling framework, possible research options when adjusting the modelling framework and relevant research options outside the modelling framework.

1. Conclusions per chapter

Not all low-voltage consumers can be considered as passive anymore in times of affordable Distributed Energy Resources (DER). The availability and the costs of these new technologies strategically interact with network tariffs to recover grid costs, as active consumers will react with their profit-maximising actions to any network tariff charged to them. In this thesis mainly the adoption of two behind-the-meter technologies are considered: solar PV and batteries. Different game-theoretical models have been developed per chapter. In the context of increasing active consumers, each chapter assess a different dimension of the distribution network tariff design problem.

1.1 Chapter 2 - On whether capacity-based network charges solve the efficiency and fairness problems experienced with volumetric charges with net-metering

The results in Chapter 2 confirm that in a world with an increasing share of consumers connected to low voltage distribution networks reacting to price signals, simple netted-out volumetric network charges to recover grid costs cannot be considered as the adequate network tariff design. However, depending on DER technology costs, also capacity-based charges can severely distort the investment decisions of consumers. This is especially true if grid costs are mainly sunk.

Further, it was shown that both under volumetric charges with net-metering and capacity-based charges active consumers make uncoordinated investment decisions to push sunk grid costs to one another which can lead to overinvestment in DER and subsequently raise fairness issues. Fairness issues are found acuter under net-metering. However, paradoxically, under capacity-based charges, a situation can occur in which not only passive consumers but also active consumers end up paying more than in a situation where nobody invests in DER. This is due to competitive pressure among active consumers in allocating sunk grid costs. This effect was captured by modelling the grid cost recovery problem as a non-cooperative game between consumers, which is unprecedented in the existing body of literature.

1.2 Chapter 3 - On how to design a least-cost distribution network tariff when faced with two real-world constraints: implementation issues with cost-reflective charges and fairness

In Chapter 3, it is shown that both considered constraints have a significant impact on the least-cost network tariff design. In theory, the least-cost distribution network tariff design has two components. First, a fixed component that is proportional to the sunk costs. And second, a capacity component to reflect the costs of grid investments that still have to be made and that can be partly avoided if it is cheaper for active customers to invest in DER. In practice, departing from volumetric charges towards higher fixed charges is often perceived as unfair as their introduction would mean that low-usage passive consumers, who are often also less wealthy consumers, would pay similar charges as high-usage active consumers, who are often richer. Also, in practice, the individual capacity or individual peak is often a relatively weak approximation of the actual cost driver(s) of the network. As a result, a three-part tariff combining fixed, volumetric and capacity-based charges may be more suitable, even though in theory, volumetric is not to be considered for a least-cost distribution network tariff design.

Further, a strong interaction between the two analysed constraints in found. If regulators do not anticipate that their implementation of cost-reflective tariffs will be imperfect, the system costs will increase, and the fairness issues will aggravate. It is therefore important to have realistic estimations of what we know and do not know about the cost drivers of distribution networks. Limited information is available, suggesting that we need to be careful in setting strong incentives. This is especially true with high shares of active consumers.

Lastly, it is shown that if most of the grid investments still have to be made, passive and active consumers can both benefit from cost-reflective tariffs, while this is not the case for passive consumers if the costs are mostly sunk. The standard network tariff design options, i.e. fixed, volumetric and capacity-based charges, do not suffice to transfer part of the welfare gains of the active consumers to compensate the passive consumers. Other solutions than standard tariff design would have to be introduced to reach a fairer outcome; examples are specific low-income programmes, differentiated instead of uniform fixed charges, the recuperation of sunk network costs through other means than the electricity bill or the taxation of active customers, which has its own issues.

1.3 Chapter 4 - On the interaction between the business case of residential storage and the distribution network tariff design

In Chapter 4, it is found that the business case of storage and overall welfare are not always aligned. Three distribution network tariff designs are evaluated: net-purchase volumetric charges, bi-directional volumetric charges and capacity-based charges. In one extreme, in the case that most grid costs are sunk and little future grid investment is expected, the evaluated network tariffs mostly over-incentivize battery storage. In the other extreme, when future grid costs are driven by the growing needs of consumers, not only do the evaluated network tariff designs give an inadequate investment signal to the consumers, but also do the consumers operate their installed batteries sub-optimally from a system point of view.

Further, it is shown that with time-varying energy retailer prices instead of flat energy prices the business case for residential storage improves for all evaluated network tariff designs. With time-of-use energy prices, the active consumers can use their batteries to arbitrage energy prices besides lowering their network charges. The introduction of time-of-use energy prices is in most cases also beneficial from a system point of view. However, far from all potential efficiency gains are exploited due to unwanted interaction between the network tariff design and retailer energy prices. Consumers react to an aggregate of both price signals and as a result, imperfect network tariff design obstructs the optimal energy arbitrage strategy. This mechanism shows that distribution network tariff design and retailer energy price schemes should not be evaluated in isolation. Even more difficulties can be expected when considering taxes and levies in the electricity bill which are left out of this analysis.

Overall, in a high future grid cost scenario, a more advanced network tariff design is needed to correctly align the business case of residential storage with system benefits and coordinate energy prices and grid charges. It is shown that peak-coincident network prices, which exhibit strong peak prices at times when there are system peaks, give optimal or near-optimal results. However, such distribution network pricing is hard to implement, much information about the grid and actions of consumers is required, and the applied charges should have a fine locational and temporal granularity. Other mechanisms could complement network tariff design to unlock consumer flexibility in terms of battery adoption and operation. Examples are flexibility markets for system services in which the DSO and/or TSO are the buyers of these services and aggregators bundle the DER resources. However, also interactions between the network tariff design and the markets for the delivery of such services can be expected. These interactions deserve further attention when designing flexibility markets.

2. Future work

Potential avenues for future work can be split up into three parts: research options within the modelling framework, research options when adjusting the modelling framework and research options outside the modelling framework.

2.1 *Within the modelling framework*

- The inclusion of other behind-the-meter technologies which could be used by consumers to react to the network tariff design could be considered. Examples are electric vehicles and heat pumps. Accounting for these (mainly) electricity consuming technologies could present new insights. For example, Hoarau and Perez (2018) base their model on the work of chapter 2 and include electrical vehicles.
- Demand response could be included. Demand response could compete with batteries to do peak shifting and/or increase self-consumption.
- The recuperation of policy costs and taxation deserves further attention. The way policy costs and taxes are recuperated in the electricity bill could severely distort the network tariff design.
- Similarly, the interaction (or substitutability) of subsidies and network tariff design is worth deeper investigation.
- More elaborated network costs functions could be evaluated, e.g. energy losses and accounting for the cost of bi-directional flows.

2.2 *When adjusting the modelling framework*

- DER operation and costs could be represented in a more advanced manner. More accurate representation implies in most cases the need for binary variables or the introduction of non-linearities, e.g. battery degradation (Cardoso et al., 2018). Binaries or non-linearities in the lower-level problems complicate the modelling significantly. Gabriel and Leuthold (2010) show when and how discretely-constraint MPECs can be solved. Also, the consumers' decision to go off-grid could be modelled with the use of binary variables.
- Due to the structure of the model, it is assumed that the regulator has perfect insight into the consumers' reaction on the network tariff design. In reality, future demand is not known ex-ante and has to be estimated. This anticipation issue could be accounted for by including stochasticity in the consumer reaction. An example is the paper by Weijde and Hobbs (2012) in which a stochastic two-stage optimisation model capturing the multistage nature of the planning of a transmission network under uncertainty is presented. Adding multiple stages and stochasticity would require an expansion of the presented model.
- The energy prices could be endogenised including wholesale energy market. Govaerts et al. (2019) build further on the model presented in Chapter 2 and capture the wholesale market effects of distribution grid tariffs. By doing so, they can have an idea of the spill-over effects from (national) distribution network tariff designs through interlinked wholesale markets. They also show that in the long-run, the average energy price is not that strongly decreased as would be expected with strong solar PV adoption. But, the volatility of the price increases. This finding confirms earlier work, e.g. Green and Vasilakos (2011).
- In this thesis, non-cooperative behaviour among consumers is modelled. Alternatively, cooperative behaviour among consumers, i.e. consumers forming an energy community, can

be modelled. Abada et al. (2018, 2017) look at the ability of such communities to adequately share the gains and look at the effects these communities have on grid tariffs.

- The model could be complemented with the option for consumers to provide flexibility services to grid operators through market mechanisms (with or without aggregation). It could be looked at how these markets perform as a function of market design and market structure. Also, the interaction between the network tariff design and the provision of services could be investigated.

2.3 Outside the modelling framework

- Locationally more granular network tariffs could become increasingly important to limit the efficiency loss of uniform network tariffs over large areas. Such an analysis would require more detailed modelling of the distribution network which complicates the possibilities to mathematically couple the loop between consumer-reactions to the network tariff design and their impact on the network and thus to come to an equilibrium. Such type of analysis can be found in MIT Energy Initiative (2016).
- Larger databases with many different consumer profiles, longer-time series and more precise network costs can be used to do specific case study analysis. Again, more data complicates the possibility to find an equilibrium and other types of analysis needs to be done. Examples are the work of Küfeoğlu and Pollitt (2019) doing a case study for GB and Passey et al. (2017) looking deeper into Australian data.
- Different assumptions regarding the behaviour of consumers can be made, other than fully rational and active or completely passive. In that regard, agent-based modelling can be of use. Interesting papers in this regard are the work of Saguan et al. (2006) in which the main differences between equilibrium and agent-based modelling to study imperfect competition in electricity markets are discussed and the work of Weidlich and Veit (2008) in which a critical survey of agent-based wholesale electricity market models is conducted.

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APPENDICES

A. The complete mathematical model

A.1 Overview of the used sets, parameters and variables

Sets

i : 1,..,N: Consumers types

t: 1,..,T: Time steps with a certain granularity

Parameters

Upper-level

$\mathrm{SunkGridCosts}$: Sunk annualised grid costs, scaled per average consumer [€]

$\mathrm{IncrGridCosts}$: Incremental annualised grid cost per kW increase/decrease of the coincident peak demand/injection, scaled per average consumer [€/kW]

DPeak: (Default) coincident peak demand before investment in DER by active consumers, scaled per average consumer [kW]

WF: Weighting factor, indicating the inaccuracy in the network cost driver [-]

NM: Factor indicating whether net-metering (1) or no net-metering (0) or bi-directional volumetric charges (-1) are in place [-]

PC_i : Proportion of consumer type i

$\mathrm{TotalOtherCosts}$: all other costs paid through the electricity bill, e.g. policy costs, annualised and scaled per consumer [€]

BGC_i : Baseline volumetric grid charges paid before investment in DER for consumer type i [€]

Cap_i: Cap on the increase of grid charges paid for consumer type i [%]

Lower level

WDT: Scaling factor to annualise, dependent on length of the used time series and time step [-]

DT: time step, as a fraction of 60 minutes [-]

$\mathrm{D}_{t,i}$: Original demand at time step t of agent i [kW]

MS_i : Maximum solar capacity that can be installed by agent i [kW]

MB_i : Maximum battery capacity that can be installed by agent i [kWh]

$\mathrm{SY}_{t,i}$: Yield of the PV panel at time step t of agent i [kWh/kW$_{peak}$]

EBP_t: Energy price to be paid by agent for buying from the grid [€/kWh]

ESP_t: Energy price received by agent for buying from the grid (feed-in tariff) [€/kWh]

AICS: Annualised investment cost solar PV [€/kW$_{peak}$]

AICB: Annualised investment cost battery [€/kWh]

BDR: Ratio of max power output of the battery over the installed energy capacity [-]

BCR: Ratio of max power input of the battery over the installed energy capacity [-]

EFD: Efficiency of discharging the battery [%]

EFC: Efficiency of charging the battery [%]

LR: Leakage rate of the battery [%]

$\mathrm{SOC_0}$: Original (and final) state of charge of the battery [kWh]

$\mathrm{OtherCosts}$: other costs paid through the electricity bill, e.g. policy costs [€]

$\mathrm{PrDSM_i}$: Max. percentage of the demand at any time step that can be shifted by DSM [%]

$\mathrm{CDSM_i}$: Cost of DSM per kWh shifted [€/kWh]

<u>*Variables*</u>

<u>UL decision variable</u>

vnt : Volumetric network tariff [€/kWh]

cnt*:* Capacity network charge [€/kW_{peak}]

fnt*:* Fixed network charge [€/connection]

cpp_t: Time-varying network charge [€/kWh] (free variable)

$CoincidentPeak$: The coincident (aggregated) peak demand after optimisation (highest absolute of value of the positive/negative coincident peak), scaled per average consumer [kW]

$CPeakDemand$: Positive coincident peak demand after optimisation, scaled per average consumer [kW]

$CPeakInjection$: Negative coincident peak demand after optimisation, scaled per average consumer [kW]

$TotalGridCost$: Total annualised grid cost, scaled per average consumer [€]

$TotalDERcosts$: Total annualised investment cost in DER, scaled per average consumer [€]

$TotalEnergyCosts$: Total annualised energy cost, scaled per average consumer [€]

$TotalDSMCosts$: Total annualised demand side management operational cost, scaled per average consumer [€]

<u>LL decision variable</u>

$GridCharges_i$: Annualised grid charges for agent i [€]

$DERCosts_i$: Annualised investment cost in DER for agent i [€]

$EnergyCosts_i$: Annualised energy cost for agent i [€]

$DSMCosts_i$: Annualised demand side management operational cost for agent i [€]

$qw_{t,i}$: Energy bought at time step t by agent i [kW]

$qi_{t,i}$: Energy sold at time step t by agent i [kW]

$qmax_i$: Peak demand of agent i over the length of the considered time series [kW]

$soc_{t,i}$: State of charge of the battery of agent i at step t [kWh]

$qbout_{t,i}$: Discharge of the battery of agent i at step t [kW]

$qbin_{t,i}$: Power input into the battery of agent i at step t [kW]

is_i: Installed capacity of solar by agent i [kW]

ib_i: Installed capacity of the battery by agent i [kWh]

$uDSM_{t,i}$: Energy increased at time step t by agent i due to DSM (shifted from another time step) [kW]

$dDSM_{t,i}$: Energy decreased at time step t by agent i due to DSM (shifted to another time step) [kW]

A.2. Original optimisation problems

The upper-level problem for a total system cost minimising regulator

Objective function, the minimisation of total system costs:

$$\text{Minimise } TotalGridCosts + TotalDERcosts + TotalEnergyCosts + TotalDSMCosts + \text{TotalOtherCosts} \quad (A.1)$$

With its components being:

$$TotalGridCosts = \text{SunkGridCosts} + \text{IncrGridCosts} * (\text{DPeak} - \text{WF} * (\text{DPeak} - OPeak)) \quad (A.2)$$

$$TotalDERcosts = \sum_{i=1}^{\text{N}} \text{PC}_i * (is_i * \text{AICS} + ib_i * \text{AICB}) \quad (A.3)$$

$$TotalEnergyCosts = \sum_{t=1}^{\text{T}} \sum_{i=1}^{\text{N}} \text{PC}_i * \left(qw_{t,i} * \text{EBP}_\text{t} - qi_{t,i} * \text{ESP}_\text{t}\right) * \text{WDT} \quad (A.4)$$

$$TotalDSMCosts = \sum_{t=1}^{\text{T}} \sum_{i=1}^{\text{N}} \text{PC}_i * \left(dDSM_{t,i}\right) * \text{CDSM}_\text{i} * \text{WDT} \quad (A.5)$$

Finding the aggregated peak demand in absolute value:

$$CoincidentPeak \equiv Max\{CPeakDemand, CPeakInjection\} \quad (A.6)$$

$$CPeakDemand \equiv Max\left\{\sum_{i=1}^{N} PC_i\left(qw_{t,i} - qi_{t,i}\right) \forall t\right\} \quad (A.7)$$

$$CPeakInjection \equiv Max\left\{\sum_{i=1}^{N} PC_i\left(qi_{t,i} - qw_{t,i}\right) \forall t\right\} \quad (A.8)$$

Cost recovery Eq. of the upper-level (A.9) with a cap on the increase of grid charges of the passive consumer (i2) (A.10):

$$TotalGridcosts = vnt * \sum_{t=1}^{\text{T}} \sum_{i=1}^{\text{N}} \text{PC}_i * \left(qw_{t,i} - \text{NM} * qi_{t,i}\right) * \text{WDT} + cnt * \sum_{i=1}^{\text{N}} \text{PC}_i * qmax_i + \sum_{t=1}^{\text{T}} \sum_{i=1}^{\text{N}} \text{PC}_i * cpp_t * (qw_{t,i} - qi_{t,i}) * \text{WDT} + fnt \quad (A.9)$$

$$vnt * \sum_{t=1}^{\text{T}} \left(qw_{t,'i2'} - \text{NM} * qi_{t,'i2'}\right) * \text{WDT} + cnt * qmax_{'i2'} + CPP_{t,i} * \sum_{t=1}^{\text{T}} \sum_{i=1}^{\text{N}} \text{PC}_i * (qw_{t,i} - qi_{t,i}) * \text{WDT} + fnt \leq \text{BGC}_{'i2'} * (1 + \text{Cap}_{'i2'}) \quad (A.10)$$

The lower level problem for an electricity cost minimising consumer

Objective function per consumer type i, the minimisation of individual electricity cost:

$$\text{Minimise } GridCharges_i + DERCosts_i + EnergyCosts_i + DSMCosts_i + \text{OtherCharges} \quad (A.11)$$

With:

$$GridCharges_i = \sum_{t=1}^{\text{T}} (qw_{t,i} - qi_{t,i} * \text{NM}) * vnt * \text{WDT} + qmax_i * cnt + \sum_{t=1}^{\text{T}} (qw_{t,i} - qi_{t,i}) * cpp_t * \text{WDT} + fnt \quad \forall i \quad (A.12)$$

$$DERCosts_i = is_i * \text{AICS} + ib_i * \text{AICB} \quad \forall i \quad (A.13)$$

$$EnergyCosts_i = \sum_{t=1}^{\text{T}} \left(qw_{t,i} * \text{EBP}_\text{t} - qi_{t,i} * \text{ESP}_\text{t}\right) * \text{WDT} \quad \forall i \quad (A.14)$$

$$DSMCosts_i = \sum_{t=1}^{\text{T}} \left(dDSM_{t,i}\right) * \text{CDSM}_\text{i} * \text{WDT} \quad \forall i \quad (A.15)$$

Constraints (including duals):

$$qw_{t,i} - qi_{t,i} + is_i * \mathrm{SY_{t,i}} + qbout_{t,i} - qbin_{t,i} + dDSM_{t,i} - uDSM_{t,i} - \mathrm{D_{t,i}} = 0 \qquad \forall\, i,t \quad (\mu^a_{t,i}) \quad (A.16)$$

$$soc_{1,i} - qbin_{1,i} * \mathrm{EFC} * \mathrm{DT} + (qbout_{1,i}/\mathrm{EFD}) * \mathrm{DT} - \mathrm{SOC_0} = 0 \qquad \forall\, i \quad (\mu^b_{1,i}) \quad (A.17)$$

$$soc_{t,i} - qbin_{t,i} * \mathrm{EFC} * \mathrm{DT} + \left(qbout_{\mathrm{t,i}}/\mathrm{EFD}\right) * \mathrm{DT} - soc_{t-1,i} * (1 - \mathrm{LR} * \mathrm{DT}) = 0 \qquad \forall\, i, t \neq 1 \quad (\mu^b_{t\neq 1,i}) \quad (A.18)$$

$$soc_{T,i} - \mathrm{SOC_0} \quad = 0 \qquad \forall\, i \quad (\mu^c_i) \quad (A.19)$$

$$\textstyle\sum_{t=1}^{\mathrm{T\in day}} \left(uDSM_{t,i} - dDSM_{t,i}\right) = 0 \qquad \forall\, i \quad (\mu^d_i) \quad (A.20)$$

$$-qmax_i + qw_{t,i} + qi_{t,i} \ \leq 0 \qquad \forall\, t,i \quad (\lambda^a_{t,i}) \quad (A.21)$$

$$soc_{t,i} - ib_i \ \leq \ 0 \qquad \forall\, t,i \quad (\lambda^b_{t,i}) \quad (A.22)$$

$$qbout_{t,i} - ib_i * \mathrm{BDR} \ \leq 0 \qquad \forall\, t,i \quad (\lambda^c_{t,i}) \quad (A.23)$$

$$qbin_{t,i} - ib_i * \mathrm{BCR} \ \leq \ 0 \qquad \forall\, t,i \quad (\lambda^d_{t,i}) \quad (A.24)$$

$$dDSM_{t,i} - \mathrm{PrDSM_i} * \mathrm{D_{t,i}} \ \leq \ 0 \qquad \forall\, t,i \quad (\lambda^e_{t,i}) \quad (A.25)$$

$$-qw_{t,i} \leq 0 \qquad \forall\, t,i \quad (\lambda^f_{t,i}) \quad (A.26)$$

$$-\,qi_{t,i} \ \leq 0 \qquad \forall\, t,i \quad (\lambda^g_{t,i}) \quad (A.27)$$

$$-soc_{t,i} \leq 0 \qquad \forall\, t,i \quad (\lambda^h_{t,i}) \quad (A.28)$$

$$-qbout_{t,i} \leq 0 \qquad \forall\, t,i \quad (\lambda^i_{t,i}) \quad (A.29)$$

$$-qbin_{t,i} \leq 0 \qquad \forall\, t,i \quad (\lambda^j_{t,i}) \quad (A.30)$$

$$-dDSM_{t,i} \leq 0 \qquad \forall\, t,i \quad (\lambda^k_{t,i}) \quad (A.31)$$

$$-uDSM_{t,i} \leq 0 \qquad \forall\, t,i \quad (\lambda^l_{t,i}) \quad (A.32)$$

$$is_i - \mathrm{MS}_i \ \leq 0 \qquad \forall\, i \quad (\lambda^m_i) \quad (A.33)$$

$$ib_i - \mathrm{MB}_i \ \leq 0 \qquad \forall\, i \quad (\lambda^n_i) \quad (A.34)$$

$$-\,is_i \ \leq 0 \qquad \forall\, i \quad (\lambda^o_i) \quad (A.35)$$

$$-\,ib_i \ \leq 0 \qquad \forall\, i \quad (\lambda^p_i) \quad (A.36)$$

$$-\,qmax_i \ \leq 0 \qquad \forall\, i \quad (\lambda^q_i) \quad (A.37)$$

$$\lambda^a_{t,i}, \lambda^b_{t,i}, \lambda^c_{t,i}, \lambda^d_{t,i}, \lambda^e_{t,i}, \lambda^f_{t,i}, \lambda^g_{t,i}, \lambda^h_{t,i}, \lambda^i_{t,i}, \lambda^j_{t,i}, \lambda^k_{t,i}, \lambda^l_{t,i} \ \geq 0 \qquad \forall\, t,i \quad (A.38)$$

$$\lambda^m_i, \lambda^n_i, \lambda^o_i, \lambda^p_i, \lambda^q_i, \geq 0 \qquad \forall\, i \quad (A.39)$$

Eq. (A.37) is noted down for completeness, the constraint is implied by Eq. A.21, A.26 and A.27.

A.3. MPEC reformulation as a MILP

A.3.1 Method 1 to transform the bilinear products in Eq. A.9: discretisation

Newly introduced sets, parameters and variables

Sets

k: 1…K: Index of auxiliary binaries (b^a_k) to discretise the bilinear product (including vnt) in Eq. (A.9)

l: 1…L: Index of auxiliary binaries (b^c_l) to discretise the bilinear product (including cnt) in Eq. (A.9)

m: 1…M: Index of auxiliary binaries ($b^c_{m,t}$) to discretise the bilinear product (including cpp_t) in Eq. (A.9)

Parameters

δ: Allowed band wherein the grid costs charges can differ from the grid charges collected as a percentage of the total grid costs [%]

$\Delta\gamma$: Step of vnt when discretised [-]

$\Delta\partial$: Step of cnt when discretised [-]

$\Delta\theta$: Step of cpp_t when discretised [-]

M^{Da}: Large scalar used to discretise the bilinear product (including vnt) in Eq. (A.9) [-]

M^{Db}: Large scalar used to discretise the bilinear product (including cnt) in Eq. (A.9) [-]

$\mathrm{M}_t^{\mathrm{Dc}}$: Large scalar used to discretise the bilinear product (including cpp_t) in Eq. (A.9) [-]

Variables

b_k^a: Binary variables used to discretise the bilinear product (including vnt) in Eq. (A.9)

b_l^b: Binary variables used to discretise the bilinear product (including cnt) in Eq. (A.9)

$b_{m,t}^c$: Binary variables used to discretise the bilinear product (including cpp_t) in Eq. (A.9)

z_k^a: (Pos.) continuous variables used to represent the bilinear product (including vnt) in Eq. (A.9)

z_l^b: (Pos.) continuous variables used to represent the bilinear product (including cnt) in Eq. (A.9)

$z_{m,t}^c$: (Pos.) continuous variables used to represent the bilinear product (including cpp_t) in Eq. (A.9)

Model transformations

Transformation of the grid cost recovery equality of the upper-level

For easier convergence of the model, the grid cost recovery Equality (A.9) is replaced by two constraints (A.40-41) making sure that the network charges collected from the consumers are within a band (1±δ) of the grid costs to be recovered. In the performed runs δ is set to 0.1%.

$$TotalGridCost * (1-\delta) - vnt * \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * \left(qw_{t,i} - \mathrm{NM} * qi_{t,i}\right) * \mathrm{WDT} + cnt * \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * qmax_i + CPP_{t,i} * \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * (qw_{t,i} - qi_{t,i}) * \mathrm{WDT} + fnt \leq 0 \tag{A.40}$$

$$-TotalGridCost * (1+\delta) + vnt * \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * \left(qw_{t,i} - \mathrm{NM} * qi_{t,i}\right) * \mathrm{WDT} + cnt * \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * qmax_i + CPP_{t,i} * \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * (qw_{t,i} - qi_{t,i}) * \mathrm{WDT} + fnt \leq 0 \tag{A. 41}$$

Discretising the bilinear products (of two positive continuous variables) to turn the NLP in a MIP

Formulation based on Momber (2015), page 102, Eq. 4.60-4.63. We define:

$$q^{tot} = \sum_{t=1}^{T} \sum_{i=1}^{N} \mathrm{PC_i} * \left(qw_{t,i} - \mathrm{NM} * qi_{t,i}\right) * \mathrm{WDT} \tag{A.42}$$

$$\text{and } vnt = \Delta\gamma * \sum_k 2^{k-1} * b_k^a \tag{A.43}$$

$$qmax^{tot} = \sum_{i=1}^{N} \mathrm{PC_i} * qmax_i \tag{A.44}$$

$$\text{and } cnt = \Delta\partial * \sum_l 2^{l-1} * b_l^b \tag{A.45}$$

$$q_t^{cpp} = \sum_{t=1}^{T} \mathrm{PC_i} * \left(qw_{t,i} - qi_{t,i}\right) * \mathrm{WDT} \qquad \forall t \tag{A.46}$$

$$\text{and } cpp_t = \Delta\theta * \sum_m 2^{m-1} * b_{l,t}^c \qquad \forall t \tag{A.47}$$

It follows that:

$$q^{tot} * vnt = q^{tot} * \Delta\gamma * \sum_k 2^{k-1} * b_k^a = \Delta\gamma * \sum_k 2^{k-1} * z_k^a \tag{A.48}$$

$$qmax^{tot} * cnt = qmax^{tot} * \Delta\partial * \sum_l 2^{l-1} * b_l^b = \Delta\partial * \sum_l 2^{l-1} * z_l^b \tag{A.49}$$

$$q_t^{cpp} * cpp_t = q_t^{cpp} * \Delta\theta * \sum_m 2^{m-1} * b_{l,t}^c = \Delta\theta * \sum_m 2^{m-1} * z_{m,t}^c \qquad \forall t \tag{A.50}$$

with:

$$z_k^a \quad \geq 0 \qquad \forall\, k \qquad (A.51)$$
$$z_k^a \quad \leq \mathrm{M^{Da}} * b_k^a \qquad \forall\, k \qquad (A.52)$$
$$q^{tot} - z_k^a \ \geq 0 \qquad \forall\, k \qquad (A.53)$$
$$q^{tot} - z_k^a \ \leq \mathrm{M^{Da}} * (1 - b_k^a\ ) \qquad \forall\, k \qquad (A.54)$$

$$z_l^b \quad \geq 0 \qquad \forall\, l \qquad (A.55)$$
$$z_l^b \quad \leq \mathrm{M^{Db}} * b_l^b \qquad \forall\, l \qquad (A.56)$$
$$qmax^{tot} - z_l^b \geq 0 \qquad \forall\, l \qquad (A.57)$$
$$qmax^{tot} - \ z_l^b \ \leq \mathrm{M^{Db}} * (1 - b_l^b\ \ ) \qquad \forall\, l \qquad (A.58)$$

$$z_{m,t}^c \quad \geq 0 \qquad \forall\, m, t \qquad (A.59)$$
$$z_{m,t}^c \quad \leq \mathrm{M}_t^{\mathrm{Dc}} * b_{m,t}^c \qquad \forall\, m, t \qquad (A.60)$$
$$q_t^{cpp} - z_{m,t}^c \ \geq 0 \qquad \forall\, m, t \qquad (A.61)$$
$$q_t^{cpp} - z_{m,t}^c \ \leq \mathrm{M}_t^{\mathrm{Dc}} * \left(1 - b_{m,t}^c\ \right) \qquad \forall\, m, t \qquad (A.62)$$

$\mathrm{M^{Da}}$, $\mathrm{M^{Db}}$ and $\mathrm{M}_t^{\mathrm{Dc}}$ are well calibrated and $\Delta\gamma$, $\Delta\partial$ and $\Delta\theta$ are chosen to balance precision and computational time. Eq. (A.40-A.41) and further transformed to (A.63- A.64) which is the final form of Eq. (A.8) included in the model formulation

$$TotalGridCost * (1 - \delta) - \ \Delta\gamma * \textstyle\sum_k 2^{k-1} * z_k^a + \ \Delta\,\partial * \sum_l 2^{l-1} * z_l^b + \sum_t^T\left(\Delta\theta * \sum_m 2^{m-1} * z_{m,t}^c\right) + fnt \leq 0 \qquad (A.63)$$
$$-TotalGridCost * (1 + \delta) - \ \Delta\gamma * \textstyle\sum_k 2^{k-1} * z_k^a + \ \Delta\,\partial * \sum_l 2^{l-1} * z_l^b + \sum_t^T\left(\Delta\theta * \sum_m 2^{m-1} * z_{m,t}^c\right) + fnt \leq 0 \qquad (A.64)$$

A.3.2 Method 2 to transform the bilinear products in Eq. A.9: strong duality theorem

The strong duality theorem says that if a problem is convex, the objective functions of the primal and dual problems have the same value at the optimum (Castillo et al., 2001). We apply this theorem to the lower-level problem. The objective function of the primal problem is stated in Eq. A.11. The dual objective is derived from (A.11-39) and formulated as follows:

$$\text{Maximise } \textstyle\sum_{t=1}^T(\mu_{t,i}^a * \mathrm{D}_{t,i}) + \ \mu_{1,i}^b * \mathrm{SOC_0} - \ \sum_{t=1}^T \mathrm{PrDSM_i} * \mathrm{D_{t,i}} * \ \lambda_{t,i}^e - \ \mathrm{MS}_i * \ \lambda_i^m - \mathrm{MB}_i * \ \lambda_i^n \qquad (A.65)$$

Thus it follows that:

$$\textstyle\sum_{t=1}^T(\mu_{t,i}^a * \mathrm{D}_{t,i}) + \ \mu_{1,i}^b * \mathrm{SOC_0} - \sum_{t=1}^T(\mathrm{PrDSM_i} * \mathrm{D_{t,i}} * \ \lambda_{t,i}^e) - \ \mathrm{MS}_i * \ \lambda_i^m - \mathrm{MB}_i * \ \lambda_i^n = \sum_{t=1}^{\mathrm{T}}(qw_{t,i} - qi_{t,i} * \mathrm{NM}) * vnt * \mathrm{WDT} + qmax_i * cnt + \sum_{t=1}^{\mathrm{T}}(qw_{t,i} - qi_{t,i}) * cpp_t * \mathrm{WDT} + \ fnt + \ \ is_i * \mathrm{AICS} + ib_i * \mathrm{AICB} + \ \sum_{t=1}^{\mathrm{T}}\left(qw_{t,i} * \mathrm{EBP_t} - qi_{t,i} * \mathrm{ESP_t}\right) * \mathrm{WDT} + \ \sum_{t=1}^{\mathrm{T}}\left(dDSM_{t,i}\right) * \mathrm{CDSM_i} * \mathrm{WDT} \qquad (A.66)$$

We can reformulate A.66 as:

$$\textstyle\sum_{t=1}^{\mathrm{T}}(qw_{t,i} - qi_{t,i} * \mathrm{NM}) * vnt * \mathrm{WDT} + qmax_i * cnt + \sum_{t=1}^{\mathrm{T}}(qw_{t,i} - qi_{t,i}) * cpp_t * \mathrm{WDT} + \ fnt = \sum_{t=1}^T(\mu_{t,i}^a * \mathrm{D}_{t,i}) + \mu_{1,i}^b * \mathrm{SOC_0} - \sum_{t=1}^T\left(\mathrm{PrDSM_i} * \mathrm{D_{t,i}} * \ \lambda_{t,i}^e\right) - \ \mathrm{MS}_i * \ \lambda_i^m - \mathrm{MB}_i * \ \lambda_i^n - \ \left(\ is_i * \mathrm{AICS} + ib_i * \mathrm{AICB} + \ \sum_{t=1}^{\mathrm{T}}\left(qw_{t,i} * \mathrm{EBP_t} - qi_{t,i} * \mathrm{ESP_t}\right) * \mathrm{WDT} + \ \sum_{t=1}^{\mathrm{T}}\left(dDSM_{t,i}\right) * \mathrm{CDSM_i} * \mathrm{WDT}\right) \qquad (A.67)$$

If we now multiply both sides by $\sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i$:

$$\sum_{i=1}^{N} \mathbf{PC}_i * \left(\sum_{t=1}^{T}(\boldsymbol{qw_{t,i}} - \boldsymbol{qi_{t,i}} * \mathbf{NM}) * \boldsymbol{vnt} * \mathbf{WDT} + \boldsymbol{qmax_i} * \boldsymbol{cnt} + \sum_{t=1}^{T}(\boldsymbol{qw_{t,i}} - \boldsymbol{qi_{t,i}}) * \boldsymbol{cpp_t} * \mathbf{WDT} + \boldsymbol{fnt}\right) =$$
$$\sum_{i=1}^{N} \mathrm{PC}_i * \Big(\sum_{t=1}^{T}(\mu_{t,i}^{a} * \mathrm{D}_{t,i}) + \mu_{1,i}^{b} * \mathrm{SOC}_0 - \sum_{t=1}^{T}(\mathrm{PrDSM_i} * \mathrm{D_{t,i}} * \lambda_{t,i}^{e}) - \mathrm{MS}_i * \lambda_i^{m} - \mathrm{MB}_i * \lambda_i^{n} -$$
$$\left(is_i * \mathrm{AICS} + ib_i * \mathrm{AICB} + \sum_{t=1}^{T}\left(qw_{t,i} * \mathrm{EBP_t} - qi_{t,i} * \mathrm{ESP_t}\right) * \mathrm{WDT} + \sum_{t=1}^{T}\left(dDSM_{t,i}\right) * \mathrm{CDSM_i} * \mathrm{WDT}\right)\Big) \quad \text{(A.68)}$$

We can see that the left-hand side of Eq. A.68 equals the right hand-side of Eq. A.9. Thus, we replace the bilinear terms in the right hand side of Eq. A.9 with the linear expression on the right-hand side of Eq. A.68.[83]

A.3.3 Karush-Kuhn-Tucker (KKT) conditions of the lower level

We derive the KKT conditions of the lower level problem (Eq. A.11-39):

$$\mathrm{WDT} * (\mathrm{EBP}_t + vnt + cpp_t) + \mu_{t,i}^{a} + \lambda_{t,i}^{a} - \lambda_{t,i}^{f} = 0 \qquad \forall\, t, i \qquad \text{(A.69)}$$
$$-\mathrm{WDT} * (\mathrm{ESP_t} + \mathrm{NM} * vnt + cpp_t) - \mu_{t,i}^{a} + \lambda_{t,i}^{a} - \lambda_{t,i}^{g} = 0 \qquad \forall\, t, i \qquad \text{(A.70)}$$
$$cnt - \sum_t \lambda_{t,i}^{a} = 0 \qquad \forall\, i \qquad \text{(A.71)}$$
$$\mu_{t,i}^{b} - \mu_{t+1,i}^{b} * (1 - \mathrm{LT} * \mathrm{DT}) + \lambda_{t,i}^{b} - \lambda_{t,i}^{h} = 0 \qquad \forall\, t \neq \{\mathrm{T}\}, i \qquad \text{(A.72)}$$
$$\mu_{T,i}^{b} + \mu_i^{c} + \lambda_{T,i}^{b} - \lambda_{T,i}^{h} = 0 \qquad \forall\, t = \mathrm{T}, i \qquad \text{(A.73)}$$
$$\mu_{t,i}^{a} + \frac{\mu_{t,i}^{b}}{\mathrm{EFD}} * \mathrm{DT} + \lambda_{t,i}^{c} - \lambda_{t,i}^{i} = 0 \qquad \forall\, t, i \qquad \text{(A.74)}$$
$$-\mu_{t,i}^{a} - \mu_{t,i}^{b} * \mathrm{EFC} * \mathrm{DT} + \lambda_{t,i}^{d} - \lambda_{t,i}^{j} = 0 \qquad \forall\, t, i \qquad \text{(A.75)}$$
$$\mathrm{CDSM}_i * \mathrm{WDT} + \mu_{t,i}^{a} - \mu_{t\in day,i}^{d} + \lambda_{t,i}^{e} - \lambda_{t,i}^{k} = 0 \qquad \forall\, t, i \qquad \text{(A.76)}$$
$$-\mu_{t,i}^{a} + \mu_{t\in day,i}^{d} - \lambda_{t,i}^{l} = 0 \qquad \forall\, t, i \qquad \text{(A.77)}$$
$$\mathrm{AICS} + \sum_t \mu_{t,i}^{a} * \mathrm{SY_{t,i}} + \lambda_i^{m} - \lambda_i^{o} = 0 \qquad \forall\, i \qquad \text{(A.78)}$$
$$\mathrm{AICB} - \sum_t \mu_{t,i}^{b} - \sum_t \lambda_{t,i}^{c} * \mathrm{BDR} - \sum_t \lambda_{t,i}^{d} * \mathrm{BCR} + \lambda_i^{n} - \lambda_i^{p} = 0 \qquad \forall\, i \qquad \text{(A.79)}$$
$$qw_{t,i} - qi_{t,i} + is_i * \mathrm{SY}_{t,i} + qbout_{t,i} - qbin_{t,i} + dDSM_{t,i} - uDSM_{t,i} - \mathrm{D}_{t,i} = 0 \qquad \mu_{t,i}^{a} free \qquad \forall\, t, i \qquad \text{(A.80)}$$
$$soc_{1,i} - qbin_{1,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{1,i}}{\mathrm{EFD}} * \mathrm{DT} - \mathrm{SOC_0} = 0 \qquad \mu_{1,i}^{b}\ free \qquad \forall\, i \qquad \text{(A.81)}$$
$$soc_{t,i} - qbin_{t,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{t,i}}{\mathrm{EFD}} * \mathrm{DT} - soc_{t-1,i} * (1 - \mathrm{LR} * \mathrm{DT}) = 0 \qquad \mu_{t\neq 1,i}^{b} free \qquad \forall\, t \neq 1, i \qquad \text{(A.82)}$$
$$soc_{T,i} - \mathrm{SOC_0} = 0 \qquad \mu_i^{c}\ free \qquad \forall\, i \qquad \text{(A.83)}$$
$$\sum_{t=1}^{\mathrm{T\in day}}\left(uDSM_{t,i} - dDSM_{t,i}\right) = 0 \qquad \mu_i^{d}\ free \qquad \forall\, i \qquad \text{(A.84)}$$
$$0 \le qmax_i - qw_{t,i} - qi_{t,i} \quad \perp\ \lambda_{t,i}^{a} \ge 0 \qquad \forall\, t, i \qquad \text{(A.85)}$$
$$0 \le ib_{\mathrm{i}} - soc_{t,i} \quad \perp\ \lambda_{t,i}^{b} \ge 0 \qquad \forall\, t, i \qquad \text{(A.86)}$$
$$0 \le ib_{\mathrm{i}} * \mathrm{BDR} - qbout_{t,i} \quad \perp\ \lambda_{t,i}^{c} \ge 0 \qquad \forall\, t, i \qquad \text{(A.87)}$$
$$0 \le ib_{\mathrm{i}} * \mathrm{BCR} - qbin_{t,i} \quad \perp\ \lambda_{t,i}^{d} \ge 0 \qquad \forall\, t, i \qquad \text{(A.88)}$$
$$0 \le \mathrm{PrDSM_i} * \mathrm{D_{t,i}} - dDSM_{t,i} \quad \perp\ \lambda_{t,i}^{e} \ge 0 \qquad \forall\, t, i \qquad \text{(A.89)}$$
$$0 \le qw_{t,i} \quad \perp\ \lambda_{t,i}^{f} \ge 0 \qquad \forall\, t, i \qquad \text{(A.90)}$$
$$0 \le qi_{t,i} \quad \perp\ \lambda_{t,i}^{g} \ge 0 \qquad \forall\, t, i \qquad \text{(A.91)}$$
$$0 \le soc_{t,i} \quad \perp\ \lambda_{t,i}^{h} \ge 0 \qquad \forall\, t, i \qquad \text{(A.92)}$$
$$0 \le qbout_{t,i} \quad \perp\ \lambda_{t,i}^{i} \ge 0 \qquad \forall\, t, i \qquad \text{(A.93)}$$
$$0 \le qbin_{t,i} \quad \perp\ \lambda_{t,i}^{j} \ge 0 \qquad \forall\, t, i \qquad \text{(A.94)}$$

[83] $\sum_{i=1}^{N} \mathrm{PC}_i * fnt = fnt$ as each consumer pays the same fixed charge. Also, fnt is a constant for the lower level objective and therefore is subtracted from the right-hand side of Eq. 68 when substituting it with the right hand side of Eq. 9.

$0 \leq dDSM_{t,i} \quad \perp \ \lambda^k_{t,i} \geq 0 \quad \forall\, t,i \quad$ (A.95)

$0 \leq uDSM_{t,i} \quad \perp \ \lambda^l_{t,i} \geq 0 \quad \forall\, t,i \quad$ (A.96)

$0 \leq \mathrm{MS}_i - is_i \quad \perp \ \lambda^m_i \geq 0 \quad \forall\, i \quad$ (A.97)

$0 \leq \mathrm{MB}_i - ib_i \quad \perp \ \lambda^n_i \geq 0 \quad \forall\, i \quad$ (A.98)

$0 \leq is_i \quad \perp \ \lambda^o_i \geq 0 \quad \forall\, i \quad$ (A.99)

$0 \leq ib_i \quad \perp \ \lambda^p_i \geq 0 \quad \forall\, i \quad$ (A.100)

Eq. (A.85-A.100) are complementarity constraints. We linearise these constraints by replacing them with disjunctive constraints using the method described in Fortuny-Amat and McCarl (1981). Alternatively, a transformation using SOS1 variables as explained in Siddiqui and Gabriel (2013) or can be implemented as indicator constraints (GAMS, 2018). In the final formulation, we can also substitute $\lambda^f_{t,i}$, $\lambda^g_{t,i}$, $\lambda^i_{t,i}$, $\lambda^j_{t,i}$, $\lambda^k_{t,i}$, $\lambda^l_{t,i}$, λ^o_i and λ^p_i out.

<u>Newly introduced sets, parameters and variables</u>

<u>Parameters</u>

$\mathrm{M^a, M^b, M^c, M^d, M^e, M^f, M^g, M^h, M^i, M^j, M^k, M^l, M^m, M^o}$, $\mathrm{M^p}$: Large scalars used to transform complementarity constraints (A.85-A.100) into disjunctive constraints [-]

<u>Variables</u>

$r^a_{t,i}, r^b_{t,i}, r^c_{t,i}, r^d_{t,i}, r^e_{t,i}, r^f_{t,i}, r^g_{t,i}, r^h_{t,i}, r^i_{t,i}, r^j_{t,i}, r^k_{t,i}, r^l_{t,i}, r^m_i, r^n_i, r^o_i, r^p_i$: Binary variables used to transform complementarity constraints (A.85-A.100) into disjunctive constraints [-]

$qmax_i - qw_{t,i} - qi_{t,i} \leq \mathrm{M^a} * (1 - r^a_{t,i}) \quad \forall\, t,i$ (A.101) and $\lambda^a_{t,i} \leq \mathrm{M^a} * r^a_{t,i} \quad \forall\, t,i$ (A.102)

$ib_i - soc_{t,i} \leq \mathrm{M^b} * (1 - r^b_{t,i}) \quad \forall\, t,i$ (A.103) and $\lambda^b_{t,i} \leq \mathrm{M^b} * r^b_{t,i} \quad \forall\, t,i$ (A.104)

$ib_i * \mathrm{BDR} - qbout_{t,i} \leq \mathrm{M^c} * (1 - r^c_{t,i}) \quad \forall\, t,i$ (A.105) and $\lambda^c_{t,i} \leq \mathrm{M^c} * r^c_{t,i} \quad \forall\, t,i$ (A.106)

$ib_i * \mathrm{BCR} - qbin_{t,i} \leq \mathrm{M^d} * (1 - r^d_{t,i}) \quad \forall\, t,i$ (A.107) and $\lambda^d_{t,i} \leq \mathrm{M^d} * r^d_{t,i} \quad \forall\, t,i$ (A.108)

$\mathrm{PrDSM}_i * \mathrm{D}_{t,i} - dDSM_{t,i} \leq \mathrm{M^e} * (1 - r^e_{t,i}) \ \forall\, t,i$ (A.109) and $\lambda^e_{t,i} \leq \mathrm{M^e} * r^e_{t,i} \quad \forall\, t,i$ (A.110)

$qw_{t,i} \leq \mathrm{M^f} * (1 - r^f_{t,i}) \quad \forall\, t,i$ (A.111) and

$\mathrm{WDT} * (\mathrm{EBP_t} + vnt + cpp_t) + \mu^a_{t,i} + \lambda^a_{t,i} \leq \mathrm{M^f} * r^{\mathrm{f}}_{t,i} \quad \forall\, t,i$ (A.112)

$qi_{t,i} \leq \mathrm{M^g} * (1 - r^g_{t,i}) \quad \forall\, t,i$ (A.113) and

$-\mathrm{WDT} * (\mathrm{ESP_t} + vnt * \mathrm{NM} + cpp_t) - \mu^a_{t,i} + \lambda^a_{t,i} \leq \mathrm{M^g} * r^g_{t,i} \quad \forall\, t,i$ (A.114)

$soc_{t,i} \leq \mathrm{M^h} * (1 - r^h_{t,i}) \quad \forall\, t,i$ (A.115) and $\lambda^h_{t,i} \leq \mathrm{M^h} * r^h_{t,i} \quad \forall\, t,i$ (A.116)

$qbout_{t,i} \leq \mathrm{M^i} * (1 - r^i_{t,i}) \quad \forall\, t,i$ (A.117) and $\mu^a_{t,i} + \frac{\mu^b_{t,i}}{\mathrm{EFD}} * \mathrm{DT} + \lambda^c_{t,i} \leq \mathrm{M^i} * r^i_{t,i} \quad \forall\, t,i$ (A.118)

$qbin_{t,i} \leq \mathrm{M^j} * (1 - r^j_{t,i}) \quad \forall\, t,i$ (A.119) and $-\mu^a_{t,i} - \mu^b_{t,i} * \mathrm{EFC} * \mathrm{DT} + \lambda^d_{t,i} \leq \mathrm{M^j} * r^j_{t,i} \quad \forall\, t,i$ (A.120)

$dDSM_{t,i} \leq \mathrm{M^k} * (1 - r^k_{t,i}) \quad \forall\, t,i$ (A.121)

and $\mathrm{CDSM_i} * \mathrm{WDT} + \mu^a_{t,i} - \mu^d_{t\in day,i} + \lambda^e_{t,i} \leq \mathrm{M^k} * r^k_{t,i} \quad \forall\, t,i$ (A.122)

$uDSM_{t,i} \leq \mathrm{M^l} * (1 - r^l_{t,i}) \quad \forall\, t,i$ (A.123) and $-\mu^a_{t,i} + \mu^d_{t\in day,i} \leq \mathrm{M^l} * r^l_{t,i} \quad \forall\, t,i$ (A.124)

$\mathrm{MS}_i - is_i \leq \mathrm{M^m} * (1 - r^m_i) \quad \forall\, i$ (A.125) and $\lambda^m_i \leq \mathrm{M^m} * r^m_i \quad \forall\, i$ (A.126)

$\mathrm{MB_i} - ib_i \leq \mathrm{M^n} * (1 - r^n_i) \quad \forall\, i$ (A.127) and $\lambda^n_i \leq \mathrm{M^n} * r^n_i \quad \forall\, i$ (A.128)

$is_i \leq \mathrm{M^o} * (1 - r^o_i) \quad \forall\, i$ (A.129) and $\mathrm{AICS} + \sum_t \mu^a_{t,i} * \mathrm{SY}_{t,i} + \lambda^j_i \leq \mathrm{M^o} * r^o_i \quad \forall\, i$ (A.130)

$ib_i \leq \mathrm{M^p} * (1 - r^p_i) \quad \forall\, i$ (A.131) and

$$\text{AICB} - \sum_t \lambda^b_{t,i} - \sum_t \lambda^c_{t,i} * \text{BDR} - \sum_t \lambda^d_{t,i} * \text{BCR} + \lambda^k_i \leq \text{M}^\text{p} * r^p_i \qquad \forall\, i \qquad \text{(A.132)}$$

A.3.4. Final model formulation

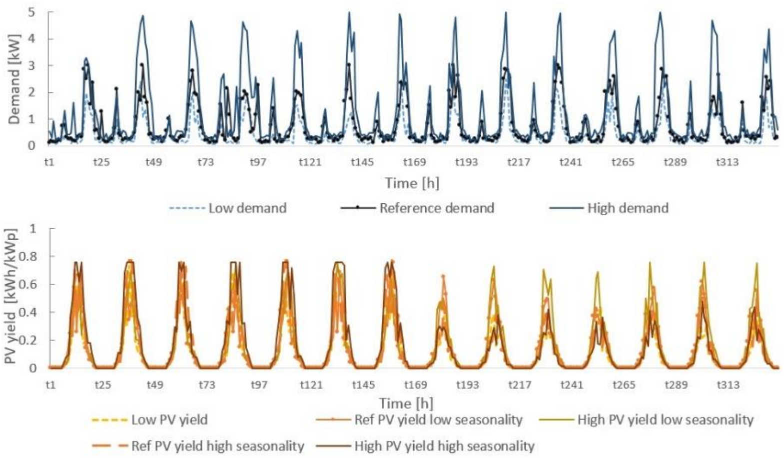
The final model formulation is composed of Eq. (A.1-8) and (A.10). Eq. (A.9) can be transformed using discretization or the strong duality theorem. The lower level problem is incorporated in the MILP by Eq. (A.16-A.39), Eq. (71-73) and (A.101-A.132).

B. Appendix Chapter 2

This Appendix has three aims. Firstly, to test the sensitivity of the results discussed in the body of the paper to the length of the time series for demand and PV yield. Second, to show the sensitivity of the results to different demand and PV yield profiles. And third, to highlight the impact of seasonality on the results. The Appendix is build up out of two sections. B.1. describes the data used for the sensitivity analysis. All other input data remains the same as in the body of the paper unless explicitly mentioned. Results are presented in B.2.

B.1.. Data sensitivity analysis

Next to the one-day reference demand and PV yield time series applied in the body of the paper, three additional time series for demand and five for the solar yield are build up. These two-week time series (336h) are obtained by randomising and scaling the original one-day reference profiles. In Figure B.1, the time series are visualised (left) and key metrics are displayed (right).



Demand profiles	*Yearly consumption [kWh]*	*Peak demand [kW]*
Low	3750	2.5
Reference	6500	3
High	11000	5
PV yield profiles	*Yearly solar yield [kWh/kWp]*	
Low	960	
Reference	1160 (l/h seasonality)	
High	1360 (l/h seasonality)	

Figure B.1: Left- Time series for demand (up) and PV yield (down). Right – key metric of the data

B..2. Results sensitivity analysis

In Table B.2 the results with the runs of the one-day reference profiles which are used in the body of the paper are compared to the runs with the same profiles, but randomised and with a length of two-weeks. The results are shown for the four states of the world, all other parameters remained the same. The trends of the results are the same, the obtained values can change slightly in some states of the worlds for certain tariff structures. In general, higher variability in the time series leads to slightly less complementarity of PV and batteries, see e.g. the installed capacity of PV and batteries under TS2 and TS3 in the maturing DER scenario for the 24h and 336h time series. Also, from e.g. TS3 under the maturing battery and expensive PV scenario and TS3 under the maturing DER scenario, it can be seen that the metric for equity issues tends to decline slightly with longer time series. This can be explained by the fact that with longer time series slightly more investment in DER is needed to reduce the grid charges of active consumers with the same amount than when shorter time series are used. In other words, it can be said that due to higher variability in demand and PV yield, the value of PV and/or batteries declines slightly for active consumers.

Table B.2: Results for the runs with the reference demand and solar profiles (24h and 336h) in the four states of the world.

	Immature DER			Maturing battery and expensive PV			Maturing PV and expensive battery					Maturing DER				
	TS1/ TS2	**TS3**		**TS1/ TS2**	**TS3**		**TS1**	**TS2**		**TS3**		**TS1**	**TS2**		**TS3**	
	24h/ 336h	24h	336h	24h/ 336h	24h	336h	24h/ 336h	24h	336h	24h	336h	24h/ 336h	24h	336h	24h	336h
Efficiency issue [%]	0	1.7	0.3	0	5.9	6.5	4.0	0.6	0.4	2.2	0.4	4.0	0.8	0.7	9.4	7.8
*Equity issue [%]**	0	7.9	1.5	0	32.7	29.1	80	5.9	4.0	9.5	1.7	80	6.7	5.8	48.5	34.7
PV active consumer [kWp]	0	0	0	0	0	0	5	0.6	0.5	0.6	0	5	0.9	0.7	2.6	0.8
Battery active consumer [kWh]	0	0.6	0.1	0	4.1	4.9	0	0	0	0.6	0.1	0	0.5	0.3	5.6	5.5

In Table B.3, the results for five additional runs under the different tariff structures are given. Four combinations are made with the new time series for demand and solar yield shown in Appendix B.1. Additionally, the run in which the high demand profile is combined with the high PV yield profile is ran twice. First, with an upper boundary of 5 kWp for the PV capacity installed by the active consumers. Second, with this upper boundary set to 10 kWp. 50 % of active consumers are assumed and the mature DER scenario (low investment cost for PV and batteries) is used. All other parameters remained the same. The relative performances of the tariff structures are in line with the results of the reference demand and PV yield series shown in the body of the paper.

Table B.3: Results for the additional runs under the different tariffs structures. Technology cost of maturing DER scenario.

	Low demand/ Low solar yield			Low demand/ High solar yield low seasonality			High demand/ Low solar yield			High demand/ High solar yield low seasonality (different max. PV)				
										TS1		TS2	TS3	
	TS1	TS2	TS3	TS1	TS2	TS3	TS1	TS2	TS3	5 kWp	10 kWp	5/10 kWp	5 kWp	10 kWp
Efficiency issue [%]	12.5	0.6	5.1	1.5	0.9	5.9	4.0	0.7	2.9	0.4	1.0	1.5	3.3	7.8
*Equity issue [%]**	100	3.8	34.0	100	7.7	42.7	27.6	3.7	16.9	44.6	100	9.6	22.3	40.4
PV active consumer [kWp]	5	0.3	0	5	0.5	2.6	5	1.0	0	5	10	1.7	5	6.9
Battery active consumer [kWh]	0	0	2.2	0	0.4	2.3	0	0.1	3.8	0	0	1.9	4.1	9.5

* An equity issue of 100 % (with 50% of active consumers) implies the grid charges for passive consumers are doubled because the active consumers are not paying any grid charges anymore. This can occur under volumetric charges with net-metering if active consumers export more electricity than they consume. It is chosen not to allow active consumers to have negative grid charges. However, the energy cost could become negative and results in a negative electricity bill when selling a high volume of electricity.

Lastly, in Table B.4 results are shown which highlight the impact of seasonality on the results. Again, the technology cost of the maturing DER scenario is assumed. Seasonality is an important factor as the behaviour of a PV-plus storage system in the middle of winter can be very different from that same system in high summer. Two additional cases are investigated. Case 1, with increased seasonality in the reference 2-week solar yield profile and the reference demand profile. And case 2, with increased seasonality in the 2-week high solar yield profile and the high demand profile. No seasonality in the 2-week randomised demand profiles is included as this is very dependent on hard-to-predict specific consumer habits and heating/cooling technologies in place. The results in Table B.4 indicate that seasonality does not impact TS1. As described before, with volumetric charges with net-metering PV adoption is over-incentivised and there is no business case for batteries, independently of seasonality. Under TS2 seasonality lowers the incentive to self-consume. In winter months the synergy between PV and batteries is weak, wherefore the investments in these technologies are slightly lower than in the run with lower seasonality.

Table B.4: Results for the additional runs under the different tariffs structures to test for the impact of increased seasonality. Technology cost of maturing DER scenario.

	Case 1: Reference demand/solar yield					Case 2: High demand/high solar yield				
	TS1	TS2		TS3		TS1	TS2		TS3	
Seasonality	**Low/High**	**Low**	**High**	**Low**	**High**	**Low/High**	**Low**	**High**	**Low**	**High**
Efficiency issue [%]	4.0	0.7	0.4	7.8	6.7	0.4	1.5	0.2	3.3	7.5
Equity issue [%]	80	5.8	4.4	34.7	30.2	44.6	9.6	4.7	22.3	40.6
PV active consumer [kWp]	5	0.7	0.6	0.8	0.5	5	1.7	1.25	5	5
Battery active consumer [kWh]	0	0.3	0.2	5.5	5	0	1.9	0.3	4.1	9.3

The most interesting results are observed for TS3, in case 1 the inefficiencies and equity issues decrease slightly with more seasonality in the solar yield profile. The opposite happens in the case 2. Snapshots of the dispatch of the active consumer under TS3 of both cases for 2 days (one summer and one winter day) under TS3 are depicted in Figure B.2 below. It can be seen in both cases that active consumers are incentivised to do peak shaving. In case 1, as the solar irradiation on winter days is very low, again the synergies between PV and batteries are slightly weakened. The reverse happens in case 2. In the case 2, a consumer following his self-interest is willing to invest in more batteries capacity to limit its injection peak which could exceed its withdrawal peak to enjoy the very high PV generation in summer. Figure B.2 shows that especially for case 2, in which the active consumer installs a high PV capacity, the seasonality impacts the dispatch.

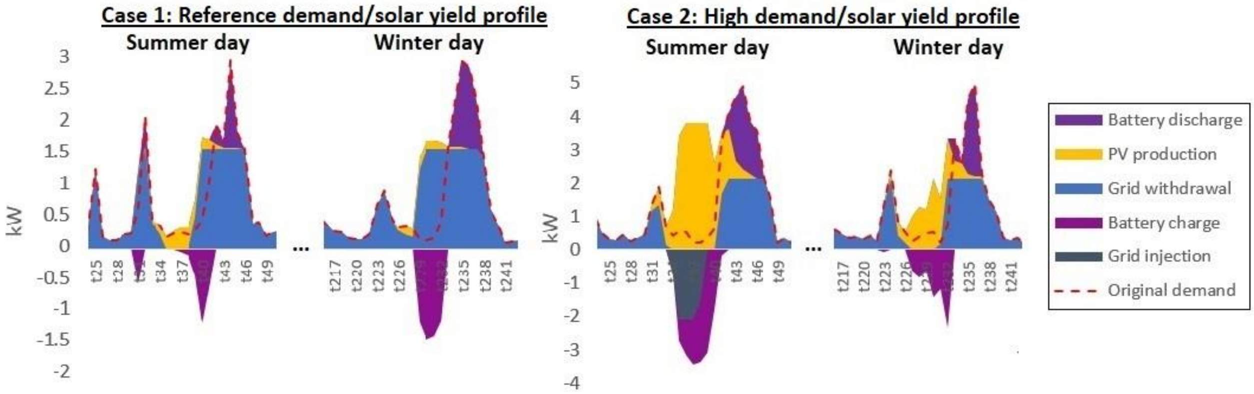


Figure B.2: Snapshots of the dispatch of the active consumer under capacity-based charges for the reference demand/solar yield profile and the high demand/high solar yield profile (max. PV installed: 5 kW), both with increased seasonality.

C. Appendix Chapter 3

C.1 The central planner model

The central planner model is formulated as a linear programme (LP). The central planner formulation has the same objective and constraints as the upper-level regulator in the MPEC (A.1-A.7) plus contains the constraints of the lower-level problem (A.14-A.31).

The main difference with the MPEC model is that there is no network tariff formulated in the central planner case, as the consumers do not need to be coordinated. As such, also no cost-recovery constraint (A.8) is included. Because of the same reason, also the lower-level objective function is removed. Instead of consumers reacting in their own interest, the central planner decides unilaterally about their actions. The central planner acts in the interest of all aggregated consumers. As there is no network tariff in place, also the notion of fairness, or redistributive effects, cannot be captured with a centralised modelling approach, plus the central planner is indifferent to which consumer installs what technology. As an example of the different results between the decentralised MPEC model and the central planner, the outcomes for the numerical example used throughout the paper is compared between both approaches in
Table B.1.

Table B.1: Comparison of the results for total system costs between the model applied in the body of the paper (Decentralised MPEC) and a central planner approach for the numerical case study presented in the body of the paper.

50 % active consumers Total system costs relative to baseline case (=no DER & volumetric network charges)		Decentralised MPEC (Table 3-4 plus Fig. 6)	Central planner
Perfect proxy, no fairness consideration	100 % Sunk grid costs	0.0 %	0.0 %
	50 % Sunk & 50 % Prospective	-1.4 %	-2.3 %
	100 % Prospective grid costs	-6.8 %	-11.3 %
Imperfect proxy (WP=75%), no fairness consideration	100 % Sunk grid costs	0.0 %	0.0 %
	50 % Sunk & 50 % Prospective	-0.3 %	-0.5%
	100 % Prospective grid costs	-4.0 %	-6.6%
Imperfect proxy (WP=75%), fairness consideration (Cap=10%)	100 % Sunk grid costs	0.6 %	No notion of fairness
	50 % Sunk & 50 % Prospective	0.1 %	
	100 % Prospective grid costs	-4.0 %	

It can be seen that in all cases except for the scenario with 100 % sunk grid costs, the central planner performs better than the decentralised model in terms of lowering the total system costs. This can be explained by the fact that the central planner is always (equally or) less constrained than the upper-level regulator in terms of optimising its objective function.

For example, regarding the result for 100 % prospective grid costs in the case we assume a perfect proxy for the network cost driver and do no fairness issues. In the central planner case, each active consumer ideally installs a battery of 6.2 kWh. By utilising this battery in an optimal way, the original system peak can be reduced with 58.3 %. This point seems to be the (theoretically) optimal trade-off between battery investment by consumers and a reduction of the needed maximum capacity of the grid. However, in the decentralised model outcome, each active consumer will install a battery of 3.7 kWh, leading to a system peak reduction of 35.0 %. In this case, the optimal trade-off point between DER adoption and grid capacity is not reached, leading to a higher total system costs. The benchmark system costs could be reached if each active consumer would increase its investment in batteries to 6.2 kWh. However, this does not happen as the regulator cannot design a network tariff by which a self-interest pursuing active consumer would reduce his individual electricity cost while increasing its investment in batteries. An active consumer will install DER until a point it is still profitable for him/herself. Possibly by applying critical (system) peak pricing, which is not implemented in this paper, the system costs could be brought closer to the system cost obtained in the central planner approach.

C.2. Additional sensitivity analysis: consumer profiles, solar yield profiles and time-varying energy prices

In order to extend the numerical results presented in the body of the paper, additional results are presented in this appendix. Sensitivity analysis is done regarding the consumer demand profiles, the solar PV yield profile and the energy prices. Results are run for three consumer demand profiles; in Figure C.1 the average demand profiles are shown. These average demand profiles are scaled so that the passive consumer consumers 2/3 of the annual electricity of the active consumer, the same proportion as in the consumer demand series presented in Section 4.2.

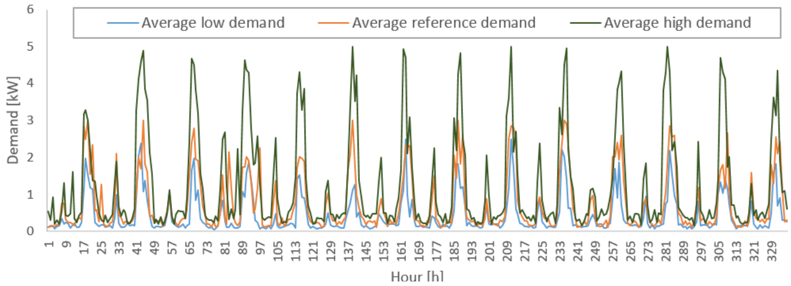


Figure C.1: Three 2-week (average) consumer profiles

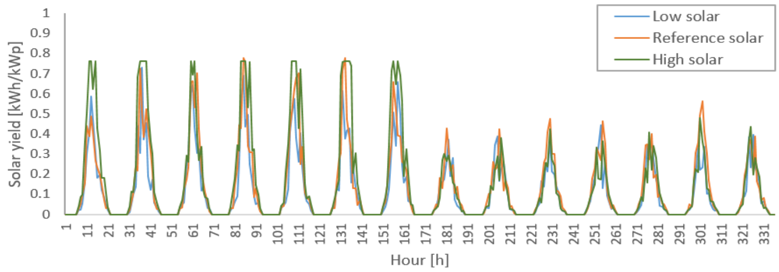


Figure C.2: Three 2-week solar PV yield profiles (including seasonality)

Table C.1: Summary additional time series

Demand profiles	*Average yearly consumption [kWh]*	*Average peak demand [kW]*
Low	3750	2.5
Reference	6500	4
High	11000	5
PV yield profiles	*Yearly PV yield [kWh/kWp]*	
Low	960 (LCOE: 0.100 €/kWh)	
Reference	1160 (LCOE: 0.083 €/kWh)	
High	1360 (LCOE: 0.070 €/kWh)	

The different solar yield profiles are shown in Figure C.2. As in the solar PV yield profile presented in the body of the paper, also seasonality is included. The reference consumer demand profile and the reference solar yield profile have the same average annual demand, peak and respectively solar yield as the numerical example in the body of the paper. However, in contrast to the time series presented in the body of the paper, the time series in this appendix are longer, namely 336h instead of 48h which represent a year. This is done because the timing of consumption and solar PV output is critically important for the economics of solar plus storage (see for example Neubauer and Simpson (2015)).

Next to consumer demand profiles and solar PV yield, additional sensitivity analysis is done for the (exogenous) retailer energy prices. In the body of the paper, a constant retailer energy price of 0.08 €/kWh is assumed. In this appendix we introduce two alternative time-of-use (TOU) profiles. In Figure C.3 the different options are shown. The TOU1 profile is 'solar PV friendly' as during hours that solar PV is producing an energy price is charged which is slightly higher than the flat energy charge. The TOU2 profile charges relatively high prices during the evening, when consumer demand is expected to peak and charges a relatively low price during the hours that solar PV is producing a lot. The TOU2 profile is less 'solar PV friendly' but might induce battery investment due to significant relative changes in the energy price during the day. These daily energy price patterns are deemed representative for the year. To be able to compare results among the three energy price profiles, the TOU1 and TOU2 profile are scaled to make sure that in the baseline scenario (no DER) the weighted average energy price per consumer type is equal over the different energy price profiles. This means that the average energy price of the TOU1 and TOU2 profile will be slightly lower than 0.08 €/kWh. This is because consumers have a higher demand during the times that the energy prices are relatively higher for these profiles.

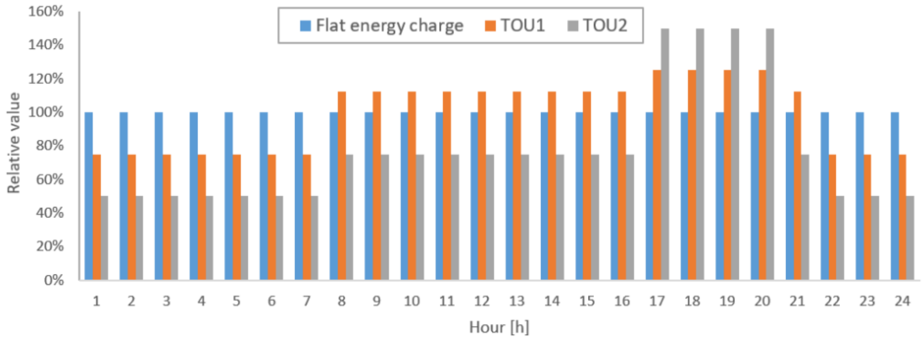


Figure C.3: Three profiles for energy prices

The results are shown in Table C.2-4. The grid cost scenario with 50 % sunk costs and 50 % prospective costs is assumed. Further, an imperfect proxy of the network cost driver is assumed (WF=0.75). The least-cost solution is computed. If multiple equilibrium network tariffs exist, the network tariff resulting in the lowest increase of network charges for the passive consumer is selected. The main findings of the sensitivity analysis are the sensitivity of results to how attractive solar PV investment is and that fact that TOU energy retail prices can interact with network tariff design. These findings are briefly discussed in Section 7.1 in the body of the paper.

Table C.2: Results for the reference demand time series (336h). Sensitivity: solar yield and energy price profiles

Results compared to baseline (=no DER & baseline network tariff)	Reference demand/ low solar irradiation (expensive solar PV)			Reference demand/ reference solar irradiation (medium price solar PV)				Reference demand/ high solar irradiation (cheap solar PV)		
Energy price (same baseline weighted average energy price per consumer)	Flat	TOU 1	TOU 2	Flat (48h)	Flat (336h)	TOU 1	TOU 2	Flat	TOU 1	TOU 2
Δ total system costs	**- 0.4 %**	**-0.7 %**	**- 1.9 %**	**-0.3 %**	**-0.4 %**	**-0.7 %**	**-1.9 %**	**- 0.5 %**	**-1.2 %**	**-1.9 %**
Δ *total grid costs*	- 6.2 %	- 6.2 %	- 8.4 %	- 7.5 %	- 6.2 %	- 6.2 %	- 8.4 %	- 6.3 %	- 6.6 %	- 8.4 %
Δ *total energy costs*	0.2 %	- 0.5 %	- 4.3 %	0.7 %	0.2 %	- 0.5 %	- 4.3 %	- 9 %	- 49 %	-4 %
PV active consumer [kWp]	0	0	0	0	0	0	0	0.9	4.7	0
Battery active consumer [kWh]	1.5	1.5	2.6	1.8	1.5	1.5	2.6	1.5	1.4	2.6
Δ network charges passive consumer	**3.8 %**	**4.4 %**	**2.6 %**	**12.2 %**	**11.9 %**	**13.2 %**	**6.6 %**	**15.2 %**	**15.2 %**	**13.1 %**
Fixed network charges	0.0 %	7.4 %	0.0 %	52.8 %	33.0 %	46.3 %	23.7 %	57.0 %	52.8 %	56.6 %
Vol. network charges (net-purchase)	46.0 %	42.2 %	52.8 %	14.3 %	11.4 %	7.5 %	36.3 %	0.0 %	0.0 %	10.0 %
Capacity-based network charges	54.0 %	50.4 %	47.2 %	32.9 %	55.6 %	46.2 %	40.0 %	43.0 %	47.2 %	33.4 %

Table C.3: Results for the low demand time series (336h). Sensitivity: solar yield and energy price profiles

Results compared to baseline (=no DER & baseline network tariff)	Low demand/ low solar irradiation (expensive solar PV)			Low demand/ reference solar irradiation (medium price solar PV)			Low demand/ high solar irradiation (cheap solar PV)		
Energy price (same baseline weighted average energy price per consumer)	Flat	TOU 1	TOU 2	Flat	TOU 1	TOU 2	Flat	TOU 1	TOU 2
∆ total system costs	**-0.2 %**	**-0.5 %**	**-0.6 %**	**-0.2 %**	**-0.5 %**	**-0.6 %**	**-0.3 %**	**-0.9 %**	**-0.9 %**
∆ *total grid costs*	- 5.0 %	- 5.0 %	- 5.0 %	- 5.0 %	- 5.0 %	- 5.0 %	- 6.1 %	- 7.3 %	- 7.2 %
∆ *total energy costs*	0.3 %	-0.5 %	-0.6%	0.3 %	-0.5 %	-0.6%	-10.1 %	-25.1 %	-13.8 %
PV active consumer [kWp]	0	0	0	0	0	0	0.6	1.4	0.74
Battery active consumer [kWh]	0.8	0.8	0.8	0.8	0.8	0.8	0.9	1.1	1.1
∆ network charges passive consumer	**4.4 %**	**5.0 %**	**4.4 %**	**12.0 %**	**13.3 %**	**12.8 %**	**15.5 %**	**15.6 %**	**15.3 %**
Fixed network charges	0.3 %	25.1 %	23.3 %	32.8 %	60.1 %	58.9 %	65.9 %	68.3 %	50.8 %
Vol. network charges (net-purchase)	35.7 %	43.9 %	46.8 %	4.3 %	11.7 %	14.2 %	0.5 %	0.5 %	0.6 %
Capacity-based network charges	64.0 %	31.0 %	29.9 %	62.9 %	28.2 %	26.9 %	33.6 %	31.2 %	48.6 %

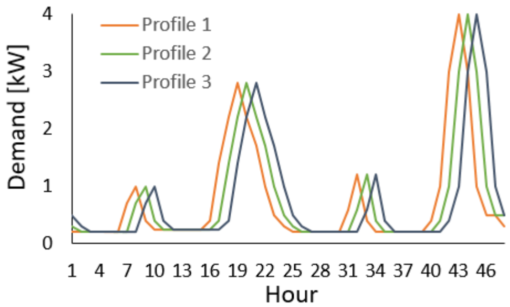
Table C.4: Results for the high demand time series (336h). Sensitivity: solar yield and energy price profiles

Results compared to baseline (=no DER & baseline network tariff)	High demand/ low solar irradiation (expensive solar PV)			High demand/ reference solar irradiation (medium price solar PV)			High demand/ high solar irradiation (cheap solar PV)		
Energy price (same baseline weighted average energy price per consumer)	Flat	TOU 1	TOU 2	Flat	TOU 1	TOU 2	Flat	TOU 1	TOU 2
∆ total system costs	**- 0.2%**	**-0.2 %**	**-0.3%**	**- 0.2%**	**- 0.2%**	**-0.3 %**	**- 0.4 %**	**-0.8 %**	**- 0.7 %**
∆ *total grid costs*	-1.6 %	- 1.6 %	-2.9 %	-1.6 %	- 1.6 %	-2.9 %	- 2.6 %	- 3.0%	- 3.8 %
∆ *total energy costs*	0.1 %	0.0 %	-0.3 %	0.1 %	0.0 %	-1.4 %	-10.3 %	-30.3 %	-17.7 %
PV active consumer [kWp]	0	0	0	0	0	0.2	1.7	5	2.9
Battery active consumer [kWh]	0.5	0.5	1.2	0.5	0.5	1.2	0.7	0.8	1.4
∆ network charges passive consumer	**5.2 %**	**7.6 %**	**6.4 %**	**13.1 %**	**15.4 %**	**14.9 %**	**14.8 %**	**15.4 %**	**15.6 %**
Fixed network charges	19.4 %	28.9 %	25.6 %	51.4 %	62.7 %	61.0 %	59.5 %	64.7 %	64.8 %
Vol. network charges (net-purchase)	33.3 %	30.8 %	33.9 %	2.3 %	0.5 %	2.7 %	0.0 %	0.0 %	0.2 %
Capacity-based network charges	47.2 %	40.2 %	40.4%	46.2 %	36.8 %	36.3 %	40.5 %	35.3 %	35.1 %

D. Appendix Chapter 4

D.1. Data sensitivity analysis

To test the robustness of the results, an additional setup was evaluated. In the numerical example in the body of the text, only two consumer profiles are used. Each consumer type, active and passive, is represented by one profile, and the profiles are coincident. In reality, many individual profiles exist, and these will not be all coincident. In this appendix, three different consumer profiles were used. These profiles are shown in Figure D.1. together with the proportion of consumers per profiles and type.



	Active	Passive
Profile 1	16.7%	0 %
Profile 2	16.7%	50 %
Profile 3	16.7%	0 %

Figure D.1: Profiles and proportions consumers per profile and active/passive

D.2. Results sensitivity analysis

The results for the battery investment costs are shown in Table D.1. All grid costs are assumed to be driven by the aggregated peak demand. Please note that now the average capacity of the batteries installed by the different active consumer groups is shown. Logically, the capacities installed differ to a certain extent from the results in Table 14 but the observations remain the same.

Table D.1: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated peak demand.

Distribution network tariff design		Benchmark – central planner	Capacity-based [€/kW]	Volumetric Net-purchase [€/kWh]	Volumetric Bi-directional [€/kWh]
	Investment cost batteries	Average battery installed per active consumer [kWh] / PV in brackets [kWp]			
No PV installed, only batteries can be invested in by the active consumers	350 €/kWh	1.9 (0)	1.2 (0)	0.0 (0)	0.0 (0)
	300 €/kWh	1.9 (0)	1.2 (0)	0.0 (0)	0.0 (0)
	250 €/kWh	1.9 (0)	1.2 (0)	0.0 (0)	0.0 (0)
	200 €/kWh	6.2 (0)	3.9 (0)	0.0 (0)	0.0 (0)
	150 €/kWh	10.1 (0)	5.7 (0)	0.0 (0)	0.0 (0)
	100 €/kWh	12.1 (0)	6.9 (0)	0.0 (0)	0.0 (0)
Batteries and PV can be installed in	350 €/kWh	1.9 (0)	1.2 (0)	0 (4.9)	0.0 (0.6)
	300 €/kWh	1.9 (0)	1.2 (0)	0 (4.9)	0.0 (0.6)

by the active consumers	250 €/kWh	1.9 (0)	1.2 (0)	0 (4.9)	0.0 (0.6)
	200 €/kWh	6.2 (0)	3.9 (0)	0 (4.9)	0.0 (0.6)
	150 €/kWh	10.1 (0)	5.7 (0)	0 (4.9)	0.5 (0.6)
	100 €/kWh	12.1 (0)	7.3 (0.7)	3.6 (5)	1.7 (1.1)
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	1.8 (5)	1.0 (5)	0.0 (5)	0.0 (5)
	300 €/kWh	2.1 (5)	1.4 (5)	0.0 (5)	0.0 (5)
	250 €/kWh	2.1 (5)	1.4 (5)	0.0 (5)	0.0 (5)
	200 €/kWh	6.2 (5)	1.8 (5)	0.0 (5)	5.2 (5)
	150 €/kWh	11.0 (5)	6.2 (5)	0.0 (5)	5.2 (5)
	100 €/kWh	12.4 (5)	7.4 (5)	3.6 (5)	11.7 (5)

When comparing the results in Figure 19 and Figure D.2, it can be seen that for expensive batteries, the performance in terms of the reduction of system costs is overestimated with coincident consumer profiles. If batteries are cheaper and thus more batteries are installed, the individual peaks will be flattened over multiple time-steps thus possibly also during the time steps other consumers have their peak demand and as a result the aggregated peak will decrease.

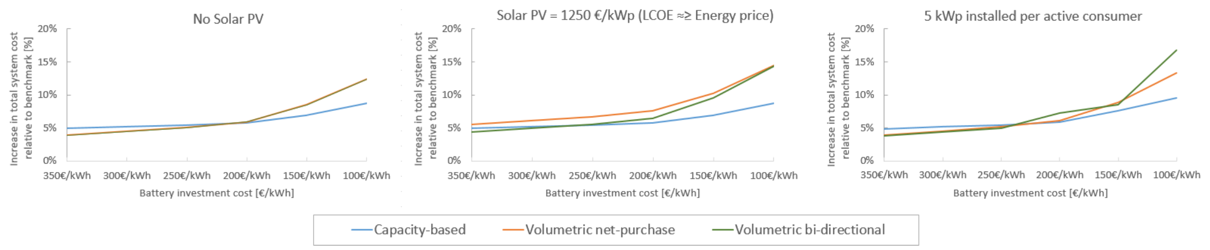


Figure D.2: Increase in total system costs for the three network tariff structures when compared with a central planner. Sensitivity for three different assumptions regarding solar PV adoption and the investment cost of storage.

Table D.2 shows the result for the battery adoption under different TOU energy prices. Again, the capacities installed differ to a certain extent from the results in Table 15 but the observations remain the same.

Table D.2: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated peak demand.

Distribution network tariff design		Benchmark – central planner		Capacity-based [€/kW]		Volumetric Net-purchase [€/kWh]		Volumetric Bi-directional [€/kWh]	
Energy price		TOU1	TOU2	TOU1	TOU2	TOU1	TOU2	TOU1	TOU2
Investment cost batteries		Battery installed per active consumer [kWh] / PV in brackets [kWp]							
No PV installed, only batteries can be invested in by the active consumers	350 €/kWh	1.9 (0)	8.6 (0)	1.2 (0)	3.7 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	300 €/kWh	1.9 (0)	12.1 (0)	1.2 (0)	6.1 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	250 €/kWh	3.5 (0)	12.7 (0)	2.1 (0)	7.0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	200 €/kWh	10.0 (0)	13.2 (0)	5.3 (0)	7.5 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	150 €/kWh	12.1 (0)	15.0 (0)	6.6 (0)	8.1 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	100 €/kWh	12.7 (0)	16.3 (0)	7.2 (0)	8.3 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Batteries and PV can be	350 €/kWh	1.9 (0.4)	8.6 (0)	1.2 (0.4)	3.7 (0)	0 (5)	0 (0.7)	0 (0.7)	0 (0.4)
	300 €/kWh	1.9 (0)	12.1 (0)	1.3 (1.4)	6.1 (0)	0 (5)	0 (0.7)	0 (0.7)	0 (0.4)

installed in by the active consumers	250 €/kWh	3.5 (0)	12.7 (0)	1.9 (1.3)	7.0 (0)	0 (5)	0 (0.7)	0 (0.7)	0 (0.4)
	200 €/kWh	10.0 (0)	13.2 (0)	5.2 (0.8)	7.5 (0)	0 (5)	0.1 (0.9)	0 (0.7)	0.1 (0.5)
	150 €/kWh	12.1 (0)	15.0 (0)	6.6 (0.7)	8.1 (0)	0 (5)	1.9 (1.5)	1.0 (0.9)	2.8 (1.4)
	100 €/kWh	12.7 (0.4)	16.3 (0)	7.3 (0.6)	8.3 (0)	4.5 (5)	8.2 (3.1)	6.8 (2.8)	8.2 (3.2)
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	2.1 (5)	8.5 (5)	1.3 (5)	2.6 (5)	0 (5)	0 (5)	0 (5)	5.2 (5)
	300 €/kWh	2.1 (5)	12.4 (5)	1.4 (5)	5.3 (5)	0 (5)	0 (5)	0 (5)	5.2 (5)
	250 €/kWh	4.1 (5)	12.4 (5)	1.5 (5)	6.3 (5)	0 (5)	3.7 (5)	4.8 (5)	5.2 (5)
	200 €/kWh	9.6 (5)	13.0 (5)	4.3 (5)	8.1 (5)	0 (5)	5.2 (5)	5.2 (5)	7.5 (5)
	150 €/kWh	12.4 (5)	14.9 (5)	6.0 (5)	9.2 (5)	0 (5)	5.2 (5)	5.2 (5)	7.6 (5)
	100 €/kWh	12.4 (5)	18.2 (5)	6.7 (5)	10.3 (5)	4.5 (5)	7.6 (5)	7.6 (5)	11.7 (5)

Table D.3 shows the relative difference in system costs between flat energy prices and TOU energy prices for different distribution network tariff designs and investment cost of batteries. Again, the exact percentages differ to a certain extent from the results in Table 16 but the observations remain the same.

Table D.3: Relative difference in system costs between flat energy prices and TOU energy prices for different distribution network tariff designs and investment cost of batteries.

Distribution network tariff design		Benchmark – central planner		Capacity-based [€/kW]		Volumetric Net-purchase [€/kWh]		Volumetric Bi-directional [€/kWh]	
Energy price		TOU1	TOU2	TOU1	TOU2	TOU1	TOU2	TOU1	TOU2
Investment cost batteries		Difference in total system costs compared to a flat energy price [%]							
No PV installed, only batteries can be invested in by the active consumers	350 €/kWh	-0.4%	-1.9%	-0.3%	-1.1%	0.0%	0.0%	0.0%	0.0%
	300 €/kWh	-0.4%	-4.4%	-0.3%	-2.2%	0.0%	0.0%	0.0%	0.0%
	250 €/kWh	-0.5%	-7.5%	-0.3%	-3.7%	0.0%	0.0%	0.0%	0.0%
	200 €/kWh	-2.0%	-10.7%	-1.0%	-5.3%	0.0%	0.0%	0.0%	0.0%
	150 €/kWh	-3.1%	-12.6%	-1.4%	-6.3%	0.0%	0.0%	0.0%	0.0%
	100 €/kWh	-3.6%	-14.5%	-1.6%	-6.9%	0.0%	0.0%	0.0%	0.0%
Batteries and PV can be installed in by the active consumers	350 €/kWh	-0.4%	-1.9%	-0.3%	-1.1%	-1.0%	-0.5%	-0.1%	0.0%
	300 €/kWh	-0.4%	-4.4%	-0.3%	-2.2%	-1.0%	-0.5%	-0.1%	0.0%
	250 €/kWh	-0.5%	-7.5%	-0.4%	-3.7%	-1.0%	-0.5%	-0.1%	0.0%
	200 €/kWh	-2.0%	-10.7%	-1.1%	-5.3%	-1.0%	-0.2%	-0.1%	**0.5%**
	150 €/kWh	-3.1%	-12.6%	-1.5%	-6.3%	-1.0%	**1.2%**	**0.4%**	**1.8%**
	100 €/kWh	-3.6%	-14.5%	-1.6%	-6.9%	-2.7%	**0.1%**	**2.9%**	**0.2%**
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	-0.9%	-0.8%	-0.8%	0.0%	-0.4%	**1.2%**	-0.1%	**3.1%**
	300 €/kWh	-0.9%	-3.1%	-0.8%	-0.9%	-0.4%	**1.2%**	-0.1%	**1.7%**
	250 €/kWh	-1.0%	-6.1%	-0.8%	-2.2%	-0.4%	**1.4%**	**1.7%**	**0.3%**
	200 €/kWh	-2.4%	-9.0%	-1.2%	-3.8%	-0.4%	-2.1%	-0.7%	-5.2%
	150 €/kWh	-3.3%	-10.8%	-1.6%	-5.1%	-0.4%	-3.5%	-0.7%	-5.9%
	100 €/kWh	-3.4%	-12.9%	-1.4%	-6.0%	-2.1%	-8.4%	-3.5%	-2.0%

List of publications and other academic activities

Peer-reviewed publications

T. Schittekatte, I. Momber & L. Meeus (2018), *''Future-proof tariff design: recovering sunk grid costs in a world where consumers are pushing back'',* **Energy Economics** 70, 484-498.
(This paper also won the 2nd prize for doctoral student papers at the French Association for Energy Economists (FAEE) in October 2017)

T. Schittekatte, M. Stadler, G. Cardoso, S. Mashayekh & N. Sankar (2016), *"The impact of short-term stochastic variability in solar irradiance on optimal micogrid design"***, IEEE Transactions on Smart Grid** 9 (3), 1647 – 1656

Under review

T. Schittekatte & L. Meeus (2018), *''Least-cost distribution network tariff design in theory and in practice'',* FSR RSCAS Working Paper 2018/19. Revise and resubmit: **The Energy Journal**

P.C. Bhagwat, T. Schittekatte, N. Keyaerts & L. Meeus (2017), *'' Assessment of Cost-Benefit Analysis for offshore electricity infrastructure development'',* FSR RSCAS Working Paper 2017/53. Under revision: **Strategic Energy Reviews**

Book chapters

L. Meeus & T. Schittekatte (2018), ''*New grey areas at the frontiers of European power grids*'', **Electricity Network Regulation in the EU: The Challenges Ahead for Transmission and Distribution**, Edward Elgar Publishing, 130-149.

Policy briefs

T. Schittekatte & L. Meeus (2018), *''Limitations of traditional distribution network tariff design and options to move beyond'',* FSR Policy Brief 2018/13

T. Schittekatte & L. Meeus (2017), *''How future-proof is your distribution network tariff?'',* FSR Policy Brief 2017/03

N. Keyaerts, T. Schittekatte & L. Meeus (2016), *''Standing still is moving backward for the ABC of the CBA'', FSR* Policy Brief 2016/18

Technical reports

T. Schittekatte, V. Reif and L. Meeus (2019), '' The EU Electricity Network Codes (2019ed.)'', FSR technical report

T. Schittekatte & L. Meeus (2018), *'' Introduction to network tariffs and network codes for consumers, prosumers, and energy communities''*, FSR technical report

L. Meeus & T. Schittekatte (2018), *'' The EU Electricity Network Codes''*, FSR technical report

P.C. Bhagwat, T. Schittekatte, L. Lind, N. Keyaerts & L. Meeus (2017), '' *Intermediate deliverable: economic framework for offshore grid planning*'', FSR technical report for H2020 project PROMOTioN

Academic conferences

Associazione Italiana di Economisti dell'Energia (AIEE) Symposium – Milan, December 2018 – Panellist of a special session "*From Consumers to nonsumers: How new behind-the-meter service options are disrupting utility business models*"

DIW: SET-Nav Modeling Workshop - Two-stage decision making and modelling for energy markets – Berlin, October 2018 – Presented: ''Distribution network tariff analysis using an MPEC approach''

World Congress for Energy and Resource Economists (WCERE) – Gothenburg, June 2018 – Panellist of policy session – '' *Smart grid for a carbon free energy future: the role of electricity pricing and distributed energy resources*''

International Conference of the International Association of Energy Economists (IAEE) – Groningen, June 2018 – Presented the paper: *''Least-cost distribution network tariffs in theory and practice''*

5th International Conference of the Armand Peugeot Chair – Electromobility: Challenging Issues – Paris, December 2017 – Presented the paper: *''Future-proof tariff design: recovering sunk grid costs in a world where consumers are pushing back*''

Other talks/presentations

India Smart Utility Week (ISUW) – EU&India Workshop on Power Markets Design (New Delhi, 14 March 2019): Presentation- *''The EU Day-Ahead Electricity* Market''

Vlerick Business School and EASE workshop - Business Models and Regulation for Energy Storage (Brussel, 30 November 2018): Presentation the paper: ''*On the interaction between distribution network tariff design and the business case for storage''*

Policy Advisory Council (PAC) – Florence School of Regulation (Florence, 4 November 2018): Presentation about the distribution network tariffs and taxes and levies in the electricity bill

CEER (Brussels, 19 October 2018): Workshop on Emerging issues in Network Tariffs – topic: the future direction of network tariff structures

SmartEN (Brussels, 9 October 2018): Active storage TF – topic: tariffs and its implication on storage

RGI-Statnett (Oslo, 9 May 2018): Mini-workshop on grid tariffs, sustainable energy prices and the role of citizens – topic: distribution network tariff design

GEODE (Brussels, 15 March 2018): WG Regulation meeting – topic: distribution network tariff design

Teaching

Instructor (autumn 2017 and 2018): EU Electricity Network Codes (8-week online training by FSR, responsible for 7 weeks together with course director)

Instructor FSR Law summer course - Unpacking the Legal content of the Clean Energy Package (June 2018), sessions: EU electricity market codes and a case study on electricity bidding zones

Instructor (April-May 2018): The EU Clean Energy package (3-week online training by FSR, responsible for 1 week together with course director)

Instructor (April 2018): Introduction to network tariffs and network codes for consumers, prosumers and energy communities (2-week online training by FSR, responsible for 2 weeks together with course director)

Instructor FSR-CEER training on introduction to the fundamentals of energy regulation (March 2018), session: The sequence of electricity markets

Reviewer

The Energy Journal, Energy Policy, IEEE Transactions on Smart Grid, Energy Research & Social Science and Sustainable Energy, Grids and Networks

Organizer

25th Young Energy Economists and Engineers (YEEES) seminar – Florence School of Regulation, Firenze, 8-9 November 2018

Curriculum Vitae

Work experience

***May. '16 –current:* Florence School of Regulation (RSCAS/EUI) – Research associate**

Research related to electricity market design and monopoly regulation

Teaching of professionals, online and residential. Topics: EU electricity network codes, electricity tariff design

***Jan. '16 –current:* Vlerick Business School, Brussel, Belgium – Research affiliate**

Affiliated with the Vlerick Energy Center

***Sep. '15– Apr. '16:* Microeconomix, Paris, France – Junior economist**

Part of the energy consulting practice (auto-entrepreneur)

Energy economics, market design, regulation and power system modelling.

***Feb. – Jul. '15:* Lawrence Berkeley National Laboratory, Berkeley, CA, USA – Visiting researcher**

Part of the Grid integration group with a focus on microgrids

Modelling and optimization of distributed energy resources and renewable energy systems (GAMS/Python)

Education

***2014- 2015:* MSc: Electric Power Industry- Universidad Pontificia Comillas, ES, greatest distinction (3pc.)**

Second year of Joint Erasmus Mundus MSc: Economics and Management of Network Industries

Thesis: "The impact of stochastic variability in insolation on optimal microgrid design" (at LBNL)

***2013-2014:* MSc: Industrial Networks and Digital Economy - Université Paris-Sud, FR, très bien (1pc.)**

First year of Joint Erasmus Mundus MSc: Economics and Management of Network Industries

***2011-2013*: MSc: Industrial Engineering and Operations Research- Ghent University, BE, great distinction (5pc.)**

Thesis: "Application of machine learning in portfolio optimization" (Electronics and Information Science Dep.). Foreign study experience: CUJAE, Havana, Cuba (Sep. '11 – Feb. '12)

***2008-2011:* BSc: Electromechanical Engineering- Ghent University, BE, distinction (25pc.)**

Thesis: "Design and controlling of an electromechanical break system" (Electrical Energy Lab)

Awards

2nd price PhD paper competition organized by the French Association of Energy Economists (November 2017)

Extraordinary Graduate Student Award - Universidad Pontificia Comillas, ICAI (July 2015): Top 3% students

Erasmus Mundus Scholarship by EACEA (full scholarship 2 years): Master in Economics and Management of Network Industries

Public speaking price and 2nd laureate ING Thesis Award (Dec. 2013): Competition for finance dissertations

Summary in French – Résume en français

La diffusion des panneaux solaires photovoltaïques à des prix abordables dans le secteur résidentiel, nous amène à repenser à la manière avec laquelle les coûts des réseaux de distribution sont récupérés auprès des consommateurs. Historiquement, les consommateurs étaient facturés pour l'utilisation du réseau de distribution principalement sur la base de leur volume (net) d'électricité consommé. Avec un tel type de tarif de réseau, les consommateurs qui installent des panneaux photovoltaïques contribuent beaucoup moins à la récupération du coût d'investissement réseau. Cependant, ces consommateurs (prosummeurs) dépendent autant du réseau qu'avant. Outre les systèmes solaires photovoltaïques, une baisse importante des coûts du stockage de l'électricité est anticipée dans le futur, avec pour effet potentiel, une augmentation des installations des batteries.

La problématique abordée dans cette thèse est de savoir comment définir le tarif du réseau de distribution dans ce contexte changeant. La transformation à long terme d'un réseau de l'électricité passif en un réseau intelligent ne peut être atteinte que par le biais d'une régulation qui minimise les incertitudes et qui donne lieu à un environnement propice aux investissements. Les changements en cours dans le secteur de la distribution d'électricité exigent des pratiques de répartition des coûts économiquement justifiées pour récupérer la totalité des coûts de ces actifs.

Des différents modèles de théorie des jeux sont développés pour faire cette analyse. Dans ces modèles, en plus des investissements dans l'énergie solaire photovoltaïque, des investissements dans les batteries du côté des consommateurs sont considérés. Plus précisément, des modèles formulés sous forme d'un problème d'optimisation avec des contraintes d'équilibre (MCP pour Mixed Complementarity Problem and MPEC pour Mathematical Programming with Equilibrium Constraints) sont développés. Ce modèle économique est basé sur les outils méthodologiques les plus avancés d'un point de vue académique. Pour étudier les effets de redistribution en terme de bien-être social, les interactions entre les décideurs sont représentées sous forme d'un équilibre hiérarchique utilisant des formulations basées sur la théorie de complémentarité.

Ce rapport de thèse consiste en un bref aperçu suivi de quatre chapitres indépendants et d'une conclusion. Dans **le premier chapitre**, le contexte de la recherche est présenté, les principes généraux des tarifs de réseau de distribution sont discutés et le défi actuel est décrit. **Le deuxième chapitre** montre que l'adoption de systèmes solaires photovoltaïques et des batteries a une répercussion sur l'efficacité du tarif actuel d'accès au réseau de distribution. De plus, ceci se traduit par des effets de

redistribution. Les magnitudes des inefficacités et des effets de redistribution sont représentées en fonction des coûts d'investissement des systèmes solaires photovoltaïques et des batteries.

Le troisième chapitre aborde la conception du tarif de réseau de distribution le moins coûteux, en tenant compte de deux contraintes auxquelles les régulateurs sont souvent confrontés dans la pratique. Les contraintes considérées sont la réflectivité des coûts dans les tarifs de réseau et l'équité dans la répartition de ces coûts. La conclusion principale est que dans le cas où la majorité des coûts de réseau est irrécupérable, il est difficile de trouver un compromis raisonnable entre la réflectivité des coûts dans les tarifs et l'équité dans la répartition de ces coûts parmi les consommateurs. D'autres outils à part les ''méthodes de tarification classiques'' seront donc nécessaires. Un exemple est un tarif de réseau fixe différencié par consommateur.

Le quatrième chapitre porte sur l'interaction entre les tarifs du réseau de distribution et les systèmes de stockage résidentiel de l'électricité. La mesure dans laquelle la conception de ces tarifs aligne la rentabilisation du stockage avec d'autres avantages plus larges est évaluée. On montre que dans le cas où une grande partie des coûts d'investissement dans le réseau devra être faite dans le future, des structures tarifaires avancées seront nécessaires pour aligner les intérêts des consommateurs avec des avantages plus larges. Enfin, une conclusion est présentée.

ÉCOLE DOCTORALE
Sciences de l'homme et de la société (SHS)

Titre : Les structures tarifaires des opérateurs de distribution et des consommateurs actifs : une analyse de la régulation économique

Mots clés : tarifs d'accès des réseaux de distribution, économie de l'énergie, systèmes photovoltaïques, batteries, théorie des jeux

Résumé : La diffusion des panneaux solaires photovoltaïques à prix abordables nous amène à repenser à la manière avec laquelle les coûts des réseaux de distribution sont récupérés auprès des consommateurs. Historiquement, les consommateurs étaient facturés pour l'utilisation du réseau de distribution principalement sur la base de leur volume (net) d'électricité consommé. Avec tel type de tarif de réseau, les consommateurs qui installent des panneaux photovoltaïques contribuent beaucoup moins à la récupération du coût d'investissement réseau. Cependant, ces consommateurs (prosummeurs) dépendent autant du réseau qu'avant. La question examinée dans cette thèse est de savoir comment définir le tarif du réseau de distribution dans ce contexte changeant. Des différents modèles de théorie des jeux sont développés pour faire cette analyse. Dans ces modèles, en plus des investissements dans l'énergie solaire photovoltaïque, des investissements dans les batteries du côté des consommateurs sont aussi considérés. Ce rapport de thèse consiste en un bref aperçu suivi de quatre chapitres indépendants et d'une conclusion.

Title: Distribution network tariff design and active consumers: a regulatory impact analysis

Keywords: distribution network tariffs, energy economics, solar PV, batteries, game theory

Abstract: The uptake of affordable solar PV panels challenges the way in which costs of distribution networks are recuperated from consumers. Historically, consumers were charged for the use of the distribution network mainly according to their (net) volume of electricity consumed over a period of time. With such volumetric network charges, consumers installing PV panels contribute a lot less towards the recuperation of network costs. However, these consumers (prosumers) still rely on the network as much as they did before. The question investigated in this thesis is how to re-design the distribution network tariff in this changing context. Different game-theoretical models are developed to conduct this analysis. In the models, not only investments in solar PV but also investments in batteries at the consumer-side are considered. The thesis consists of a brief overview followed by four standalone chapters and a conclusion.