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Least-cost distribution network tariff design in theory and practice

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Abstract[+]

In this paper a game-theoretical model with self-interest pursuing consumers is introduced in order 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 on 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 to its net consumption from the grid over a certain period (e.g. a month), are deemed inadequate given the massive deployment of solar Photovoltaics (PV). Consumers with solar PV pay significantly lower network charges but still rely on the distribution grid as much as 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 of suspending net-metering and moving more towards capacity-based (€/kW), fixed network tariffs (€/connection) or a combination of both (CEER, 2017). 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 against 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 Distributed Energy Resources (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 active, self-interest pursuing consumers, and the aggregate effect of consumer actions on the total network costs which need to be recovered by the network charges. Although the rise in 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 network charges avoided by active consumers will simply be 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). At 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 they can opt for a combination of the three. The regulator anticipates the reaction of the consumers represented at the lower-level and the network tariff is determined in a way that the total system costs (including 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.[1] 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. Active consumers 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 '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 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)[2] 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

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[1] 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. More specifically, 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 equalling its network costs. Finally, in addition 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.

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

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 so as 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 in California is very heterogeneous. 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; for example, 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 is 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, 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, 2015). 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 now to the second considered constraint in this paper.

There is a fear that network tariff reforms, which aim to increase cost-efficiency, may 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 certain conditions, it can be optimal from an efficiency point of view to recover a large share of the network costs through fixed network charges: when an over-dimensioned network in place, there is low load growth, there is a limited possibility to fully disconnect from the grid and the relevant externalities are correctly incorporated into the other components of the electricity bill. 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.[3] Although increased fixed network charges could be welcomed by DSOs, as 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 where active consumers invest 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] 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.

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 nor that 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. In 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 to minimise total system costs (here equivalent to maximising social welfare).[4] 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 taxes and levies 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 and parameters in standard style. An overview of the nomenclature used can be found in Appendix A.1.

$$\textbf{Minimise}\;\; TotalEnergyCosts + TotalDERcosts + TotalGridCosts + \mathrm{TotalOtherCosts} \tag{1}$$

The total net energy costs to meet the electricity demand of all consumers are calculated by Eq. 2. Assuming one retailer for all consumers, $TotalEnergyCosts$ would be equal to the revenue of the retailer minus the money received by consumers for the electricity injected into 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 of buying a kWh of electricity from the retailer and $\mathrm{ESP_t}$ is the price received when selling a kWh of electricity (excluding grid or other costs). Further, $qw_{\mathrm{t,i}}$ and $qi_{\mathrm{t,i}}$ represent respectively the quantities of

[4] 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.

electricity withdrawn from and injected into the network by a consumer i for a certain timestep 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 timestep the PV production exceeds the consumer's demand. For that timestep, $qw_{\mathrm{t,i}}$ 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, they would have the choice of injecting the excess electricity directly into the network ($qi_{\mathrm{t,i}}$) or storing it in the battery to lessen the need to draw from the grid ($qw_{\mathrm{t,i}}$) at a later moment. Finally, WDT is a factor for annualising 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 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 Eq. 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. AICS and AICB are the annualised investment costs for respectively solar PV and batteries. No maintenance costs for the DER technologies are assumed.

$$TotalDERcosts = \sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{PC}_i * (is_{\mathrm{i}} * \mathrm{AICS} + ib_{\mathrm{i}} * \mathrm{AICB}) \quad (3)$$

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 discusses network tariff design with active consumers and throughout that work grid costs are all assumed to be sunk. 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, a term for prospective grid costs ($\mathrm{IncrGridCosts} * CoincidentPeak$) is added in Eq. 4.[5] 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 (2016). In case consumer reactions, in terms of consumption from the grid (or injection), affect the network cost and, in turn, the network charges. The network tariff should guide consumers to cost-efficient behaviour beyond purely allocating network costs.

$$TotalGridCosts = \mathrm{SunkGridCosts} + \mathrm{IncrGridCosts} * CoincidentPeak \quad (4)$$

[5] 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, 2017). 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.

Abdelmotteleb et al. (2017), Pérez-Arriaga et al. (2017) and Simshauser (2016) describe how 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 greater weighting for solar PV.[6] Alongside the coincident peak demand, other network cost drivers can be identified, such as thermal losses and the investment cost of replacing 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 timestep 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 on the part of the consumer. A regulator cannot directly decide on the optimal trade-off. Instead, they can only indirectly influence the consumer's 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 static volumetric charge vnt (€/kWh), an individual capacity-based charge cnt (€/kW) and a uniform fixed charge fnt (€/connection). vnt, cnt and fnt are the decision variables at the upper-level, while $qw_{\mathrm{t,i}}$, $qi_{\mathrm{t,i}}$ and

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[6] 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 to 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.

$qmax_{\mathrm{i}}$ are decision variables at the lower-level. $qmax_i$ is the maximum observed capacity (for withdrawal or injection) of consumer i over the time series under consideration.

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

NM is a parameter and determines the type of volumetric charge.[7] 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. They can lower their dependency from the grid if 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.

$$\textbf{Minimise} \quad GridCharges_{\mathrm{i}} + DERCosts_{\mathrm{i}} + EnergyCosts_{\mathrm{i}} + \mathrm{OtherCharges} \qquad (9)$$

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 of a consumer minus the feed-in remuneration.

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

with $qmax_{\mathrm{i}} \equiv \mathrm{Max}\left\{qw_{\mathrm{t,i}} - qi_{\mathrm{t,i}}\ \forall \mathrm{t}\right\} \quad \forall \mathrm{i}$ (11)

$$DERCosts_{\mathrm{i}} = is_{\mathrm{i}} * \mathrm{AICS} + ib_{\mathrm{i}} * \mathrm{AICB} \quad \forall\, \mathrm{i} \qquad (12)$$

[7] 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.

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

A consumer is subject to a number of constraints, which are described by Eq. 14-21. Eq. 14 shows the demand balance for consumer i. The demand $\mathrm{D_{t,i}}$ 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 ($is_{\mathrm{i}} * \mathrm{SY_{t,i}}$). 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 timestep 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. $\mathrm{BRD/BRC}$ 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.[8]

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

$$soc_{1,\mathrm{i}} = qbin_{1,\mathrm{i}} * \mathrm{EFC} * \mathrm{DT} - \left(qbout_{1,\mathrm{i}}/\mathrm{EFD}\right) * \mathrm{DT} + \mathrm{SOC_0} \quad \forall\, \mathrm{i} \tag{15}$$

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

$$soc_{\mathrm{T,i}} = \mathrm{SOC_0} \quad \forall\, \mathrm{i} \tag{17}$$

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

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

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

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

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 performed 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). Finally, 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 A.3.

[8] No binary variables are introduced to ensure that no electricity is withdrawn/injected and that the battery is not charged/discharged at the same timestep. 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. Thereafter, four subsections consider four groups of input data. These data are used to calibrate the model.

4.1. Setup

Two consumer types are modelled for simplicity: passive and active consumers, as is also the case 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 somewhere in the middle. Some consumers will remain passive for a number of reasons. Other consumers may be installing DER even when they do not financially profit from it, but for other reasons which are harder to monetise; for example, 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.[9]

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 lead to overall efficiency gains, as no consumer can invest in DER and demand elasticity is zero. The historically accepted practice is to have 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 of an issue to recover grid costs through 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 higher network contributions correlated rather well with richer households, making such practice acceptable.

In the baseline scenario, the two different types of consumers pay their baseline consumer bill as presented in Subsection 4.3. In this 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

[9] 50 % active consumers 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 costs 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.

to invest in DER, the relative proportion and absolute values of the bill components can change for both the active and 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 is the sum of the aggregated consumer bills and the investment costs of the installed solar PV and batteries by the active consumers.

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 timesteps and are shown in Figure 1 (left). The yield per kWp of solar PV installed is shown in Figure 1 (right).

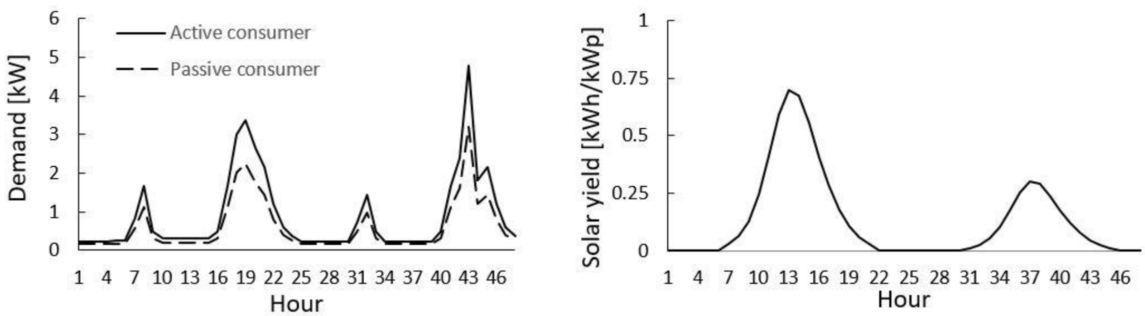

Figure 1: Original 48-hour electricity demand profiles (left) and PV yield profile (right)

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 thinking 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 1 (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 a day of low PV yield. Letting the peak demand day coincide with a day of 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 left virtually 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 B.

4.3. Baseline consumer bills

In Table 1 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 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 to 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), where 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 1: 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.[10] 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

[10] 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 B.

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 to be 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, 2016a, 2016b; MIT Energy Initiative, 2016; RMI, 2015).[11] Regarding solar PV, in the Utility of the Future Study by the MIT Energy Initiative (2016) 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 in 2010. The levelized cost of energy (LCOE) of solar PV is 0.083 €/kWh[12], 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 for.[13] 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 2. Technical DER data is in line with Schittekatte et al. (2016).

Table 2: 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 wholesale 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-term for a given set of connections and probably cannot be reduced significantly within a five to ten-year period. Based on Crawford (2014) and Hanser (2013), Simshauser (2016) assumes that

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

[12] 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 dependent.

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

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, policy costs are also 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. Last, 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.

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 1) 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.[14] In the first case, grid costs are assumed to be 100% sunk, the parameters $\mathrm{SunkGridCosts}$ and $\mathrm{IncrGridCosts}$ in Eq. 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.[15] 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, besides not having a perfect proxy of the network cost driver, could be a correct estimation of the incremental network cost, or the network cost function in general.

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.

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[14] 4kW = 0.5*4.8 kW + 0.5*3.2 kW and 404 € = 0.5*485 € + 0.5*324 €

[15] 50.5 €/kW = 0.5*404 €/4kW

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 gives the result that a reduction of the individual peak demand of a consumer of 1 kW leads to a reduction in its contribution to the coincident peak demand by less than 1 kW. In other words, this constraint implies that the regulator is unable to implement a network charge that sends a price signal that perfectly aligns the reduction of the individual peak demand of each consumer with the reduction of the overall coincident peak demand, which drives the network costs. A perfectly implemented network charge would imply a network charge with a very fine temporal and spatial granularity, i.e. almost a consumer-to-consumer tailored charge.

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 that 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.

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

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 consumers adapt their individual peak demand, total grid costs are not significantly affected. This effect would be witnessed if consumers were being incentivised to lower their demand at a certain time that does not coincide with the time of the system peak. In an extreme case, 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 and in an extreme case we end up with a fully cost-reflective tariff as implied by Eq. 2 in Section 3 (WF equals 1).

Also, the introduction of the implementation constraint can be seen as a way to address the assumption of identically shaped demand profiles; the implementation constraint leads to a reduction of 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. More specifically, even though the upper-level regulator has perfect insight in the reaction of the lower-level consumers due to the modelling set up, the regulator has only 'traditional' network tariff design options at her disposal. In order to induce the consumers to adapt their demand in such a way that their individual demand reductions would lead to a proportional reduction in the overall coincident peak demand, the regulator would have to set peak-coincident capacity-based charges (or strongly time-varying volumetric charges) which we assume is an option that is not available to the regulator. As an example, Passey et al. (2017) find low correlation coefficients in the range of 0.48 to 0.62 between consumer payments under a monthly individual capacity-based charge and the responsibility for the network peak. The correlation increases to 0.92 with peak-coincident capacity-based charges.

Lastly, please note that the implication of Eq. 22 could also be interpreted from a reliability point of view. It is difficult to assume that DER at a consumer's premise can be a perfect substitute for the grid as it can happen that 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 2 and Table 3. In Table 3, two metrics are calculated for the different grid cost structures. First, there is 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 1). 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 to be.

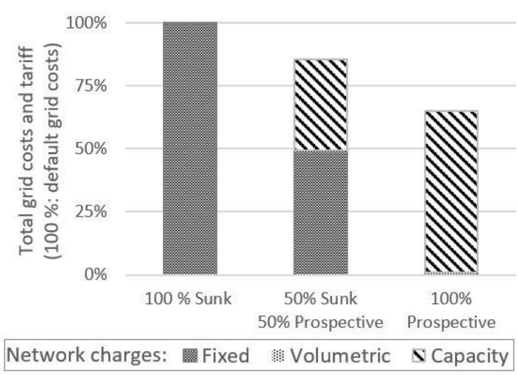

Figure 2: Network tariff components and grid costs compared to the baseline scenario for the three different grid cost structures. Perfect proxy for the network cost drivers is assumed.

Table 3: Total system costs and increase network charges per passive consumer compared to the baseline scenario. Perfect proxy for the network cost drivers is assumed.

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 2, the least-cost network tariff consists of a capacity-based charge equal to the incremental grid cost parameter ($\mathrm{IncrGridCosts}$ in Eq. 4) and of a fixed charge equal to the sunk grid costs per consumer ($\mathrm{SunkGridCosts}$ in Eq. 4).[16] This corresponds to the theoretical optimal network tariff structure as described by Abdelmotteleb et al. (2017) and the MIT Energy Initiative (2016).

When grid costs are 100% sunk, the least-cost network tariff design consists solely of a non-distortive uniform fixed charge (Figure 2), and there is no impact on the total system cost (Table 3). 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 their network charges significantly increase since 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 3. In this case, the active consumers reduce their grid charges proportionally to the reduction in total system costs and the passive consumers do not see any change in the grid charges paid.

[16] 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 different values for the lower-level objectives. In this case, one of these equilibria is the theoretical least-cost network tariff, while 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 on 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.

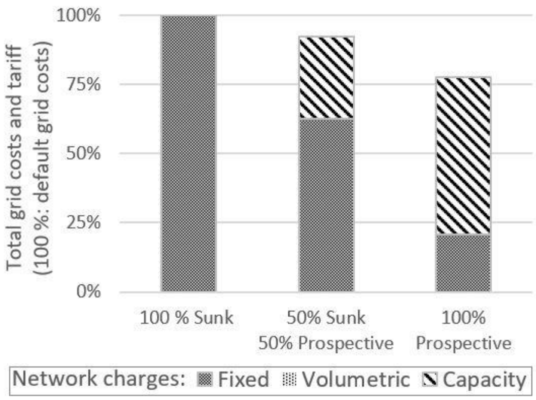

Figure 3: Network tariff components and total grid costs compared to the baseline for the three grid cost structures. Imperfect proxy for the network cost driver assumed (WF=0.75).

Table 4: Total system costs and increase network charges per passive consumer compared to the baseline scenario with an imperfect proxy for the network cost driver assumed (WF=0.75).

50 % active consumers – Results compared to the baseline scenario (=no DER & volumetric network charges)		Imperfect proxy for the network cost driver (WF=0.75)
Total system costs	100 % Sunk grid costs	0.0 %
	50 % Sunk & 50 % Prospective	-0.3 %
	100 % Prospective grid costs	-4.0 %
Network charges passive consumer	100 % Sunk grid costs	25.0 %
	50 % Sunk & 50 % Prospective	15.6 %
	100 % Prospective grid costs	7.0 %

Figure 3 shows the network least-cost network 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 results with (Table 4) and without (Table 3) 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 system cost reduction and a higher increase of the passive consumers' network charges when compared to the case without implementation constraint.

The intuition behind these results with the implementation constraint is the following: if the capacity-based charge is set as equal to the incremental grid costs as in the case with a perfect implementation of capacity-based charges, batteries are over-incentivised. An individual consumer installs batteries as they are profitable from their individual perspective. However, the grid costs decrease less as the cost-reflective charge is imperfectly implemented, i.e. 1 kW of individual peak reduction results in a reduction of 0.75 kW, instead of 1 kW, of the coincident peak.[17] In other words, individual peak reduction, enabled through batteries, is not as effective due to the implementation issue with cost-reflective charges. In order to come to the lowest possible total system costs under the given implementation constraint, there is a different trade-

[17] Another issue is that the grid costs reduce less than the reduction in grid charges paid by active consumers. Similarly as volumetric charges with net-metering results in an over-incentive in PV adoption, this distortion induces non-cooperative active consumers to compete with each other to escape from high grid costs by installing more and more batteries. We come back to this point in Section 6.2.

off between batteries adoption and grid cost reduction when compared to the case with no implementation constraint. This translates in a least-cost network tariff with a lower capacity-based charge to reduce the over-incentive in battery adoption. Further, the grid costs, which did not decrease significantly due to the less investment in batteries and less effectiveness of these batteries, need to be recovered. Therefore, the fixed network charge increases. As a consequence, the grid charges for smaller passive consumers increase which 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, the 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 $\mathrm{BGC}_{'i2'}$ 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.

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

6.2. Results and discussion with a fairness constraint

In this section, the results for the numerical example are discussed. Figure 4 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 ($\mathrm{Cap}_{'i2'}$ = 0.10) are shown for the case in which the grid costs are assumed to be 100 % sunk and the case in which the grid costs are assumed to be 50% sunk and 50% prospective costs. In the case grid costs are assumed to be 100 % prospective, the fairness cap is not binding; thus, the results are not affected.

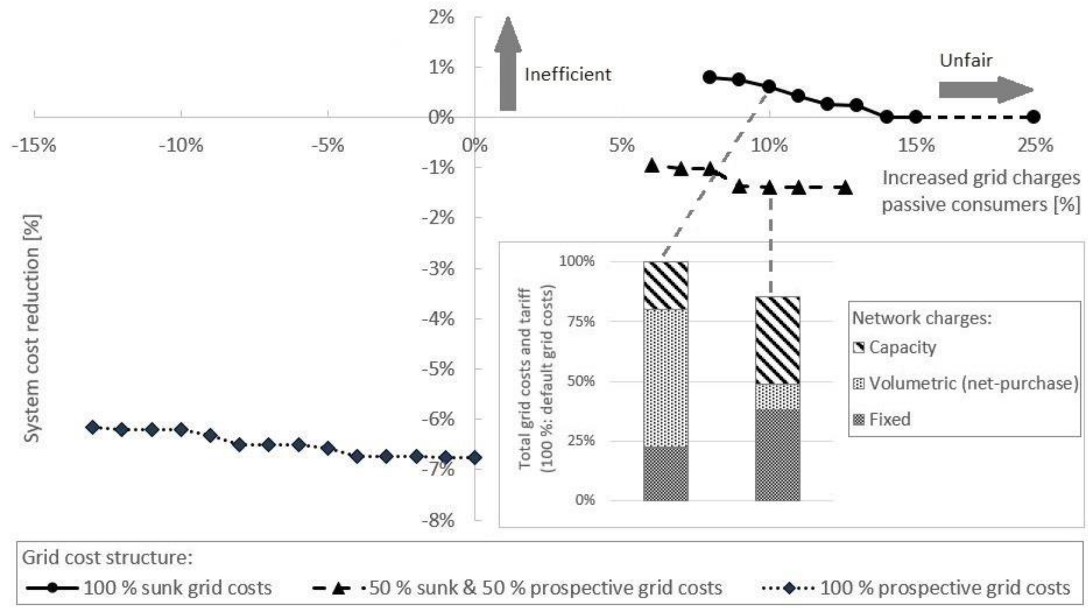

Figure 4: Total system cost increase trade-off with the increase of grid charges of passive consumers for different grid cost structures. Perfect proxy for the grid cost drivers assumed.

The first state of the grid is 100% sunk costs. In this case, 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 4, 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 in the same figure), the network tariff will be distortionary.[18] This implies that active consumers can exploit opportunities that might be beneficial to themselves but which are not necessarily optimal from a system point of view.[19] 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 against each other 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 the passive consumers is capped at a level lower than 8%. Note that the significant improvement in fairness comes with a relatively small increase in total system cost.

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[18] 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.

[19] 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 in volumetric and capacity-based charges in the network tariff, which are needed to respect cost-recovery, are large enough to impact on 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 significant 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 towards passive consumers, but they are always worse off in this case.

6.3. Results and discussion with a fairness and implementation constraint

Figure 5 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 being 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 as 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.

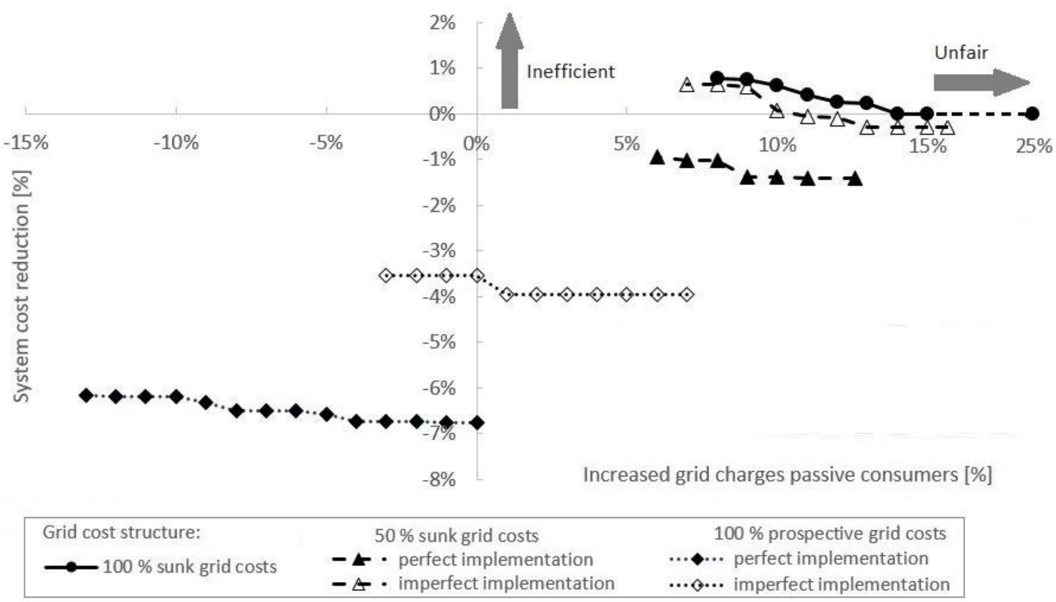


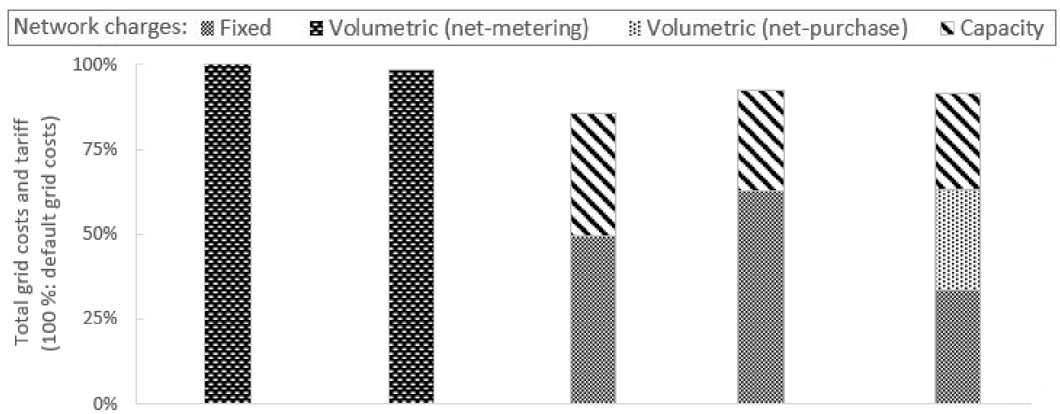
Figure 5: Total system cost increase trade-off with the increase of grid charges of passive consumers for different grid cost structures. Results with and without implementation issues with cost-reflective network tariffs are shown.

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 B. Secondly, the main policy implications are derived.

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

Figure 6 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 affected 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. We do four observations in Figure 6.



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

Firstly, it can be seen that there is a clear case for redesigning the historical in-place baseline network tariff, volumetric charges with net-metering, as also argued in the introduction to 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, there is 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 the grid. Also, active consumers significantly lower their grid charges but the grid costs do not reduce proportionally. Instead, these costs are shifted to the passive consumers (+78 % in grid charges compared to the baseline) and a significant fairness issue results.

Secondly, Figure 6 shows that the least-cost network tariff 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 %).[20]

Thirdly, in case of not having a perfect proxy, the cost-efficiency decreases and the fairness issue is aggravated.

Fourthly, 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.

When making the above four observations, it is important to keep in mind the three main assumptions we work with. They are highlighted in what follows with reference to the sensitivity analysis that can be found in Appendix B.

First, no positive externalities from solar PV adoption are assumed. If decentralised solar PV adoption (partly) replaced polluting central generation plants, and a carbon mark-up in the energy price and subsidies were 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).[21] 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). These 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,

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[20] 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 from 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.

[21] 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.

but one can imagine that some demand shifting can be done fairly cheaply 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 is easier for active consumers with automated appliances to 'shift' network charges to passive consumers who do not own such appliances.

Third, a limitation of the modelling approach is that the retailer energy price a consumer pays is not considered endogenous.[22] 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 in 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 B. It is found that with TOU energy prices instead of flat energy prices, the decrease in system costs (compared to the baseline) is more evident than in the presented numerical example the system costs. 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 the adoption of batteries but also that of solar PV.

Note that Appendix B also illustrates that results are sensitive to how financially attractive solar PV investment is. If we assume that the retailer energy price is higher than the cost of generating electricity from solar PV on rooftops, logically, the total system costs reduce alongside solar PV adoption by active consumers.[23] 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 when solar PV is cheaper. This is true because the investment distortion in solar PV investment becomes more sensitive to these increased volumetric charges. Indeed, 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.

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[22] 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.

[23] 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, 2017) 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 many more stakeholders. These stakeholders require an 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 solutions other 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 to 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 on 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. Unrecovered 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 a least-cost and fair distribution network tariff in practice. We did assume that policy costs do not 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 option 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 more desirable than 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 to 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 be aggravated. 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 numbers 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. Also, due to the structure of the model, it is assumed that the regulator has perfect insight into the consumer's reaction to 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 extension to the presented model.

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Appendices

A. The 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 [%]
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 [€]

Variables

UL decision variable

vnt : Volumetric network tariff [€/kWh]

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

fnt: Fixed network charge [€/connection]

$CoincidentPeak$: 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 [€]

LL decision variable

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

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

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

$qw_{t,i}$: 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]

A.2. Original optimisation problems

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

Objective function, the minimisation of total system costs:

$$\text{Minimise } TotalGridCosts + TotalDERcosts + TotalEnergyCosts + \text{TotalOtherCosts} \tag{A.1}$$

With its components being:

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

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

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

Finding the aggregated peak demand in absolute value:

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

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

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

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

$$TotalGridcosts = vnt * \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * \left(qw_{t,i} - \mathrm{NM} * qi_{t,i}\right) * \mathrm{WDT} + cnt * \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * qmax_i + fnt \quad \text{(A.8)}$$

$$vnt * \sum_{t=1}^{T} \left(qw_{t,'i2'} - \mathrm{NM} * qi_{t,'i2'}\right) * \mathrm{WDT} + cnt * qmax_{'i2'} + fnt \leq \mathrm{BGC}_{'i2'} * (1 + \mathrm{Cap}_{'i2'}) \quad \text{(A.9)}$$

The lower level problem for an electricity cost minimising consumer

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

$$\text{Minimise } GridCharges_i + DERCosts_i + EnergyCosts_i + \text{OtherCharges} \quad \text{(A.10)}$$

With:

$$GridCharges_i = \sum_{t=1}^{\mathrm{T}} (qw_{t,i} - qi_{t,i} * \mathrm{NM}) * vnt * \mathrm{WDT} + qmax_i * cnt + fnt \quad \forall i \quad \text{(A.11)}$$

$$DERCosts_i = is_i * \mathrm{AICS} + ib_i * \mathrm{AICB} \quad \forall i \quad \text{(A.12)}$$

$$EnergyCosts_i = \sum_{t=1}^{\mathrm{T}} \left(qw_{t,i} * \mathrm{EBP_t} - qi_{t,i} * \mathrm{ESP_t}\right) * \mathrm{WDT} \quad \forall i \quad \text{(A.13)}$$

Constraints (including duals):

$$qw_{t,i} - qi_{t,i} + is_i * \mathrm{SY_{t,i}} + qbout_{t,i} - qbin_{t,i} - \mathrm{D_{t,i}} = 0 \quad \forall i,t \quad (\mu_{t,i}^a) \quad \text{(A.14)}$$

$$soc_{1,i} - qbin_{1,i} * \mathrm{EFC} * \mathrm{DT} + (qbout_{1,i}/\mathrm{EFD}) * \mathrm{DT} - \mathrm{SOC_0} = 0 \quad \forall i \quad (\mu_{1,i}^b) \quad \text{(A.15)}$$

$$soc_{t,i} - qbin_{t,i} * \mathrm{EFC} * \mathrm{DT} + \left(qbout_{\mathrm{t,i}}/\mathrm{EFD}\right) * \mathrm{DT} - soc_{t-1,i} * (1 - \mathrm{LR} * \mathrm{DT}) = 0 \quad \forall i, t \neq 1 \quad (\mu_{t\neq 1,i}^b) \quad \text{(A.16)}$$

$$soc_{T,i} - \mathrm{SOC_0} = 0 \quad \forall i \quad (\mu_i^c) \quad \text{(A.17)}$$

$$-qmax_i + qw_{t,i} + qi_{t,i} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^a) \quad \text{(A.18)}$$

$$soc_{t,i} - ib_i \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^b) \quad \text{(A.19)}$$

$$qbout_{t,i} - ib_i * \mathrm{BDR} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^c) \quad \text{(A.20)}$$

$$qbin_{t,i} - ib_i * \mathrm{BCR} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^d) \quad \text{(A.21)}$$

$$-qw_{t,i} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^e) \quad \text{(A.22)}$$

$$- qi_{t,i} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^f) \quad \text{(A.23)}$$

$$-soc_{t,i} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^g) \quad \text{(A.24)}$$

$$-qbout_{t,i} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^h) \quad \text{(A.25)}$$

$$-qbin_{t,i} \leq 0 \quad \forall t,i \quad (\lambda_{t,i}^i) \quad \text{(A.26)}$$

$$is_i - \mathrm{MS}_i \leq 0 \quad \forall i \quad (\lambda_i^j) \quad \text{(A.27)}$$

$$ib_i - \mathrm{MB}_i \leq 0 \quad \forall i \quad (\lambda_i^k) \quad \text{(A.28)}$$

$$- is_i \leq 0 \quad \forall i \quad (\lambda_i^l) \quad \text{(A.29)}$$

$$- ib_i \leq 0 \quad \forall i \quad (\lambda_i^m) \quad \text{(A.30)}$$

$$- qmax_i \leq 0 \quad \forall i \quad (\lambda_i^n) \quad \text{(A.31)}$$

$$\lambda_{t,i}^a, \lambda_{t,i}^b, \lambda_{t,i}^c, \lambda_{t,i}^d, \lambda_{t,i}^e, \lambda_{t,i}^f, \lambda_{t,i}^g, \lambda_{t,i}^h, \lambda_{t,i}^i \geq 0 \quad \forall t,i \quad \text{(A.32)}$$

$$\lambda_i^j, \lambda_i^k, \lambda_i^l, \lambda_i^m, \lambda_i^n, \geq 0 \quad \forall i \quad \text{(A.33)}$$

Eq. (A.31) is noted down for completeness, the constraint is implied by Eq. A.18, A.22 and A.23.

A.3. MPEC reformulation as a MILP

Newly introduced sets, parameters and variables

Sets

k: 1…K: Index of auxiliary binaries (b_k^a) needed to discretise the bilinear product (including vnt) in Eq. (A.8)

l: 1…L: Index of auxiliary binaries (b_l^c) needed to discretise the bilinear product (including cnt) in Eq. (A.8)

Parameters

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

Δγ: Step of vnt when discretised [-]

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

$\mathrm{M^{Da}}$: Large scalar used to discretise the bilinear product (including vnt) in Eq. (A.8) [-]

$\mathrm{M^{Db}}$: Large scalar used to discretise the bilinear product (including cnt) in Eq. (A.8) [-]

$\mathrm{M^a, M^b, M^c, M^d, M^e, M^f, M^g, M^h, M^i, M^j, M^k, M^l}$ and $\mathrm{M^m}$: Large scalars used to transform complementarity constraints (A.62-A.74) into disjunctive constraints [-]

Variables

b_k^a: Binary variables used to discretise the bilinear product (including vnt) in Eq. (A.8)

b_l^b: Binary variables used to discretise the bilinear product (including cnt) in Eq. (A.8)

z_k^a: (Pos.) continuous variables used to represent the bilinear product (including vnt) in Eq. (A.8)

z_l^b: (Pos.) continuous variables used to represent the bilinear product (including cnt) in Eq. (A.8)

$r_{t,i}^a, r_{t,i}^b, r_{t,i}^c, r_{t,i}^d, r_{t,i}^e, r_{t,i}^f, r_{t,i}^g, r_{t,i}^h, r_{t,i}^i, r_i^j, r_i^k, r_i^l$ and r_i^m: Binary variables used to transform complementarity constraints (A.62-A.74) into disjunctive constraints [-]

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.8) is replaced by two constraints (A.34-35) 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%.

$$TotalGridCost * (1-\delta) - vnt * \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * \left(qw_{t,i} - \mathrm{NM} * qi_{t,i}\right) * \mathrm{WDT} + cnt * \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * qmax_i + fnt \le 0 \quad \text{(A.34)}$$
$$-TotalGridCost * (1+\delta) + vnt * \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * \left(qw_{t,i} - \mathrm{NM} * qi_{t,i}\right) * \mathrm{WDT} + cnt * \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * qmax_i + fnt \le 0 \quad \text{(A.35)}$$

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:

$$q^{tot} = \sum_{t=1}^{T} \sum_{i=1}^{N} \mathrm{PC_i} * \left(qw_{t,i} - \mathrm{NM} * qi_{t,i}\right) * \mathrm{WDT} \quad \text{(A.36)} \quad \text{and} \quad qmax^{tot} = \sum_{i=1}^{N} \mathrm{PC_i} * qmax_i \quad \text{(A.37)}$$
$$vnt = \Delta\gamma * \sum_k 2^{k-1} * b_k^a \quad \text{(A.38)} \quad \text{and} \quad cnt = \Delta\partial * \sum_l 2^{l-1} * b_l^b \quad \text{(A.39)}$$

It follows that:

$$q^{tot} * vnt = q^{tot} * \Delta\gamma * \sum_k 2^{k-1} * b_k^a = \Delta\gamma * \sum_k 2^{k-1} * z_k^a \quad \text{(A.40)}$$
$$qmax^{tot} * cnt = qmax^{tot} * \Delta\partial * \sum_l 2^{l-1} * b_l^b = \Delta\partial * \sum_l 2^{l-1} * z_l^b \quad \text{(A.41)}$$

with:

$$z_k^a \ge 0 \quad \forall k \quad (A.42) \quad \text{and} \quad z_l^b \ge 0 \quad \forall l \quad \text{(A.43)}$$
$$z_k^a \le \mathrm{M^{Da}} * b_k^a \quad \forall k \quad (A.44) \quad \text{and} \quad z_l^b \le \mathrm{M^{Db}} * b_l^b \quad \forall l \quad \text{(A.45)}$$
$$q^{tot} - z_k^a \ge 0 \quad \forall k \quad (A.46) \quad \text{and} \quad qmax^{tot} - z_l^b \ge 0 \quad \forall l \quad \text{(A.47)}$$
$$q^{tot} - z_k^a \le \mathrm{M^{Da}} * (1 - b_k^a) \quad \forall k \quad (A.48) \quad \text{and} \quad qmax^{tot} - z_l^b \le \mathrm{M^{Db}} * (1 - b_l^b) \quad \forall l \quad \text{(A.49)}$$

Karush-Kuhn-Tucker conditions of the lower level

$$\mathrm{WDT} * (\mathrm{EBP}_t + vnt) + \mu_{t,i}^a + \lambda_{t,i}^a - \lambda_{t,i}^e = 0 \quad \forall t,i \quad \text{(A.50)}$$
$$-\mathrm{WDT} * (\mathrm{ESP}_t + \mathrm{NM} * vnt) - \mu_{t,i}^a + \lambda_{t,i}^a - \lambda_{t,i}^f = 0 \quad \forall t,i \quad \text{(A.51)}$$
$$cnt - \sum_t \lambda_{t,i}^a = 0 \quad \forall i \quad \text{(A.52)}$$
$$\mu_{t,i}^b - \mu_{t+1,i}^b * (1 - \mathrm{LT} * \mathrm{DT}) + \lambda_{t,i}^b - \lambda_{t,i}^g = 0 \quad \forall t \ne \{\mathrm{T}\}, i \quad \text{(A.53)}$$
$$\mu_{T,i}^b + \mu_i^c + \lambda_{T,i}^b - \lambda_{T,i}^g = 0 \quad \forall t = \mathrm{T}, i \quad \text{(A.54)}$$
$$\mu_{t,i}^a + \frac{\mu_{t,i}^b}{\mathrm{EFD}} * \mathrm{DT} + \lambda_{t,i}^c - \lambda_{t,i}^h = 0 \quad \forall t,i \quad \text{(A.55)}$$
$$-\mu_{t,i}^a - \mu_{t,i}^b * \mathrm{EFC} * \mathrm{DT} + \lambda_{t,i}^d - \lambda_{t,i}^i = 0 \quad \forall t,i \quad \text{(A.56)}$$
$$\mathrm{AICS} + \sum_t \mu_{t,i}^a * \mathrm{SY_{t,i}} + \lambda_i^j - \lambda_i^l = 0 \quad \forall i \quad \text{(A.57)}$$
$$\mathrm{AICB} - \sum_t \mu_{t,i}^b - \sum_t \lambda_{t,i}^c * \mathrm{BDR} - \sum_t \lambda_{t,i}^d * \mathrm{BCR} + \lambda_i^k - \lambda_i^m = 0 \quad \forall i \quad \text{(A.58)}$$
$$qw_{t,i} - qi_{t,i} + is_i * \mathrm{SY}_{t,i} + qbout_{t,i} - qbin_{t,i} - \mathrm{D}_{t,i} = 0 \quad \mu_{t,i}^a free \quad \forall t,i \quad \text{(A.59)}$$

$$soc_{1,i} - qbin_{1,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{1,i}}{\mathrm{EFD}} * \mathrm{DT} - \mathrm{SOC}_0 = 0 \quad \mu^b_{1,i}\ free \quad \forall\, i \quad \text{(A.60)}$$
$$soc_{t,i} - qbin_{t,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{t,i}}{\mathrm{EFD}} * \mathrm{DT} - soc_{t-1,i} * (1 - \mathrm{LR} * \mathrm{DT}) = 0 \quad \mu^b_{t\neq 1,i}\ free \quad \forall\, t \neq 1, i \quad \text{(A.61)}$$
$$soc_{T,i} - \mathrm{SOC}_0 = 0 \quad \mu^c_i\ free \quad \forall\, i \quad \text{(A.62)}$$
$$0 \le qmax_i - qw_{t,i} - qi_{t,i} \quad \perp \ \lambda^a_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.63)}$$
$$0 \le ib_{\mathrm{i}} - soc_{t,i} \quad \perp \ \lambda^b_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.64)}$$
$$0 \le ib_{\mathrm{i}} * \mathrm{BDR} - qbout_{t,i} \quad \perp \ \lambda^c_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.65)}$$
$$0 \le ib_{\mathrm{i}} * \mathrm{BCR} - qbin_{t,i} \quad \perp \ \lambda^d_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.66)}$$
$$0 \le qw_{t,i} \quad \perp \ \lambda^e_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.67)}$$
$$0 \le qi_{t,i} \quad \perp \ \lambda^f_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.68)}$$
$$0 \le soc_{t,i} \quad \perp \ \lambda^g_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.69)}$$
$$0 \le qbout_{t,i} \quad \perp \ \lambda^h_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.70)}$$
$$0 \le qbin_{t,i} \quad \perp \ \lambda^i_{t,i} \ge 0 \quad \forall\, t,i \quad \text{(A.71)}$$
$$0 \le \mathrm{MS}_i - is_i \quad \perp \ \lambda^j_i \ge 0 \quad \forall\, i \quad \text{(A.72)}$$
$$0 \le \mathrm{MB}_i - ib_i \quad \perp \ \lambda^k_i \ge 0 \quad \forall\, i \quad \text{(A.73)}$$
$$0 \le is_i \quad \perp \ \lambda^l_i \ge 0 \quad \forall\, i \quad \text{(A.74)}$$
$$0 \le ib_i \quad \perp \ \lambda^m_i \ge 0 \quad \forall\, i \quad \text{(A.75)}$$

Final model formulation

The final model formulation is composed of Eq. (A.1-7) and (A.9). Eq. (A.8) is turned into two constraints described by Eq. (A.34-A.35) and further transformed to (A.76- A.77) which is the final form of Eq. (A.8) included in the model formulation. Eq. (A.36-A.39) and Eq. (A.42-A.49) are included to complete the discretisation of the bilinear products. M^{Da} and M^{Db} are well calibrated and $\Delta\gamma$ (0.0001) and $\Delta\partial$ (0.01) are chosen to balance precision and computational time.

$$TotalGridCost * (1 - \delta) - \Delta\gamma * \textstyle\sum_k 2^{k-1} * z^a_k + \Delta\partial * \sum_l 2^{l-1} * z^b_l + fnt \le 0 \quad \text{(A.76)}$$
$$-TotalGridCost * (1 + \delta) - \Delta\gamma * \textstyle\sum_k 2^{k-1} * z^a_k + \Delta\partial * \sum_l 2^{l-1} * z^b_l + fnt \le 0 \quad \text{(A.77)}$$

Further, the lower level problem is incorporated in the MILP by Eq. (A.50-A.62) and (A.78-A.103). Eq. (A.78-A.103) are disjunctive constraints replacing the complementarity constraints (A.63-A.75) 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 $\lambda^e_{t,i}$, $\lambda^f_{t,i}$, $\lambda^h_{t,i}$, $\lambda^i_{t,i}$, λ^l_i and λ^m_i out.

$$qmax_i - qw_{t,i} - qi_{t,i} \le \mathrm{M^a} * (1 - r^a_{t,i}) \quad \forall\, t,i \ \text{(A.78) and} \ \lambda^a_{t,i} \le \mathrm{M^a} * r^a_{t,i} \quad \forall\, t,i \quad \text{(A.79)}$$
$$ib_i - soc_{t,i} \le \mathrm{M^b} * (1 - r^b_{t,i}) \quad \forall\, t,i \ \text{(A.80) and} \ \lambda^b_{t,i} \le \mathrm{M^b} * r^b_{t,i} \quad \forall\, t,i \quad \text{(A.81)}$$
$$ib_i * \mathrm{BDR} - qbout_{t,i} \le \mathrm{M^c} * (1 - r^c_{t,i}) \quad \forall\, t,i \ \text{(A.82) and} \ \lambda^c_{t,i} \le \mathrm{M^c} * r^c_{t,i} \quad \forall\, t,i \quad \text{(A.83)}$$
$$ib_i * \mathrm{BCR} - qbin_{t,i} \le \mathrm{M^d} * (1 - r^d_{t,i}) \quad \forall\, t,i \ \text{(A.84) and} \ \lambda^d_{t,i} \le \mathrm{M^d} * r^d_{t,i} \quad \forall\, t,i \quad \text{(A.85)}$$
$$qw_{t,i} \le \mathrm{M^e} * (1 - r^e_{t,i}) \quad \forall\, t,i \ \text{(A.86) and} \ \mathrm{WDT} * (\mathrm{EBP_t} + vnt) + \mu^a_{t,i} + \lambda^a_{t,i} \le \mathrm{M^e} * r^{\mathrm{e}}_{t,i} \quad \forall\, t,i \quad \text{(A.87)}$$
$$qi_{t,i} \le \mathrm{M^f} * (1 - r^f_{t,i}) \quad \forall\, t,i \ \text{(A.88) and} \ -\mathrm{WDT} * (\mathrm{ESP_t} + vnt * \mathrm{NM}) - \mu^a_{t,i} + \lambda^a_{t,i} \le \mathrm{M^f} * r^f_{t,i} \ \forall\, t,i \quad \text{(A.89)}$$
$$soc_{t,i} \le \mathrm{M^g} * (1 - r^g_{t,i}) \quad \forall\, t,i \ \text{(A.90) and} \ \lambda^g_{t,i} \le \mathrm{M^g} * r^g_{t,i} \quad \forall\, t,i \quad \text{(A.91)}$$
$$qbout_{t,i} \le \mathrm{M^h} * (1 - r^h_{t,i}) \quad \forall\, t,i \ \text{(A.92) and} \ \mu^a_{t,i} + \frac{\mu^b_{t,i}}{\mathrm{EFD}} * \mathrm{DT} + \lambda^c_{t,i} \le \mathrm{M^h} * r^h_{t,i} \quad \forall\, t,i \quad \text{(A.93)}$$
$$qbin_{t,i} \le \mathrm{M^i} * (1 - r^i_{t,i}) \quad \forall\, t,i \ \text{(A.94) and} \ -\mu^a_{t,i} - \mu^b_{t,i} * \mathrm{EFC} * \mathrm{DT} + \lambda^d_{t,i} \le \mathrm{M^i} * r^i_{t,i} \quad \forall\, t,i \quad \text{(A.95)}$$
$$\mathrm{MS}_i - is_i \le \mathrm{M^j} * (1 - r^j_i) \quad \forall\, i \ \text{(A.96) and} \ \lambda^j_i \le \mathrm{M^j} * r^j_i \quad \forall\, i \quad \text{(A.97)}$$
$$\mathrm{MB_i} - ib_i \le \mathrm{M^k} * (1 - r^k_i) \quad \forall\, i \ \text{(A.98) and} \ \lambda^k_i \le \mathrm{M^k} * r^k_i \quad \forall\, i \quad \text{(A.99)}$$
$$is_i \le \mathrm{M^l} * (1 - r^l_i) \quad \forall\, i \ \text{(A.100) and} \ \mathrm{AICS} + \textstyle\sum_t \mu^a_{t,i} * \mathrm{SY}_{t,i} + \lambda^j_i \le \mathrm{M^l} * r^l_i \quad \forall\, i \quad \text{(A.101)}$$
$$ib_i \le \mathrm{M^m} * (1 - r^m_i) \quad \forall\, i \ \text{(A.102) and}$$
$$\mathrm{AICB} - \textstyle\sum_t \lambda^b_{t,i} - \sum_t \lambda^c_{t,i} * \mathrm{BDR} - \sum_t \lambda^d_{t,i} * \mathrm{BCR} + \lambda^k_i \le \mathrm{M^m} * r^m_i \quad \forall\, i \quad \text{(A.103)}$$

B. 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 B.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.

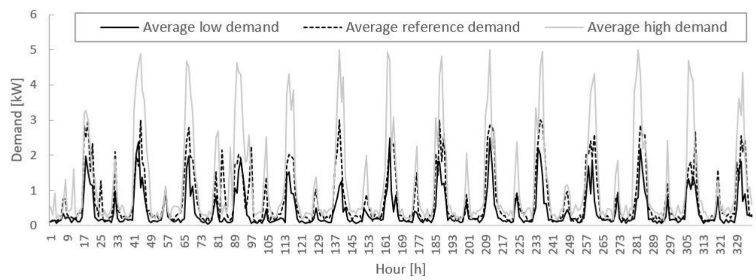

Figure B.1: Three 2-week (average) consumer profiles

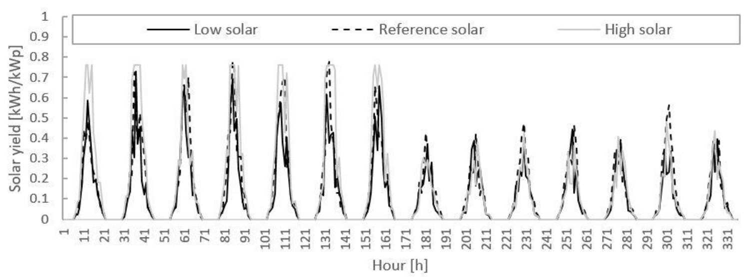

Figure B.2: Three 2-week solar PV yield profiles (including seasonality)

Table B.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 B.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 B.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.

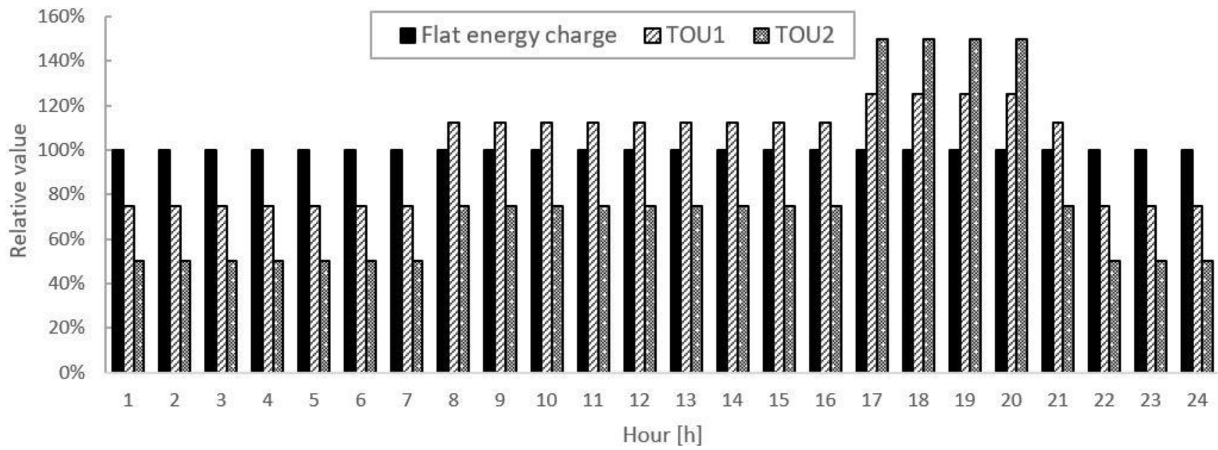

Figure B.3: Three profiles for energy prices

The results are shown in Table B.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 B.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 B.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
Δ total system costs	**-0.2 %**	**-0.5 %**	**-0.6 %**	**-0.2 %**	**-0.5 %**	**-0.6 %**	**-0.3 %**	**-0.9 %**	**-0.9 %**
Δ total grid costs	- 5.0 %	- 5.0 %	- 5.0 %	- 5.0 %	- 5.0 %	- 5.0 %	- 6.1 %	- 7.3 %	- 7.2 %
Δ 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
Δ 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 B.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
Δ total system costs	**- 0.2%**	**-0.2 %**	**-0.3%**	**- 0.2%**	**- 0.2%**	**-0.3 %**	**- 0.4 %**	**-0.8 %**	**- 0.7 %**
Δ total grid costs	-1.6 %	- 1.6 %	-2.9 %	-1.6 %	- 1.6 %	-2.9 %	- 2.6 %	- 3.0%	- 3.8 %
Δ 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
Δ 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 %