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RSCAS 2018/19
Robert Schuman Centre for Advanced Studies
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EUI Working Paper **RSCAS** 2018/19

ISSN 1028-3625

Printed in Italy, April 2018
European University Institute
Badia Fiesolana
I – 50014 San Domenico di Fiesole (FI)
Italy
www.eui.eu/RSCAS/Publications/
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For further information
Florence School of Regulation
Robert Schuman Centre for Advanced Studies
European University Institute
Casale, Via Boccaccio, 121
I-50133 Florence, Italy
Tel: +39 055 4685 878
E-mail: FSR.Secretariat@eui.eu
Web: http://fsr.eui.eu/

Abstract

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

Keywords

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

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

1. Introduction

Pérez-Arriaga et al. (2017)[1] discuss and Abdelmotteleb et al. (2017) show with simulations and numerical examples that in a new world with active consumers the least-cost distribution network tariff consists of a forward-looking-peak-coincident capacity charge plus a fixed charge. If the capacity-based charge is computed as the incremental cost of the network divided by expected load growth, the tariff is cost-reflective; consumers will make optimal choices with regard to the trade-off between their consumption levels and grid reinforcements. A fixed network charge complements the capacity-based charge to collect the remaining residual network cost in a non-distorting manner.

However, there are many difficulties which constrain the implementation of this theoretical optimal tariff. Abdelmotteleb et al. (2017), Batlle et al. (2017) , Passey et al. (2017), Pollitt (2018), Pérez-Arriaga et al. (2017) and Simshauser (2016) discuss 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 tariff design. We focus on two often-discussed constraints which are of a different nature.

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

Pérez-Arriaga et al. (2017) and Pollitt and Anaya (2016) agree that from an efficiency point of view, a network tariff with very fine temporal and locational granularity would be needed. 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, predictability for the consumer and, as also described by e.g. Batlle et al. (2017) and Neuteleers et al. (2017), fairness, thereby leading us to the second constraint.

There is a fear that network tariff reforms, which aim to increase efficiency, will result in an unfair allocation of the network costs, i.e. passive, often smaller or poorer, consumers would see their electricity bills increase. An important issue is the increase of fixed network charges. Pollitt (2018) notes that under some conditions, e.g. where there is an over-dimensioned network combined with low load growth, a limited possibility to fully disconnect from the grid and when all externalities are incorporated in the other components of the electricity bill, then it can be optimal from an efficiency point of view to

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

recover a large share of the network costs through fixed network charges. However, in many countries, there is a strong opposition to high fixed network charges. Borenstein (2016) states that a high uniform fixed charge always raises objections on equity and distributional grounds. 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 the German case 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 energy 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.[2] 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 such discontent could eventually put grid cost recovery in danger.

However, if higher fixed network charges are not acceptable even when efficient, other network tariff components (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 network charges but not necessarily optimal from a system point of view. Moreover, the benefits active consumers obtain could be at the expense of passive consumers. Brown and Sappington (2017a) estimate the welfare and distributional impact of a vertical utility not being allowed to recover its costs by raising fixed charges in addition to volumetric charges with net-metering. Indeed, they find that in a context with active consumers investing in solar PV, negative distributional and aggregate welfare effects can be more pronounced when the regulator is not allowed to raise fixed charges. In short, a trade-off exists between a fairness issue with increased fixed charges, i.e. raising the network charges of smaller households, and sustaining a distortion in the tariff which could finally also lead to a fairness issue due to active consumers reacting to the distortive network tariff.

In this paper, a game-theoretical model is introduced to assess how the distribution network tariff departs from its theoretical least-cost design under the considered constraints. The model allows us to capture the interaction between network tariff design, decentralised decision making of self-interest pursuing active consumers investing in solar PV and batteries, and their aggregated effect on the network costs. The model has a bi-level structure. In the upper-level, a regulator can opt for a combination of capacity-based charges, volumetric charges (with or without net-metering) and fixed charges to recover grid costs. The regulator anticipates the reaction of consumers represented in the lower-level and the tariff is determined in a way that total system costs (incl. network costs, energy costs and DER investment costs by consumers) are minimised. Modelled consumers can be passive or active. Passive consumers are assumed not to react to prices; active consumers pursue their own self-interest, i.e. their objective is to minimise their cost to satisfy their electricity demand. They have the option to invest in two technologies: solar PV and batteries.

The paper is structured as follows. In Section 2, we introduce the modelling approach. In Section 3, the setup and data for a numerical example are introduced. In Section 4 and 5, the two considered tariff design constraints are introduced, their modelling implication is described, and the results of a numerical example are presented to gain insights into their impact on network tariff design. Lastly, a conclusion is formulated.

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[2] 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.

2. Model formulation[3]

In this section, the game-theoretical model, incorporating decentralised decision-making steered by the design of the network charges, is described. In theory, a centralised planner, optimising social welfare by deciding unilaterally on the optimal trade-off between the utilisation of the network and the adoption of DER by consumers, would lead to the lowest total system costs. However, in reality there is no central planner that has information about the network cost function and at the same time decides on behalf of the consumers what technology to install in order to minimise the total system costs. On the contrary, decision-making is decentralised.

The relevant modelling literature is briefly summarised below. Also, the reasoning behind the use of this modelling approach for studying network tariff design is discussed. After that, 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.

2.1 Literature and reasoning behind the modelling approach

Relevant literature regarding the modelling approach includes the work of Brown and Sappington (2017a, 2017b, 2018). In their papers, they apply a welfare analysis to gain insights into the issue of optimal retail tariffs in a setting where consumers with a certain elasticity are adopting distributed generation (DG). An important difference with our work is that Brown and Sappington focus on the design of the entire retail tariff and model one vertically integrated utility responsible for generation, transmission and distribution. The advantage of their approach is that the cost of centralised generation is endogenised, while in this paper the energy price is considered as exogenous. The disadvantage of modelling a vertically integrated utility is that the collection of network charges is decoupled from network costs. Namely, in the work of Brown and Sappington cross-subsidisation between generation and network activities by the vertical utility is allowed, while in this paper network charges and network costs need to converge as is generally the case for an unbundled DSO. Another difference is that Brown and Sappington do not use inter-temporal data series. As a consequence, batteries at consumer level cannot be modelled. In Schittekatte et al. (2018) a welfare analysis is also conducted, taking into account self-interest pursuing active consumers reacting to network tariffs. The main difference is that the grid costs are assumed to be sunk in that work. This means the objective of a network tariff is mainly allocative, i.e. socialising the grid costs in a non-distortive and fair manner. While in this paper, reactions of the consumers in terms of consumption from the grid (or injection) affect the network cost and in its turn the network charges. This implies that the tariff should guide consumers to efficient behaviour apart from purely socialising network costs.

The main advantage of modelling decentralised decision-making instead of centralised decision-making or exogenously determined consumer investment decisions (as in Abdelmotteleb et al. (2017), Hledik and Greenstein (2016) and Simshauser (2016)) is that the decisions of consumers can result in an overall efficiency loss when price signals, in this case network charges, are not properly designed. Although the rise of active consumers is rightly welcomed, the model takes into account the fact that it can also be a double-edged sword. On the one hand, the more consumers have the ability to react to price signals, 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 consumers are able to react to price signals, the more significant negative welfare impacts can result if these price signals are badly designed. Active consumers could be guided in ‘the wrong direction’ by inadequate tariff design, e.g. investing in DER which are profitable when viewed from their individual point of view but which do not reduce or even increase total system costs. The more consumers have the possibility to react to price signals, the more important it becomes to get the tariff design right.

[3] Variables are represented in italics, parameters in standard style.

2.2 The upper-level regulator

The upper-level of the model represents the tariff design problem of the regulator. The objective of the regulator is to minimise total system costs (here equivalent to maximising social welfare). It is assumed that the regulator can set the network tariff. 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. Total system costs consist of four components: energy costs, DER investment costs, grid costs, and other costs. Other costs represent taxes and levies recovered from consumers; it is assumed that the total level of these costs is invariant. The three variable components of the objective function are displayed by Eq. 2-4. All costs are annualised and scaled per (average) consumer. All introduced variables are positive continuous variables. The nomenclature used can be found in Appendix A.1.

$$Minimise\ \ SystemEnergyCosts + SystemDERcosts + SystemGridCosts + \mathrm{SystemOtherCosts} \tag{1}$$

The system net energy costs are calculated by Eq. 2. $\mathrm{EBP_t}$ stands for the price to buy a kWh of electricity and $\mathrm{ESP_t}$ is the price received when selling a kWh of electricity (purely energy, excluding grid or other costs). 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. Further, $qw_{t,i}$ and $qi_{t,i}$ represents respectively the electricity withdrawn and injected from the network by consumer *i* and for a certain time step *t*. WDT is a factor to annualise the values and is a function of the length of the utilised time series (T).

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

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

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

Finally, the function describing 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. In contrast, prospective grid costs ($\mathrm{IncrGridCosts} * CoincidentPeak$) are variable 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 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).

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

Abdelmotteleb et al. (2017), Pérez-Arriaga et al. (2017) and Simshauser (2016) describe that the coincident peak demand (or injection if higher) is generally considered as the main cost driver of a distribution network. Brown and Sappington (2018) apply a similar formula by stating that the network costs are a function of the maximum potential demand for electricity supplied by centralised generation. In Brown and Sappington (2017a) a different approach is used, and it is assumed that the network costs are a function of the capacity of centralised generation and solar PV installed, with a higher weight for solar PV. Next to the coincident peak demand, other network cost drivers can be identified, such as thermal losses and investment cost to replace electronic components (e.g. protection) to deal with bi-directional flows due to high concentrations in PV adoption (see e.g. MIT Energy Initiative (2015) and Cohen et al. (2016)). These other network cost drivers are not included in the current analysis.

How the coincident peak demand (or injection) is obtained is shown by Eq. 5-7. $CPeakDemand$ stands for the coincident peak demand, i.e. the maximum value of the sum of the consumer demands ($qw_{t,i}$) minus injections ($qi_{t,i}$) for a certain time step *t*. Please note that when at time step *t* the demand of consumer i ($qw_{t,i}$) is positive, the injection ($qw_{t,i}$) of that same consumer is zero and vice-versa. Similarly, the coincident peak injection of the network $CPeakInjection$ is obtained. The $CoincidentPeak$ is determined as the maximum of the two.

$$CoincidentPeak = \max(CPeakDemand, CPeakInjection) \quad (5)$$

$$CPeakDemand \geq \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * \left(qw_{t,i} - qi_{t,i}\right) \quad \forall t \quad (6)$$

$$CPeakInjection \geq \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * \left(qi_{t,i} - qw_{t,i}\right) \quad \forall t \quad (7)$$

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

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

NM is a parameter and determines the type of volumetric charge. If NM is set as equal to 1, volumetric charges with net-metering are introduced. With NM set equal to 0, volumetric charges without net-metering, solely charging for the total volume of electricity withdrawn are in place. The last variant can be obtained by setting NM equal to -1. In that case, bi-directional volumetric charges charging vnt for each kWh withdrawn and injected are in place. Please note that for the latter two 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 ($qmax_i$). The fixed network charge fnt is assumed to be uniform for all consumers i.

2.2.1 The lower-level consumers

The objective of the individual consumers' optimisation problems is to minimise the cost of serving their electricity demand. Active consumers are enabled to invest in solar PV or batteries to lower their dependency from the grid when they have the financial incentive to do so. The objective function of a consumer i is represented by Eq. 9. The total electricity 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 by a fixed charge per consumer. The other three components of the consumers' electricity costs are variables.

$$\text{Minimise } GridCharges_i + DERCosts_i + EnergyCosts_i + \text{OtherCharges} \tag{9}$$

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

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

$$\text{with } qmax_i \geq qw_{t,i} - qi_{t,i} \quad \forall i, t \tag{11}$$

$$DERCosts_i = is_i * \mathrm{AICS} + ib_i * \mathrm{AICB} \quad \forall\, i \tag{12}$$

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

A consumer is subject to a number of constraints; these constraints are demonstrated 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 ($qw_{t,i}$), a discharging battery ($qbout_{t,i}$) or electricity produced by installed solar PV ($is_i * \mathrm{SY_{t,i}}$). Electricity can also be injected into the grid ($qi_{t,i}$) or used to charge the battery ($qbin_{t,i}$). Meeting the electricity demand is a hard constraint. Eq. 15-17 describe the battery balance, where $soc_{t,i}$ is the state of the battery at time step t, EFC the charge efficiency, EFD the discharge efficiency and LR the leakage rate of the battery. DT is the time step as a fraction of 60 minutes used to convert all numbers to kWhs. Eq. 18-20 constrain the battery in terms of energy stored and instantaneous (dis)charging. 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.[4]

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

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

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

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

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

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

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

$$qw_{t,i}, qi_{t,i}, soc_{t,i}, qbout_{t,i}, qbin_{t,i}, is_i, ib_i \geq 0 \quad \forall\, i, t \tag{21}$$

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

2.2.2 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 to a single level problem is done by including the Karush-Kuhn-Tucker (KKT) conditions of the linear and thus convex lower-level as constraints to the upper-level problem. A non-linear MPEC results. The non-linearities in Eq. 8 are discretised using the technique described in Momber (2015, p. 102), and the complementarity constraints are transformed into disjunctive constraints using the technique described in Fortuny-Amat and McCarl (1981). A Mixed Integer Linear Program (MILP) results that can be solved by off-the-shelf optimisation software. The reformulation of the bi-level problem can be found in Appendix A.2.

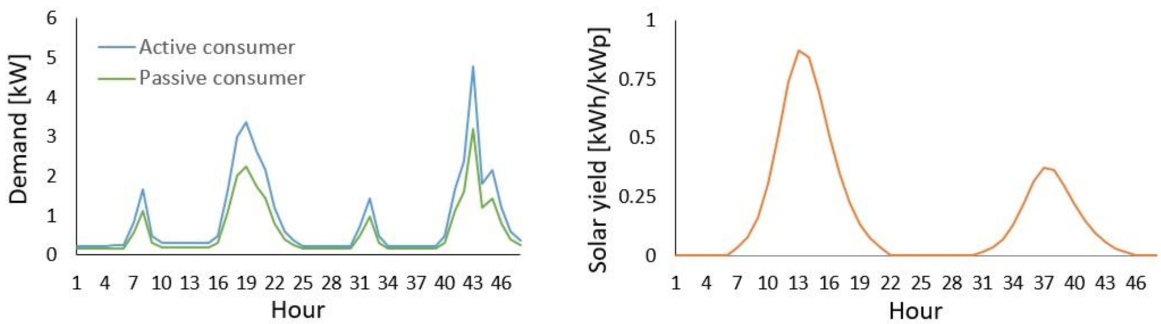
3. Numerical example: data and setup

In this section, the setup and data of a numerical example are described. The numerical example is used in the subsequent sections to gain insights from the model when introducing the implementation and fairness constraints. This section is split into four parts, dividing key data into four different groups.

3.1 Consumer types, demand and solar yield

Two consumer types are modelled for simplicity: passive and active consumers, as is also done in Brown and Sappington (2017a, 2017b, 2018). 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. The (original) consumer demand profiles and yield of PV are represented using a time series of 48-hours with hourly time steps and is shown in Figure 1.

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



Household demand for electricity shows for both modelled days a small peak in the morning and a stronger peak in the evening, the typical ‘humped-camel shape’ (Faruqui and Graf 2018). For both consumer types the shape of the demand profile is identical; however, it is scaled differently. As a result, passive consumers have a slightly lower electricity demand than active consumers. The passive consumer has an annual consumption of 5,200 kWh with a peak demand of 3.2 kW and the active consumer a 7,800 kWh annual consumption with a peak demand of 4.8 kW. In Europe, average annual electricity consumption per household ranged from 20,000 kWh (Sweden) to 1,400 kWh (Romania) in 2015. In the same year, the average electricity consumption per household in the USA was about 10,800 kWh (EIA 2016). The idea behind this difference in the level 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 that 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 PV installed scales up to 1,160 kWh per year. As a reference, this level is similar to the average yield in the territory of France (Šúri et al. 2007). Seasonality is introduced in the PV yield profile by having a daily average PV yield of 40% of either side of the annual mean. The peak demand coincides with the day with the low PV yield. Letting the peak demand day coincide with the day with lower solar irradiation and vice-versa produces two effects. First, a high capacity of PV installed does not necessarily mean that the peak demand can be reduced. Faruqui and Graf (2018) investigate load profiles in Kansas and find that after the installation of PV systems, logically the net energy consumption reduces; nevertheless, the peak demand is virtually left unchanged. Second, if a high capacity of PV is installed, the injection peak of active consumers can become significant.

3.2 Consumer bills

Table 1 shows the default electricity bill, paid by the consumers when no one installs any DER technology. If active consumers decide to invest in DER, the relative proportion and absolute values of the bill components can change for both the active and the passive consumers. The annual electricity cost for the active and passive consumer equals respectively 1,340 €/year (0.172 €/kWh delivered) and 971 €/year (0.187 €/kWh delivered). This total cost is near 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). There, the breakdown of the different components of the electricity bill for an average consumer in the EU for the year 2015 is presented. The energy component in the EU in 2015 is estimated to be 37%. In absolute terms, this means a cost of 0.077 €/kWh. Further, 26% of the bill consisted of network charges and 13% is made up of 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 (see e.g. ACER and CEER (2016) for the EU).

Table 1: Consumer bill in the default case (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 energy price is set at 0.08 €/kWh.[5] Other charges are recovered through a fixed fee and as such do not interfere with the analysis. However, this is not always the case. How to collect such charges, or

[5] In this work, the energy price component is modelled exogenously. In case of high PV adoption, this might be a simplification as a higher PV penetration can depress the wholesale prices and thus the final energy price a retail consumer has to pay (see e.g. Darghouth et al. (2016)).

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 default case recovered through (net-metered) volumetric charges equal to 0.062 €/kWh. In the recent past, with highly inelastic consumers, it was less an issue to recover grid costs with volumetric charges. Limited inefficiencies were introduced as consumers had few options to serve their electricity needs other than from the grid. Also, as discussed, high-usage and thus higher network contributions correlated rather well with richer households, making such practice acceptable. How to adapt network tariff design when dealing with active consumers is the main contribution of this paper and is discussed in Sections 4 and 5.

3.3 DER investment cost and technical parameters

Two DER technologies are assumed at the disposition of active consumers in this work: solar PV and batteries. A scenario with low PV and battery investment costs can be expected to materialise soon as pointed out by many studies (Lazard 2016a, 2016b; MIT Energy Initiative 2016; RMI 2015). 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 2010 costs. The levelised cost of energy (LCOE) of solar PV is 0.083 €/kWh[6], slightly higher than the price for energy from the grid (excluding grid and other charges). 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. 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 function of the battery, shifting power demand from the grid in time, could also be provided by demand response (DR) through smart devices for which it is harder to put a price tag on. 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. 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 energy price)	90 %	Efficiency charging & discharging	90 %
		Leakage rate	2 %

3.4 Grid cost structure and setup

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

[6] 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 imporantly the solar irradiation profile, which is location dependendent.

and 20% variable operating costs. Jenkins and Pérez-Arriaga (2017) provide a more detailed discussion of the different network costs components.

When conducting the analysis in Sections 4 and 5 using this numerical example, three different grid cost structures are considered. First, grid costs are assumed to be 100% sunk, a short-term vision, i.e. the grid is over-dimensioned, and the electricity usage of consumers has no effect on the total grid costs. In some countries also policy costs are recovered through the network charges, which from a cost allocation point of view is no different than recovering sunk network costs. Second, half of the grid costs are considered sunk and the other half prospective, i.e. driven by the coincident consumer peak demand. Lastly, the grid costs are assumed to be driven completely by the coincident consumer peak demand. In the very long run grid costs are also variable. The network capacity will adjust to the coincident peak demand need from the consumers. If the coincident peak demand augments, the increase in grid costs could be seen as the cost of reinforcements or additional capacity. If the coincident peak demand is reduced, the decrease in grid costs could be seen as the avoided cost for replacing existing capacity or maintenance. In all cases, short-run marginal costs, e.g. energy losses, are not considered as they typically only contribute to a small proportion of the total cost of a network operator. Different network cost functions could be introduced in future work.

The values for the parameters of the grid cost function (Eq. 4), $\mathrm{SunkGridCosts}$ and $\mathrm{IncrGridCosts}$, are derived from the ‘default’ network costs of the modelled consumers (shown in Table 1) and are a function of the proportion of active and passive consumers. At one extreme, all consumers can be passive, as in the recent past. At the other extreme, all consumers can be active, i.e. install DER when it can reduce their overall electricity cost. Reality presumably lies in the middle. Some consumers will remain passive for a number of reasons. Other consumers could be installing DER even when they do not financially profit from it, but because of other reasons which are harder to monetise, e.g. independence from the grid, sustainability motives etc. In the numerical example, it is assumed that 50% of all consumers are active and 50% are passive. With these proportions, the (scaled) coincident consumer peak demand equals 4 kW in the ‘default case’ when no active consumer installs DER, and the average grid costs equal 404 €/consumer.[7] In the first case, grid costs are assumed 100% sunk, the parameters $\mathrm{SunkGridCosts}$ and $\mathrm{IncrGridCosts}$ in Equation 2 are set as equal to € 404 and 0 €/kW respectively. In the second case, 50% of the costs are assumed sunk and 50% perspective, $\mathrm{SunkGridCosts}$ equals € 202 and $\mathrm{IncrGridCosts}$ is set to 50.5 €/kW.[8] In the third case, $\mathrm{SunkGridCosts}$ is zero and $\mathrm{IncrGridCosts}$ are set to 101 €/kW. As a reference, Brown et al. (2015) assume the (annualised) cost to be 75 $ for a kW of incremental household demand. Please note that another implementation constraint would be a correct estimation of the incremental network cost, or the network cost function in general, next to inaccuracy of the network cost driver proxy.

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

In this section, the model described in Section 2 is used to provide insights into the impact of the implementation constraint, i.e. the inaccuracy of the network cost driver proxy. 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.

4.1 Revisiting the model

A simple, yet effective change has been made to Eq. 4 to incorporate inaccuracy around the network cost driver in our model. This change reduces the impact of the optimised coincident peak demand, i.e.

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7 4kW = 0.5*4.8 kW + 0.5*3.2 kW and 404 € = 0.5*485 € + 0.5*324 €

8 50.5 €/kW = 0.5*404 €/4kW

the coincident peak demand after DER adoption by active consumers, on total grid costs. Eq. 22 shows the updated version of Eq. 4 after taking into account inaccuracy of the network cost driver proxy. DPeak is a parameter and stands for the default coincident peak demand, i.e. the coincident peak demand in the case no consumer installs DER, and $CoincidentPeak$ is a variable and stands for the optimised coincident peak demand, i.e. the coincident peak demand after active consumers installed DER when profitable. The parameter WF represents a weighting factor.

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

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

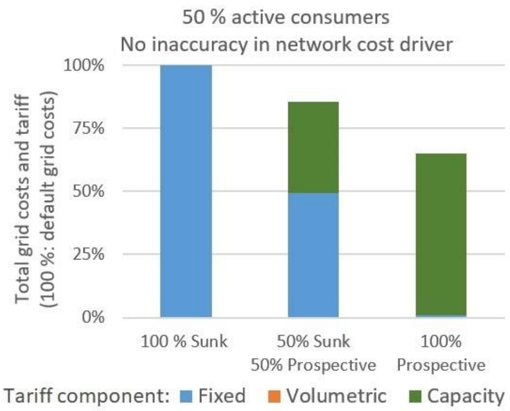
By introducing Eq. 22 also the assumption of identically shaped demand profiles is relaxed. Namely, with Eq. 22 the impact of the optimised coincident peak demand on total grid costs is reduced. A similar effect could be witnessed with heterogeneous demand profiles optimising their individual peak demand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

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

4.2 Results and discussion

First, a run is done without inaccuracy in the network cost driver proxy (WF equals 1). The results for the least-cost tariff design are shown in Figure 2 and Table 3. In Table 3, two metrics are calculated for the different grid cost structures. First, the change in total system costs compared to the 'default situation' when no consumer installs DER is shown. 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 'default situation' (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.

Figure 2 and Table 3: Tariff components and grid costs (Figure 2). Total system costs and increase network charges per passive consumer (Table 3). Results are relative to the default situation with no active consumers and volumetric network tariffs. Sensitivity for three grid states and no inaccuracy in the network cost driver proxy assumed.



50 % active consumers – Results compared to default (=no DER & volumetric network charges)		No inaccuracy in network cost driver proxy
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 %

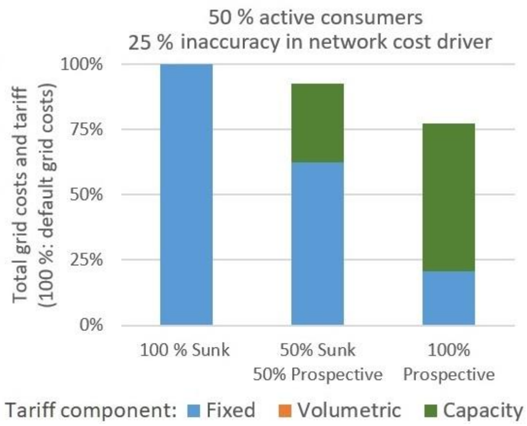
In Figure 2, the least-cost tariff consists of a capacity-based charge equal to the incremental grid cost parameter (IncrGridCosts in Eq. 4) and a fixed charge equal to the sunk grid costs (SunkGridCosts in Eq. 4).[9] This corresponds to the tariff structure described by Abdelmotteleb et al. (2017) and the MIT Energy Initiative (2016).

When grid costs are 100% sunk, the least-cost 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 energy price of electricity sourced from the grid. However, due to the high uniform fixed network charge smaller passive consumers see their network charges significantly increase as some of the network costs, previously allocated to larger consumers by 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 energy price of electricity 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 with the reduction in total system costs and the passive consumers do not see any change in the grid charges paid.

9 There can exist an interval around the value of the coefficients of the least-cost tariff structures for which the total system costs are the same. This interval contains the theoretical least-cost tariff. The reasoning behind this is that if a capacity-based/volumetric charge is set slightly higher or lower it might not impact consumer decisions and thus the total system costs. The richer the data (e.g. number of consumer types or the length of the time series) the more sensitive consumer decisions and thus the total system costs are to a minor change in the network tariff.

Figure 3 and Table 4: Tariff components and grid costs (Figure 3). Total system costs and increase network charges per passive consumer (Table 4). All results are relative to the default situation with no active consumers and volumetric network tariffs. Sensitivity for three grid states and 25% inaccuracy in the network cost driver proxy assumed.



50 % active consumers – 25 % inaccuracy in network cost driver proxy Results compared to the default (=no DER & volumetric network charges)		Least-cost tariff	Capacity-based charge = incremental grid cost
Total system costs	100 % Sunk grid costs	0.0 %	0.0 %
	50 % Sunk & 50 % Prospective	-0.3 %	-0.1 %
	100 % Prospective grid costs	-4.0 %	-3.7 %
Network charges passive consumer	100 % Sunk grid costs	25.0 %	25.0 %
	50 % Sunk & 50 % Prospective	15.6 %	15.9 %
	100 % Prospective grid costs	7.0 %	10.9 %

Figure 3 shows the least-cost tariff structure when introducing an implementation constraint in the form of a 25% of inaccuracy in the network cost driver proxy. Two observations can be made when comparing the tariff structure with and without an implementation constraint.

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

The reason for this change in the network tariff when introducing the implementation constraint can be deducted from the results in Table 4. Two result columns are introduced for the runs with 25% inaccuracy in the network cost driver proxy. First, the regulator is free to optimise the tariff structure which would lead to a lowest total system cost (first column). The tariff structure shown in Figure 3 results from this run. This can be viewed as the case where the regulator is aware of the inaccuracy in the network cost driver proxy. After, a run is computed in which the capacity-based charge is set as equal to the incremental grid cost (second column). This would be the situation when the regulator ignores the inaccuracy in the network cost driver proxy. It is evident that by taking into account the inaccuracy and departing from the theoretical least-cost tariff, a lower total system cost can be obtained.

The intuition behind these results is the following: if the capacity-based charge is set as equal to the incremental grid costs, batteries are over-incentivised. An individual consumer installs batteries as they are profitable from his individual perspective. However, the grid costs decrease less than the cost of the DER investment. Overall, in that case, total system costs are higher than when active consumers install fewer batteries, demonstrating what Pollitt (2018) and Pérez-Arriaga et al. (2017) mean by distortive tariff design, that is, it might appear privately beneficial but can result in a deadweight loss for society. Further, the grid costs, which did not decrease significantly due to the inaccuracy in the cost driver proxy, need to be recovered.

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

5. 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 2 and amended in Section 4. The section consists of four parts. First, the modelling implication is pointed out. Second, the results obtained with a fairness constraint, using the same numerical example as introduced in the previous section, are shown and discussed. Third, results are discussed when jointly applying the fairness and implementation constraint. Lastly, the policy implication of the results is discussed.

5.1 Revisiting the model

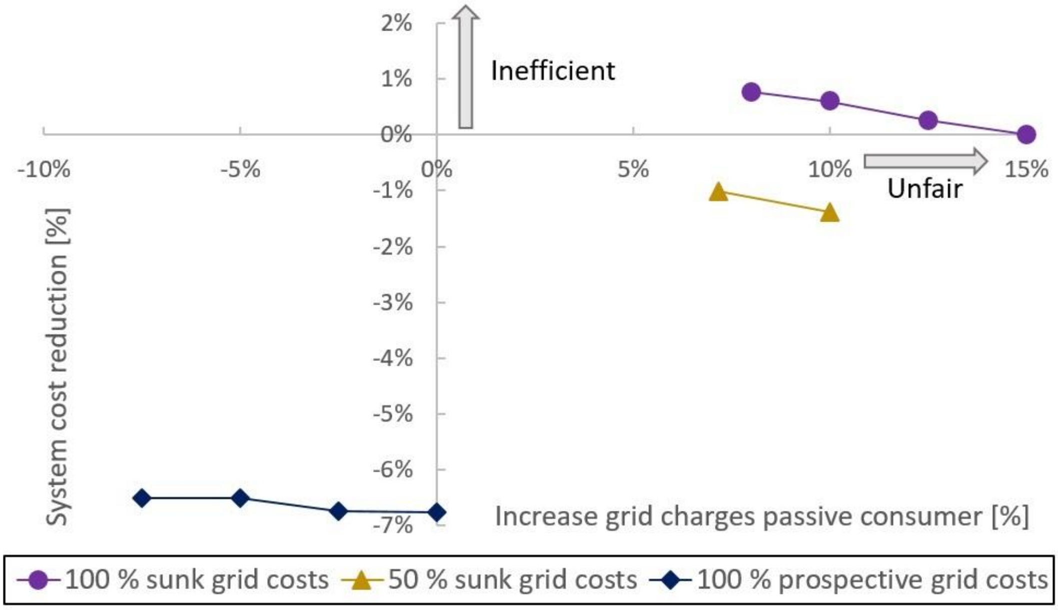
In order to assess least-cost tariff design with a cap on the increase of network charges paid by passive consumers, Eq. 23 is added to the upper-level problem. The index ‘i2’ stands for the passive consumer type and $\mathrm{DGC}_{'i2'}$ are the network charges paid by the passive consumer in the ‘default case’. 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 default network charges paid. If the cap is set very high, the fairness constraint will not be binding and thus will not influence the least-cost 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.

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

5.2 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 customers. The results are completely different for the three illustrated grid states.

Figure 4: Total system cost reduction trade-off with the increase of grid charges of passive consumers for the three grid states. All results are relative to the default situation with no active consumers and volumetric network tariffs. No inaccuracy in the network cost driver proxy assumed.



The first state of the grid is 100% sunk costs. In this state of the grid, the least-cost distribution network tariff is a fixed charge, which significantly increases the costs for small passive consumers. By reducing the fixed component and adding a volumetric and/or capacity charge it is possible to improve the fairness, but it comes at a cost because self-interested active customers will react to the incentives by installing more solar PV and/or batteries. The irony is that they end up paying for it themselves because passive consumers do pay less for small deviations from the pure fixed charge. Of course, there is a point where the model becomes infeasible. By pushing the model towards fairer tariffs, we are increasing total system costs, which eventually also increases the costs for passive customers so that the model cannot find a solution that satisfies all constraints. In the numerical example that we use in this paper, we can improve fairness from 15% cost increase for passive consumers (the lowest possible cost increase for the passive consumer without the active consumers reacting to the tariff) towards 7%, but beyond that point, the model becomes infeasible. Note that the significant improvement in fairness comes at a relatively small increased total system cost.

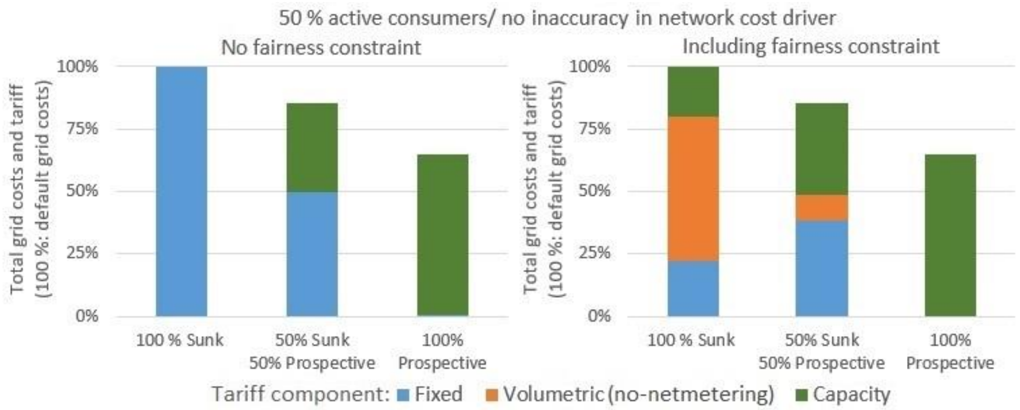
The second state of the grid is 100% prospective costs. In this case, a cost-reflective tariff can achieve a lot of cost savings thanks to the incentives given to active consumers. These system benefits also lead to a price reduction for passive consumers. It is possible to push the model towards a tariff 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 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 tariff that somewhat softens the unfairness for passive consumers, but they are always worse off in this case.

Figure 5 illustrates how the model deviates from the least-cost network tariff design to improve fairness. We illustrate this for one of the points in Figure 4, i.e. the model outcome for a fairness constraint with a maximum cost increase of 10% for passive customers. As we know from Figure 4, this constraint is not binding in the case of 100% prospective costs, but it is binding for the other two cases. Figure 5, confirms what we discussed above, namely that the model reacts to a binding fairness constraint by moving away from the least-cost tariff structure to a structure that is fairer. We also know from Figure 4, that the 10% constraint is feasible in our numerical example.

As can be seen from Figure 5, the fairer tariff structure is a three-part tariff combining fixed with capacity and volumetric components. Volumetric charges without net-metering, only charging for the electricity withdrawn from the network, are opted for by the regulator. With volumetric charges with bi-directional charges, paying a charge for each kWh withdrawn and injected, similar results are obtained for the numerical example. Volumetric charges with net-metering lead to a higher system cost and create a fairness issue as they strongly over-incentivise PV adoption.

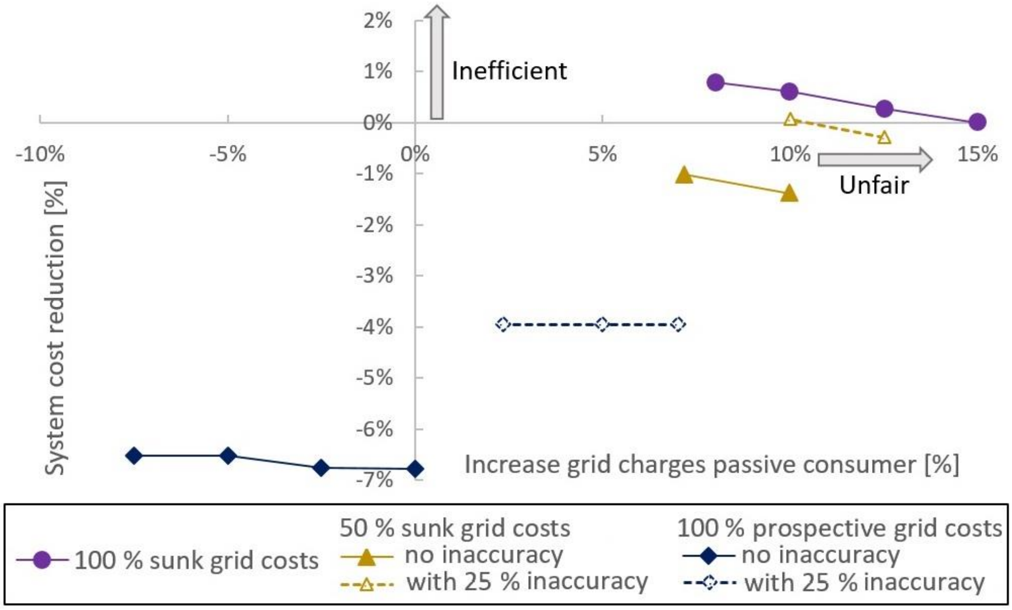
Figure 5: Tariff components and grid costs. Results without and with 10 % cap on the increase in network charges for the passive consumers relative to the default situation with no active consumers and volumetric network tariffs. No inaccuracy in the network cost driver proxy assumed.



5.3 Results and discussion with a fairness and implementation constraint

Figure 6 is even more sobering for passive consumers than the results in the previous section. If we cannot get the cost-driver right, we risk passive consumers are worse off in all cases. The results for the case of 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 inaccuracy of the cost driver makes the system, and also the passive consumers, relatively worse off. In the case of 100% prospective costs, the impact is most significant for passive consumers: they end up 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 6: Total system cost reduction trade-off with the increase of grid charges of passive consumers for the three grid states. All results are relative to the default situation with no active consumers and volumetric network tariffs. Results with 25 % and without inaccuracy in the network cost driver proxy shown.



5.4 Policy implication: overcoming the limitations of standard tariff design

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 tariff design. However, in practice, our results regarding fairness might be overestimated as such issues can be improved through other solutions than standard 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 uniform fixed network charge as in our analysis, but differentiate the fixed network charges per consumer or consumer groups without distorting the use of electricity, e.g. by income, property value, property size, kW connection capacity (Pollitt 2018; MIT Energy Initiative 2016; Abdelmotteleb et al. 2017). It might also be possible to improve fairness by introducing some form of taxation for active consumers. However, taxation is also difficult to implement and could conflict with other public policy goals. In the case of high sunk grid costs, under-recovery of the grid costs could be an option as full cost recovery leads to inefficiencies. Not recovered sunk network costs could be recuperated through other means than the electricity bill, an option also discussed in the report by the MIT Energy Initiative (2016). An alternative could be to let taxpayers pay for these costs, as is done for roads in some countries.

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

6. Conclusion

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

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

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

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

Regarding future work, it would be interesting to include electric vehicles and heat pumps in the analysis. Taking into account these (mainly) electricity consuming technologies could present new insights. More granular network tariffs could become increasingly important to limit the efficiency loss caused by inaccurate tariffs. Finally, the interaction between network tariff design, public policies (e.g. energy efficiency and DER subsidies) and taxation deserves further analysis.

7. Bibliography

Abdelmotteleb, Ibtihal, Tomás Gómez, José Pablo Chaves Ávila, and Javier Reneses. 2017. "Designing Efficient Distribution Network Charges in the Context of Active Customers." *Applied Energy,* no. May. Elsevier: 1–12. doi:10.1016/j.apenergy.2017.08.103.

ACER, and CEER. 2016. "Annual Report on the Results of Monitoring the Internal Electricity and Gas Markets in 2015. Electricity and Gas Retail Markets Volume."

———. 2017. "Annual Report on the Results of Monitoring the Internal Electricity and Gas Markets in 2016. Electricity and Gas Retail Markets Volume."

Batlle, Carlos, José Pablo, Chaves Avila, Paolo Mastropietro, Jesse Jenkins, and Pablo Rodilla. 2017. "Regulated Charges and Electricity Bills for a Distributed Future : Efficient Price Signals for Increasingly Elastic End-Users." *MITEI Working Paper. Version of May 2017*.

Bohringer, Christoph, Florian Landis, and Miguel Angel Tovar Reanos. 2017. "Economic Impacts of Renewable Energy Increase in Germany." *The Energy Journal* 38: 263–72. doi:10.1007/978-3-319-45659-1.

Borenstein, Severin. 2016. "The Economics of Fixed Cost Recovery by Utilities." *Electricity Journal* 29 (7): 5–12. doi:10.1016/j.tej.2016.07.013.

———. 2017. "Private Net Benefits of Residential Solar PV : The Role of Electricity Tariffs , Tax Incentives and Rebates." *Journal of the Association of Environmental and Resource Economists* 4 (S1): S85–122.

Brown, David P., and David E. M. Sappington. 2017a. "Designing Compensation for Distributed Solar Generation: Is Net Metering Ever Optimal?" *Energy Journal* 38 (3): 1–32. doi:10.5547/01956574.38.3.dbro.

———. 2017b. "Optimal Policies to Promote Efficient Distributed Generation of Electricity." *Journal of Regulatory Economics* 52 (2). Springer US: 159–88. doi:10.1007/s11149-017-9335-9.

———. 2018. "On the Role of Maximum Demand Charges in the Presence of Distributed Generation Resources." *Energy Economics* 69. Elsevier B.V.: 237–49. doi:10.1016/j.eneco.2017.11.023.

Brown, Toby, Ahmad Faruqui, and Léa Grausz. 2015. "Efficient Tariff Structures for Distribution Network Services." *Economic Analysis and Policy* 48 (9). Elsevier B.V.: 139–49. doi:10.1016/j.eap.2015.11.010.

Cohen, M. A., P. A. Kauzmann, and D. S. Callaway. 2016. "Effects of Distributed PV Generation on California's Distribution System, Part 2: Economic Analysis." *Solar Energy* 128: 139–52.

Crawford, G. 2014. "Written Down Value?" *Energy Networks Publication, Canberra*.

Darghouth, Naïm R., Ryan Wiser, Galen Barbose, and Andrew Mills. 2016. "Net Metering and Market Feedback Loops - Exploring the Impact of Retail Rate Design on Distributed PV Deployment." *Applied Energy* 162: 713–22.

EIA. 2016. "Average Price of Electricity to Ultimate Customers: 2006-2016." https://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_5_3.

European Commission. 2015. "Study on Tariff Design for Distribution Systems." https://ec.europa.eu/energy/sites/ener/files/documents/20150313 Tariff report fina_revREF-E.PDF.

Eurostat. 2016. "News Release - Energy Prices in the EU in 2015."

Faruqui, Ahmad, and Walter Graf. 2018. "Do Load Shapes of PV Customers Differ?" *Fortnightly Magazine*. https://www.fortnightly.com/fortnightly/2018/02/do-load-shapes-pv-customers-differ.

Fortuny-Amat, José, and Bruce McCarl. 1981. "A Representation and Economic Interpretation of a Two-Level Programming Problem." *The Journal of the Operational Research Society* 32 (9): 783–92.

Gabriel, S. A., A.J. Conejo, J.D. Fuller, B.F Hobbs, and Ruiz C. 2012. *Complementarity Modeling in Energy Markets*. Springer Science & Business Media.

GAMS. 2018. "GAMS – Documentation." https://gams.com/latest/docs/gams.pdf.

Gómez, Tomás. 2013. "Electricity Distribution." In *Regulation of the Power Sector*, edited by Ignacio J Pérez-Arriaga, 199–250. Springer. doi:10.1007/978-1-4471-5034-3.

Hanser, Philip Q. 2013. "Commonwealth Edison Company: Rebuttal Testimony of Philip Q. Hanser." *Docket Number 13-0387 CommEd. 10.0. State of Illinois, Illinois Commerce Commission.*

Hledik, Ryan. 2014. "Rediscovering Residential Demand Charges." *Electricity Journal* 27 (7). Elsevier Inc.: 82–96. doi:10.1016/j.tej.2014.07.003.

Hledik, Ryan, Ahmad Faruqui, Jurgen Weiss, Toby Brown, and Nicole Irwin. 2016. "The Tariff Transition: Considerations for Domestic Distribution Tariff Redesign in Great-Britain." *Volume I - Final Report for Citizens Advice*.

Hledik, Ryan, and Gus Greenstein. 2016. "The Distributional Impacts of Residential Demand Charges." *Electricity Journal* 29 (6). Elsevier Inc.: 33–41. doi:10.1016/j.tej.2016.07.002.

Jenkins, Jesse D, and Ignacio J Pérez-Arriaga. 2017. "Improved Regulatory Approaches for the Remuneration of Electricity Distribution Utilities with High Penetrations of Distributed Energy Resources." *The Energy Journal* 38 (3): 63–92.

Koliou, Elta, Cajsa Bartusch, Angela Picciariello, Tobias Eklund, S Lennart, and Rudi A Hakvoort. 2015. "Quantifying Distribution-System Operators' Economic Incentives to Promote Residential Demand Response." *Utilities Policy* 35: 28–40. doi:10.1016/j.jup.2015.07.001.

Kolokathis, Christos, Michael Hogan, and Andreas Jahn. 2018. "Cleaner, Smarter, Cheaper: Network Tariff Design for a Smart Future." *Working Paper from the Regulatory Assistance Project (RAP)*, no. January.

Lazard. 2016a. "Lazard's Levelized Cost of Energy Analysis (' LCOE ') Version 10.0," no. December.

———. 2016b. "Levelized Cost of Storage - Volume 2," no. December. doi:10.1080/14693062.2006.9685626.

MIT Energy Initiative. 2015. "The Future of Solar Energy." doi:10.1002/yd.20002.

———. 2016. *Utility of the Future. An MIT Energy Initiative Response to an Industry in Transition*.

Momber, Ilan. 2015. "Benefits of Coordinating Plug-In Electric Vehicles in Electric Power Systems." *Doctoral Thesis*.

Neuteleers, Stijn, Machiel Mulder, and Frank Hindriks. 2017. "Assessing Fairness of Dynamic Grid Tariffs." *Energy Policy* 108 (June). Elsevier Ltd: 111–20. doi:10.1016/j.enpol.2017.05.028.

Passey, Robert, Navid Haghdadi, Anna Bruce, and Iain MacGill. 2017. "Designing More Cost Reflective Electricity Network Tariffs with Demand Charges." *Energy Policy* 109 (April): 642–49. doi:10.1016/j.enpol.2017.07.045.

Pérez-Arriaga, Ignacio J., Jesse D Jenkins, and Carlos Batlle. 2017. "A Regulatory Framework for an Evolving Electricity Sector: Highlights of the MIT Utility of the Future Study." *Economics of Energy & Environmental Policy* 6 (1): 71–92. doi:10.5547/2160-5890.6.1.iper.

Pollitt, Michael G. 2018. “Electricity Network Charging in the Presence of Distributed Energy Resources: Principles, Problems and Solutions.” *Economics of Energy & Environmental Policy* 7 (1): 89–104. doi:10.5547/2160-5890.7.1.mpol.

Pollitt, Michael G, and Karim L Anaya. 2016. “Can Current Electricity Markets Cope with High Shares of Renewables? A Comparison of Approaches in Germany, the UK and the State of New York.” *The Energy Journal* 37: 69–88.

RMI. 2015. “The Economics of Load Defection.” *Rocky Mountain Institute*, no. April: 71. doi:10.1002/0471755621.ch15.

Ruester, Sophia, Sebastian Schwenen, Carlos Batlle, and Ignacio Pérez-Arriaga. 2014. “From Distribution Networks to Smart Distribution Systems: Rethinking the Regulation of European Electricity DSOs.” *Utilities Policy* 31. Elsevier Ltd: 229–37. doi:10.1016/j.jup.2014.03.007.

Schittekatte, Tim, Ilan Momber, and Leonardo Meeus. 2018. “Future-Proof Tariff Design: Recovering Sunk Grid Costs in a World Where Consumers Are Pushing Back.” *Energy Economics* 70: 484–498. doi:10.1016/j.eneco.2018.01.028.

Schittekatte, Tim, Michael Stadler, Gonçalo Cardoso, Salman Mashayekh, and Narayanan Sankar. 2016. “The Impact of Short-Term Stochastic Variability in Solar Irradiance on Optimal Microgrid Design.” *IEEE Transactions on Smart Grid* 99. doi:10.1109/TSG.2016.2596709.

Siddiqui, S., and S. A. Gabriel. 2013. “An SOS1-Based Approach for Solving MPECs with a Natural Gas Market Application.” *Networks and Spatial Economics* 13 (2): 205–27. doi:10.1007/s11067-012-9178-y.

Simshauser, Paul. 2016. “Distribution Network Prices and Solar PV: Resolving Rate Instability and Wealth Transfers through Demand Tariffs.” *Energy Economics* 54. Elsevier B.V.: 108–22. doi:10.1016/j.eneco.2015.11.011.

Šúri, Marcel, Thomas A. Huld, Ewan D. Dunlop, and Heinz A. Ossenbrink. 2007. “Potential of Solar Electricity Generation in the European Union Member States and Candidate Countries.” *Solar Energy* 81 (10): 1295–1305. doi:10.1016/j.solener.2006.12.007.

Wood, Lisa, Ross Hemphill, John Howat, Ralph Cavanagh, Severin Borenstein, Jeff Deason, and Lisa Schwartz. 2016. “Recovery of Utility Fixed Costs: Utility, Consumer, Environmental and Economist Perspectives.” doi:10.2172/1342757.

A. Appendix: the mathematical model

A1. 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
$\mathrm{SystemOtherCosts}$: all other costs paid through the electricity bill, e.g. policy costs, annualised and scaled per consumer [€]
DGC_i : Default 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/$\mathrm{kW_{peak}}$]
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 [€/$\mathrm{kW_{peak}}$]
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 [€/$\mathrm{kW_{peak}}$]
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]
$SystemGridCost$: Total annualised grid cost, scaled per average consumer [€]
$SystemDERcosts$: Total annualised investment cost in DER, scaled per average consumer [€]
$SystemEnergyCosts$: 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 [€]
$pw_{t,i}$: Energy bought at time step t by agent i [kW]
$pi_{t,i}$: Energy sold at time step t by agent i [kW]
$pmax_i$: 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]
$pbout_{t,i}$: Discharge of the battery of agent i at step t [kW]
$pbin_{t,i}$: 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]

A2. Original optimisation problems

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

Objective function, the minimisation of total system costs:

$$\text{Minimise } SystemGridCosts + SystemDERcosts + SystemEnergyCosts + \text{SystemOtherCosts} \quad (A.1)$$

With its components being:

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

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

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

Finding the aggregated peak demand in absolute value:

$$CoincidentPeak = \max(CPeakDemand, CPeakInjection) \quad (A.5)$$

$$CPeakDemand \geq \sum_{i=1}^{N} \text{PC}_i * \left(qw_{t,i} - qi_{t,i}\right) \quad \forall t \quad (A.6)$$

$$CPeakInjection \geq \sum_{i=1}^{N} \text{PC}_i * \left(qi_{t,i} - qw_{t,i}\right) \quad \forall t \quad (A.7)$$

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

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

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

The lower level problem for an electricity cost minimising consumer

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

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

With:

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

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

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

Constraints (including duals):

$$qw_{t,i} - qi_{t,i} + is_i * \text{SY}_{t,i} + qbout_{t,i} - qbin_{t,i} - \text{D}_{t,i} = 0 \quad \forall\, i,t \quad (\mu^a_{t,i}) \quad (A.14)$$

$$soc_{1,i} - qbin_{1,i} * \text{EFC} * \text{DT} + (qbout_{1,i}/\text{EFD}) * \text{DT} - \text{SOC}_0 = 0 \quad \forall\, i \quad (\mu^b_{1,i}) \quad (A.15)$$

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

$$soc_{T,i} - \text{SOC}_0 = 0 \quad \forall\, i \quad (\mu^c_i) \quad (A.17)$$

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

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

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

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

$$-qw_{t,i} \leq 0 \quad \forall\, t, i \quad (\lambda^e_{t,i}) \quad (A.22)$$

$$-qi_{t,i} \leq 0 \quad \forall\, t, i \quad (\lambda^f_{t,i}) \quad (A.23)$$

$$-soc_{t,i} \leq 0 \quad \forall\, t, i \quad (\lambda^g_{t,i}) \quad (A.24)$$

$$-qbout_{t,i} \leq 0 \quad \forall\, t, i \quad (\lambda^h_{t,i}) \quad (A.25)$$

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

$$is_i - \text{MS}_i \leq 0 \quad \forall\, i \quad (\lambda^j_i) \quad (A.27)$$

$$ib_i - \text{MB}_i \leq 0 \quad \forall\, i \quad (\lambda^k_i) \quad (A.28)$$

$$-is_i \leq 0 \quad \forall\, i \quad (\lambda^l_i) \quad (A.29)$$

$$-ib_i \leq 0 \quad \forall\, i \quad (\lambda^m_i) \quad (A.30)$$

$$-qmax_i \leq 0 \quad \forall\, i \quad (\lambda^n_i) \quad (A.31)$$

$$\lambda^a_{t,i}, \lambda^b_{t,i}, \lambda^c_{t,i}, \lambda^d_{t,i}, \lambda^e_{t,i}, \lambda^f_{t,i}, \lambda^g_{t,i}, \lambda^h_{t,i}, \lambda^i_{t,i} \geq 0 \quad \forall\, t, i \quad (A.32)$$

$$\lambda^j_{t,i}, \lambda^k_{t,i}, \lambda^l_{t,i}, \lambda^m_{t,i}, \lambda^n_{t,i}, \geq 0 \quad \forall\, i \quad (A.33)$$

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^a_k) needed to discretise the bilinear product (including vnt) in Eq. (A.8)

l: 1…L: Index of auxiliary binaries (b^c_l) 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 [%]

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

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

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

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

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

Variables

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

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

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

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

$r^a_{t,i}, r^b_{t,i}, r^c_{t,i}, r^d_{t,i}, r^e_{t,i}, r^f_{t,i}, r^g_{t,i}, r^h_{t,i}, r^i_{t,i}, r^j_i, r^k_i, r^l_i$ and r^m_i: 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.32-33) 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%.

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

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

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:

$$z_k^a \geq 0 \quad \forall k \quad (A.42) \quad \text{and} \quad z_l^b \geq 0 \quad \forall l \quad \text{(A.43)}$$

$$z_k^a \leq \mathrm{M^{Da}} * b_k^a \quad \forall k \quad (A.44) \quad \text{and} \quad z_l^b \leq \mathrm{M^{Db}} * b_l^b \quad \forall l \quad \text{(A.45)}$$

$$q^{tot} - z_k^a \geq 0 \quad \forall k \quad (A.46) \quad \text{and} \quad qmax^{tot} - z_l^b \geq 0 \quad \forall l \quad \text{(A.47)}$$

$$q^{tot} - z_k^a \leq \mathrm{M^{Da}} * (1 - b_k^a) \quad \forall k \quad (A.48) \quad \text{and} \quad qmax^{tot} - z_l^b \leq \mathrm{M^{Db}} * (1 - b_l^b) \quad \forall l \quad \text{(A.49)}$$

Karush-Kuhn-Tucker conditions of the lower level

$$\mathrm{WDT} * (\mathrm{EBP}_t + vnt) + \mu_{t,i}^a + \lambda_{t,i}^a - \lambda_{t,i}^e = 0 \quad \forall t,i \quad \text{(A.50)}$$

$$-\mathrm{WDT} * (\mathrm{ESP}_t + \mathrm{NM} * vnt) - \mu_{t,i}^a + \lambda_{t,i}^a - \lambda_{t,i}^f = 0 \quad \forall t,i \quad \text{(A.51)}$$

$$cnt - \sum_t \lambda_{t,i}^a = 0 \quad \forall i \quad \text{(A.52)}$$

$$\mu_{t,i}^b - \mu_{t+1,i}^b * (1 - \mathrm{LT} * \mathrm{DT}) + \lambda_{t,i}^b - \lambda_{t,i}^g = 0 \quad \forall t \neq \{\mathrm{T}\}, i \quad \text{(A.53)}$$

$$\mu_{T,i}^b + \mu_i^c + \lambda_{T,i}^b - \lambda_{T,i}^g = 0 \quad \forall t = \mathrm{T}, i \quad \text{(A.54)}$$

$$\mu_{t,i}^a + \frac{\mu_{t,i}^b}{\mathrm{EFD}} * \mathrm{DT} + \lambda_{t,i}^c - \lambda_{t,i}^h = 0 \quad \forall t,i \quad \text{(A.55)}$$

$$-\mu_{t,i}^a - \mu_{t,i}^b * \mathrm{EFC} * \mathrm{DT} + \lambda_{t,i}^d - \lambda_{t,i}^i = 0 \quad \forall t,i \quad \text{(A.56)}$$

$$\mathrm{AICS} + \sum_t \mu_{t,i}^a * \mathrm{SY_{t,i}} + \lambda_i^j - \lambda_i^l = 0 \quad \forall i \quad \text{(A.57)}$$

$$\mathrm{AICB} - \sum_t \mu_{t,i}^b - \sum_t \lambda_{t,i}^c * \mathrm{BDR} - \sum_t \lambda_{t,i}^d * \mathrm{BCR} + \lambda_i^k - \lambda_i^m = 0 \quad \forall i \quad \text{(A.58)}$$

$$qw_{t,i} - qi_{t,i} + is_i * \mathrm{SY}_{t,i} + qbout_{t,i} - qbin_{t,i} - \mathrm{D}_{t,i} = 0 \quad \mu_{t,i}^a free \quad \forall t,i \quad \text{(A.59)}$$

$$soc_{1,i} - qbin_{1,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{1,i}}{\mathrm{EFD}} * \mathrm{DT} - \mathrm{SOC_0} = 0 \quad \mu_{1,i}^b\ free \quad \forall i \quad \text{(A.60)}$$

$$soc_{t,i} - qbin_{t,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{t,i}}{\mathrm{EFD}} * \mathrm{DT} - soc_{t-1,i} * (1 - \mathrm{LR} * \mathrm{DT}) = 0 \quad \mu_{t\neq 1,i}^b free \quad \forall t \neq 1, i \quad \text{(A.61)}$$

$$soc_{T,i} - \mathrm{SOC_0} = 0 \quad \mu_i^c\ free \quad \forall i \quad \text{(A.62)}$$

$$0 \leq qmax_i - qw_{t,i} - qi_{t,i} \quad \perp \ \lambda_{t,i}^a \geq 0 \quad \forall t,i \quad \text{(A.63)}$$

$$0 \leq ib_\mathrm{i} - soc_{t,i} \quad \perp \ \lambda_{t,i}^b \geq 0 \quad \forall t,i \quad \text{(A.64)}$$

$$0 \leq ib_\mathrm{i} * \mathrm{BDR} - qbout_{t,i} \quad \perp \ \lambda_{t,i}^c \geq 0 \quad \forall t,i \quad \text{(A.65)}$$

$$0 \leq ib_\mathrm{i} * \mathrm{BCR} - qbin_{t,i} \quad \perp \ \lambda_{t,i}^d \geq 0 \quad \forall t,i \quad \text{(A.66)}$$

$$0 \leq qw_{t,i} \quad \perp \ \lambda^{e}_{t,i} \geq 0 \quad \forall\, t,i \tag{A.67}$$

$$0 \leq qi_{t,i} \quad \perp \ \lambda^{f}_{t,i} \geq 0 \quad \forall\, t,i \tag{A.68}$$

$$0 \leq soc_{t,i} \quad \perp \ \lambda^{g}_{t,i} \geq 0 \quad \forall\, t,i \tag{A.69}$$

$$0 \leq qbout_{t,i} \quad \perp \ \lambda^{h}_{t,i} \geq 0 \quad \forall\, t,i \tag{A.70}$$

$$0 \leq qbin_{t,i} \quad \perp \ \lambda^{i}_{t,i} \geq 0 \quad \forall\, t,i \tag{A.71}$$

$$0 \leq \mathrm{MS}_i - is_i \quad \perp \ \lambda^{j}_{i} \geq 0 \quad \forall\, i \tag{A.72}$$

$$0 \leq \mathrm{MB}_i - ib_i \quad \perp \ \lambda^{k}_{i} \geq 0 \quad \forall\, i \tag{A.73}$$

$$0 \leq is_i \quad \perp \ \lambda^{l}_{i} \geq 0 \quad \forall\, i \tag{A.74}$$

$$0 \leq ib_i \quad \perp \ \lambda^{m}_{i} \geq 0 \quad \forall\, i \tag{A.75}$$

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.

$$SystemGridCost * (1 - \delta) - \Delta\gamma * \textstyle\sum_k 2^{k-1} * z^{a}_{k} + \Delta\partial * \sum_l 2^{l-1} * z^{b}_{l} + fnt \leq 0 \tag{A.76}$$

$$-SystemGridCost * (1 + \delta) - \Delta\gamma * \textstyle\sum_k 2^{k-1} * z^{a}_{k} + \Delta\partial * \sum_l 2^{l-1} * z^{b}_{l} + fnt \leq 0 \tag{A.77}$$

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.

$qmax_i - qw_{t,i} - qi_{t,i} \leq \mathrm{M^a} * \left(1 - r^{a}_{t,i}\right) \quad \forall\, t,i$ (A.78) and $\lambda^{a}_{t,i} \leq \mathrm{M^a} * r^{a}_{t,i} \quad \forall\, t,i$ (A.79)

$ib_i - soc_{t,i} \leq \mathrm{M^b} * \left(1 - r^{b}_{t,i}\right) \quad \forall\, t,i$ (A.80) and $\lambda^{b}_{t,i} \leq \mathrm{M^b} * r^{b}_{t,i} \quad \forall\, t,i$ (A.81)

$ib_i * \mathrm{BDR} - qbout_{t,i} \leq \mathrm{M^c} * \left(1 - r^{c}_{t,i}\right) \quad \forall\, t,i$ (A.82) and $\lambda^{c}_{t,i} \leq \mathrm{M^c} * r^{c}_{t,i} \quad \forall\, t,i$ (A.83)

$ib_i * \mathrm{BCR} - qbin_{t,i} \leq \mathrm{M^d} * \left(1 - r^{d}_{t,i}\right) \quad \forall\, t,i$ (A.84) and $\lambda^{d}_{t,i} \leq \mathrm{M^d} * r^{d}_{t,i} \quad \forall\, t,i$ (A.85)

$qw_{t,i} \leq \mathrm{M^e} * \left(1 - r^{e}_{t,i}\right) \quad \forall\, t,i$ (A.86) and $\mathrm{WDT} * (\mathrm{EBP_t} + vnt) + \mu^{a}_{t,i} + \lambda^{a}_{t,i} \leq \mathrm{M^e} * r^{\mathrm{e}}_{t,i} \quad \forall\, t,i$ (A.87)

$qi_{t,i} \leq \mathrm{M^f} * \left(1 - r^{f}_{t,i}\right) \quad \forall\, t,i$ (A.88) and

$-\mathrm{WDT} * (\mathrm{ESP_t} + vnt * \mathrm{NM}) - \mu^{a}_{t,i} + \lambda^{a}_{t,i} \leq \mathrm{M^f} * r^{f}_{t,i} \quad \forall\, t,i$ (A.89)

$soc_{t,i} \leq \mathrm{M^g} * \left(1 - r^{g}_{t,i}\right) \quad \forall\, t,i$ (A.90) and $\lambda^{g}_{t,i} \leq \mathrm{M^g} * r^{g}_{t,i} \quad \forall\, t,i$ (A.91)

$qbout_{t,i} \leq \mathrm{M^h} * \left(1 - r^{h}_{t,i}\right) \quad \forall\, t,i$ (A.92) and $\mu^{a}_{t,i} + \frac{\mu^{b}_{t,i}}{\mathrm{EFD}} * \mathrm{DT} + \lambda^{c}_{t,i} \leq \mathrm{M^h} * r^{h}_{t,i} \quad \forall\, t,i$ (A.93)

$qbin_{t,i} \leq \mathrm{M^i} * \left(1 - r^{i}_{t,i}\right) \quad \forall\, t,i$ (A.94) and $-\mu^{a}_{t,i} - \mu^{b}_{t,i} * \mathrm{EFC} * \mathrm{DT} + \lambda^{d}_{t,i} \leq \mathrm{M^i} * r^{i}_{t,i} \ \forall\, t,i \quad \forall\, t,i$ (A.95)

$\mathrm{MS}_i - is_i \leq \mathrm{M^j} * \left(1 - r^{j}_{i}\right) \quad \forall\, i$ (A.96) and $\lambda^{j}_{i} \leq \mathrm{M^j} * r^{j}_{i} \quad \forall\, i$ (A.97)

$\mathrm{MB_i} - ib_i \leq \mathrm{M^k} * \left(1 - r^{k}_{i}\right) \quad \forall\, i$ (A.98) and $\lambda^{k}_{i} \leq \mathrm{M^k} * r^{k}_{i} \quad \forall\, i$ (A.99)

$is_i \leq \mathrm{M^l} * \left(1 - r^{l}_{i}\right) \quad \forall\, i$ (A.100) and $\mathrm{AICS} + \sum_t \mu^{a}_{t,i} * \mathrm{SY}_{t,i} + \lambda^{j}_{i} \leq \mathrm{M^l} * r^{l}_{i} \quad \forall\, i$(A.101)

$ib_i \leq \mathrm{M^m} * (1 - r^{m}_{i}) \quad \forall\, i$ (A.102) and

$\mathrm{AICB} - \sum_t \lambda^{b}_{t,i} - \sum_t \lambda^{c}_{t,i} * \mathrm{BDR} - \sum_t \lambda^{d}_{t,i} * \mathrm{BCR} + \lambda^{k}_{i} \leq \mathrm{M^m} * r^{m}_{i} \quad \forall\, i$ (A.103)

Author contacts:

Tim Schittekatte (Corresponding author)

Florence School of Regulation, Robert Schuman Centre for Advanced Studies, European University Institute, Via Boccaccio 121, I-50133 Florence, Italy

Réseaux Innovation Territoire et Mondialisation Université Paris-Sud, 91400 Orsay, France

Vlerick Business School, Vlerick Energy Centre, Bolwerklaan 21, B-1210 Brussels, Belgium

Email: tim.schittekatte@eui.eu

Leonardo Meeus

Florence School of Regulation, Robert Schuman Centre for Advanced Studies, European University Institute, Via Boccaccio 121, I-50133 Florence, Italy

Vlerick Business School, Vlerick Energy Centre, Bolwerklaan 21, B-1210 Brussels, Belgium

Email: leonardo.meeus@vlerick.com