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

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Abstract[1]

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

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

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1. **Introduction**

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

Historically, volumetric distribution network charges (€/kWh) were in place in most jurisdictions around the world. This practice is being challenged in recent years. More specifically, volumetric charges with net-metering, implying that a consumer's network charges are proportional to its net consumption from the grid over a period of time (e.g. month), are deemed inadequate with the massive deployment of solar PV. Consumers with solar PV pay significantly lower network charges but still rely on the distribution grid as much as they did before. In other words, such network charges serve as an implicit subsidy for solar PV which ends up being paid by consumers without solar PV.[2] Therefore, regulators in many countries are thinking to suspend net-metering and move more towards network tariffs which are capacity-based (€/kW) or stimulate self-consumption of the on-site generated electricity (CEER, 2017; European Commission, 2015; Hledik, 2014). Such types of distribution network charges are deemed to align better what consumers pay for the network with the costs they cause. Batteries are identified as a key enabling technology to allow the reduction of capacity needs of a consumer or to allow for more self-consumption.

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

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

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

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

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

2. Evaluated distribution network tariff designs

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

2.1 Capacity-based network charges

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

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

2.2 Self-consumption incentivising network charges

Besides capacity-based network charges, we also evaluate two distribution network tariff design that stimulates self-consumption.[3] With net-purchase volumetric charges, a consumer pays a €/kWh fee for all electricity withdrawn from the network. Contrarily to the historical practice of volumetric charges with net-metering, the meter does not turn backwards when excess electricity is injected in

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

the network. With bi-directional volumetric network charges, a €/kWh network fee is paid for each kWh of electricity withdrawn and injected into the network.[4]

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

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

3. **Methodology**

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

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

model serves as a first-best benchmark. The full formulation of both models can be found in the Appendix A.

3.1 Game-theoretical model

The game-theoretical model has a bi-level structure. A regulator is represented in the upper-level. The regulator decides upon the distribution network tariff in place anticipating the reactions of the consumers represented in the lower-level. The objective of the regulator is to minimise the total system cost under the condition that the total network costs equal the network charges collected from the consumers. The total system costs consist of four components: total grid costs, total retailer energy costs, total DER investment costs and other costs.[5] The relative share of the different components of the total system costs are a function of the incentives of the consumers, i.e. the mix of the energy sourced from the retailer and delivered by the grid and the energy delivered directly from installed DER at the consumer-side.

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

Consumers react to the electricity bill as a whole, but the accounting of the cost components is separate as we consider an unbundled setting. Besides the endogenously considered network charges, the consumers buy electricity, the commodity, from a retailer who bought this energy in the wholesale market and sells it to downstream consumers for an exogenous price. Finally, next to the retailer energy price and the network charges, a consumer pays taxes and levies; the level of these costs is

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

considered invariant, and the way these are collected does not interfere with the analysis. 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 the cost to satisfy their electricity demand. They have the option to invest in two technologies, solar PV and batteries, to lower their dependence on grid supplied electricity.

The incentives of the active consumers will not always align with system benefits and can have negative distributional consequences. An intuitive example is what happens with volumetric charges with net-metering in place. In that case, an active consumer will be incentivised to install solar PV; the investment cost of solar PV is compared to the avoided retailer energy costs ánd network charges. From a system perspective, the total retailer energy costs will go down as consumers buy less energy from the retailer, the total DER investment costs will go up due to investment in solar PV and the total grid costs will more or less stay the same as stand-alone solar PV does not affect the grid costs much. High PV generation and the aggregated consumer peak demand often do not coincide. As a result, the reduction in grid charges for consumers is higher than the avoided grid cost. Overall, the total system costs might even go up due to the solar PV adoption compared to a situation in which no consumer installs solar PV.[6] In addition, the network charges (in €/kWh) need to increase to allow full grid cost recovery. As a result of this increase, mostly passive consumers, which did not install solar PV, will see their electricity bill increase. Similarly, in this paper, we focus on battery adoption and do this analysis for capacity-based charges, net-purchase volumetric charges, bi-directional volumetric charges in Sections 5.1 to 5.3 and for (time-varying) peak-coincident network charges in Section 6.

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

3.2 Central planner model

Besides the game-theoretical model, a centralised planner model is used as a benchmark. The difference with the game-theoretical model is that there is no distribution network tariff formulated

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

in the central planner model; the consumers do not need to be coordinated. Instead of consumers acting in their own interest, the central planner decides unilaterally about their actions. [7] The central planner model is formulated as a linear programme (LP). By comparing the results for the evaluated network tariff designs with the game-theoretical model and this benchmark, we can show how much storage is under- or over incentivised due to imperfect distribution network tariff design. Also, the impact on system cost due to the imperfect network tariff design can be estimated.

4. Numerical example

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

4.1 Consumer types, demand and solar yield

Two consumer types are modelled for simplicity: passive and active consumers, as is also done in Brown and Sappington (2017a, 2017b, 2018) and Schittekatte et al. (2018). The passive consumer does not have the option to invest in solar PV and batteries, unlike an active consumer, who can opt to invest in DER. Passive consumers do not have the financial means, are strongly risk averse or are uninformed about the possibility to invest in DER. Active consumers minimise their costs to meet their electricity demand and may invest in DER to do so. At one extreme, all consumers can be passive, as in the recent past. At the other extreme, all consumers can be active, i.e. install DER when it can reduce their overall electricity cost. Reality presumably lies in the middle. Some consumers will remain passive for a number of reasons. Other consumers could be installing DER even when they do not financially profit from it, but because of other reasons which are harder to monetise, e.g. independence from the grid, sustainability motives etc. In the numerical example, it is assumed that 50% of all consumers are active and 50% are passive.[8] The consumer demand and solar PV yield profiles are represented

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

[8] 50 % active consumer might seem quite a lot today. Today many consumers are passive because they are indifferent or vulnerable. A lower proportion of active consumers result in a lower impact of distortive network tariff design on total system costs. However, distortions result in costs shifts from active to passive consumers. In their turn, these cost shifts could again convert more (indifferent) passive consumers into active ones, increasing the impact of the distortion. Also, with dropping costs in DER, rising electricity bills, digitalisation and more climate awareness, a proportion of indifferent passive consumers might turn active.

using a time series of 48-hours with hourly time steps and are shown in Figure 1 (left). The yield per kWp of solar PV installed is shown in Figure 1 (right).

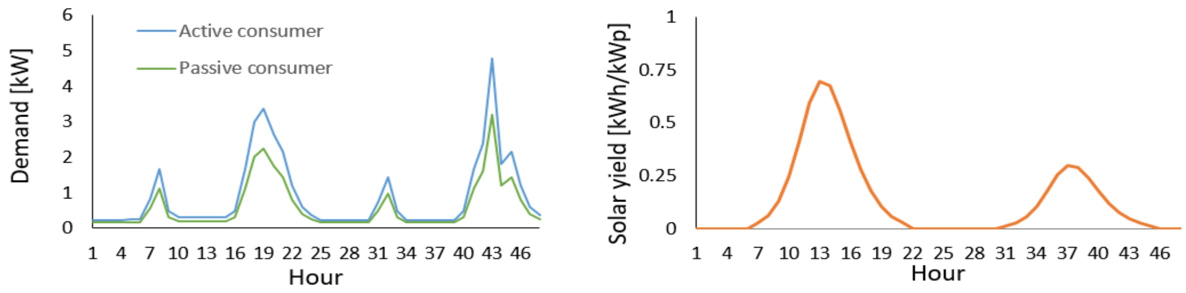

Figure 1: Original 48-hour electricity demand profiles (left) and PV yield profile (right)

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

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

4.2 Baseline consumer bills

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

Table 1: Consumer bill in the baseline scenario (no investment in DER by active consumers)

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

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

4.3 Grid cost structure

The values for the parameters of the grid cost function (Eq. A.9) are derived from the 'baseline network costs' of the modelled consumers (shown in Table 1) and are a function of the proportion of active and passive consumers. With 50 % active and 50 % passive consumers, the (scaled) coincident consumer peak demand equals 4 kW in the baseline scenario, and the average grid costs equal 404 €/consumer.[9]

In Section 5.1 grid costs are assumed 100% sunk. In Section 5.2-6, all grid costs are assumed to be driven by consumers. In that case, the incremental grid cost is set to 101 €/kW. As a reference, Brown et al. (2015) assume the (annualised) cost to be 75$/kW.

4.4 DER investment cost and technical parameters

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

The investment cost of solar PV is set equal to 1250 €/kWp. Under flat energy prices, this means that the levelised cost of energy (LCOE) of solar PV is 0.086 €/kWh.[10] Excluding grid charges, an active consumer is assumed to receive 98 % of the retailer energy price when injecting solar energy.[11] An important assumption is that no investment subsidy for PV is introduced in this work and no reduced social losses from environmental externalities due to the installation of solar PV are accounted for. Table 2 shows the other DER parameters. 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*
Lifetime PV	20 years	Lifetime battery	10 years
Discount factor PV	5 %	Discount factor battery	5 %
Maximum solar capacity installed	5 kWp	Maximum battery capacity installed	No limit
Price received for electricity injected (% of retailer energy price)	98 %	Efficiency charging & discharging	90 %
		Leakage rate	2 %

[9] 4kW = 0.5*4.8 kW + 0.5*3.2 kW and 404 € = 0.5*485 € + 0.5*324 €

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

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

Sensitivity is done regarding the batteries investment costs. Investment costs between 350 €/kWh and 100 €/kWh with steps of 50 €/kWh are tested for. All batteries are assumed to have a C-rate of 1, i.e. the battery can fully (dis)charge in one hour. Schmidt et al. (2017) find that regardless of electricity storage technology, capital costs are on a trajectory towards US$ 340± 60kWh^{-1} for installed stationary systems and US$175±25$kWh^{-1}$ for battery packs by 2027-2040. Hledik et al. (2018) review many studies and are more bullish. They state that the investment cost of residential storage could be declined to 250 $/kWh by 2025.

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

5. **Results**

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

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

5.1 Sunk grid costs

First, grid costs are assumed to be 100% sunk, a short-term vision, i.e. the grid is over-dimensioned, and the electricity usage of consumers has no effect on the total grid costs. In some countries, also policy costs are recovered through the network charges, which from a cost allocation point of view is no different than recovering sunk network costs. In Table 3, the capacity of the battery installed per active consumer is shown for the different distribution network tariff designs. Sensitivity analysis regarding the investment costs of the batteries is done. The benchmark is the central planner. Also fixed network charges (€/consumer) give the same results as the central planner. This is true as it is assumed that all grid costs are sunk, no consumers go off-grid completely and that all externalities (e.g. CO_2 emissions) are priced correctly in the other components of the electricity bill.

The results are split up in three parts to single out the interaction between investment in solar PV and batteries by active consumers. First, it is assumed that there is no possibility for the active consumer to invest in solar PV. Second, the active consumer is free to install solar PV up to 5 kWp if this investment lowers its costs to fulfil its electricity needs. Third, it is assumed that the active consumer always installs a 5 kWp solar PV installation at its premises.[12]

Table 3: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed sunk.

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

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

Figure 2 shows the impact on the total system costs of the different distribution network tariff designs. Again the results are split up for the three cases of solar PV investment and the results are shown relative to the benchmark.

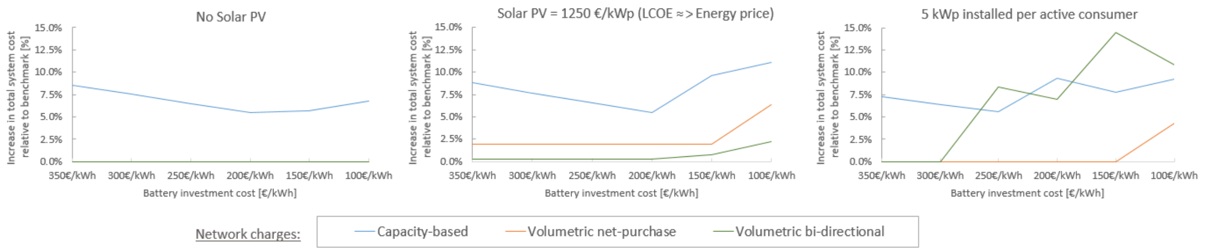

Figure 2: Increase in total system costs for the three network tariff structures when compared with the benchmark. Sensitivity for three different assumptions regarding solar PV adoption and the investment cost of storage.

Three observations can be made from Table 3 and Figure 2. First, capacity-based network charges over-incentivise battery adoption for all runs. Under capacity-based charges, active consumers can lower their individual peak demand by investing in a battery. By lowering their peak demand, they reduce their individual grid charges to be paid. But as we assume that grid costs are sunk, the total grid costs do not reduce. Therefore, when looking at the overall system cost in Figure 2, an increase results due to the investment in batteries by active consumers and accompanied energy losses in the battery. The reductions in grid charges by the active consumers are simply transferred to the passive consumers who see their electricity bill increase, and the investment cost in batteries by active consumers adds to the total system costs. The blue line in the left graph in Figure 2, which represents the cost of the distortion under the given assumptions, has a U-shape. This can be explained by the fact that the cost of the distortion is a function of the capacity of batteries adopted, the losses in the batteries and the investment costs of batteries. Logically, the cheaper batteries are, the higher the capacity of the batteries installed and the higher the losses are but, the lower the cost per kWh of battery installed. The results for when active consumers can invest in both batteries and solar PV in Table 3 show that there are some synergies between solar PV and battery investment under capacity-based network charges; higher capacities of solar PV are installed than under the benchmark network tariff, and the capacity of the batteries generally increases when compared to the case when no solar PV investment is enabled.

The second observation is that no investment in batteries is made under the network tariff designs which incentivise self-consumption when no solar PV investment is enabled or when batteries are relatively expensive. It makes sense that under these network tariff designs, no batteries are invested in when no solar PV is enabled. In that case, the only other potential revenue from a battery investment would be arbitraging the energy price, but the energy price is assumed constant. This assumption is relaxed in Section 5.3. The left graph in Figure 2 shows that these two tariff structures have the same performance as the benchmark, i.e. they do not cause any distortions. The middle graph in Figure 2 shows that under net-purchase volumetric charges there is a constant minor distortion, excluding the case when the battery investment costs are 100 €/kWh. This can be explained by the fact that the active consumers each invest in 5 kWp while under the benchmark in no solar PV is invested; net-purchase volumetric charges over-incentivise solar PV adoption in this case.[13] The cost of the distortion is rather small as the LCOE of solar PV is just slightly higher than the energy price. A similar but less significant result is found for volumetric charges with bi-directional metering as less solar PV investment is done by the active consumers.

Third, when active consumers have solar PV installed, and batteries are relatively cheap, batteries with a significant capacity are invested in under the network tariff designs that strongly incentivises self-consumption. In that case, it makes sense for an active consumer to invest in a (relatively cheap) battery to avoid paying network charges by increasing self-consumption. We split this observation up into two. First, when the active consumer can choose to invest in solar PV, it can be seen in Table 3 that under net-purchase volumetric charges the over-investment in solar PV can suddenly also trigger a significant over-investment in batteries. This happens when the battery investment costs drop to a low level. Again, this battery investment does not lower the grid costs and slightly increase the retailer energy costs due to losses. Therefore, the orange line the middle graph in Figure 2 shows a strong increase at that point. Second, when assumed that 5 kWp solar PV is already installed per active consumer, batteries are most over-incentivised under bi-directional volumetric charges. As a result, the self-consumption rate increases from 32.4 % without batteries to 59.0 % with batteries of 250 €/kWh to finally 80.8 % when the cost of batteries reaches 150 €/kWh.[14] This means that if the cost of batteries drops to that low level (alternatively, if the grid charges are very high), it is optimal for an active consumer to install a battery in order to strongly reduce the injection of any electricity generated by its solar PV panels into the network. Figure 2 (right) shows that this distortion has a high cost at relative cheap battery prices. The cost of the distortions becomes even higher than under capacity-based charges.

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[13] 1/ This over-incentive is much less strong than under volumetric network charges with net-metering and a function of the coincidence of the solar PV generation and the demand of the consumer. 2/ This distortion vanishes in the right graph in Figure 2 as in that case also 5 kWp is assumed to be installed by the active consumers under the benchmark network tariff, thus there is no difference in solar PV investment anymore between the benchmark and net-purchase volumetric charges.

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

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

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

In Table 4, the capacity of the batteries installed per active consumer is shown for the different distribution network tariff designs. Again, sensitivity analysis regarding the investment costs of the batteries is conducted. The benchmark network tariff design is again the central planner. In this case, fixed network charges do not replicate the outcome of the central planner anymore. Namely, with fixed network charges, active consumers are not incentivised to adjust their electricity withdrawal or injection patterns and thus to limit the incurred network cost. A fully informed central planner who can decide unilaterally on behalf of the consumers on how many batteries to install and how to operate them in order to obtain the lowest system costs is the first best outcome. In reality, however, there is no central planner. Instead, consumer decisions are driven by price signals, in this case network tariffs.

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

Table 4: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated consumer peak demand.

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

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

Figure 3 shows the impact on the total system costs for the different distribution network tariff designs. Again, the results are split up for the three cases of solar PV investment, and the results are shown relative to the benchmark.

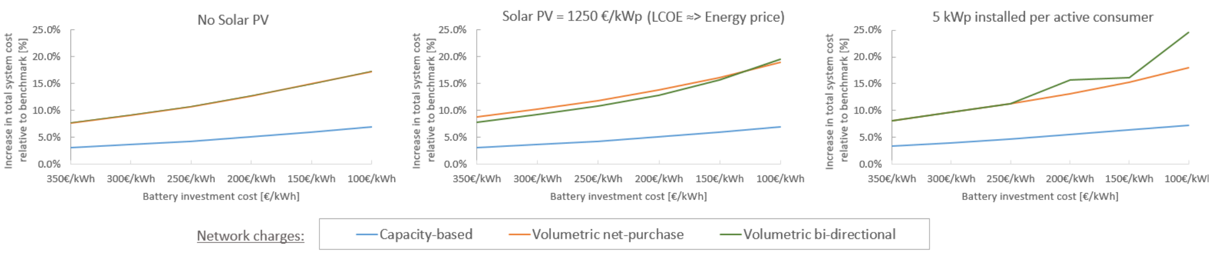

Figure 3: Increase in total system costs for the three network tariff structures when compared with a central planner. Sensitivity for three different assumptions regarding solar PV adoption and the investment cost of storage.

Four observations are derived from Table 4 and Figure 3. First, under capacity-based charges, batteries are always under-incentivised when all grid costs are driven by the aggregated peak demand. More striking, when comparing these results with the results in Table 3, it can be seen that batteries with a lower capacity are installed than in the case grid costs are assumed sunk even though they are more useful from a system perspective. This can be explained as follows. Under the grid cost assumption, each investment in batteries by active consumers increases the value of additional investment in batteries until a certain point of saturation. This happens as, by each investment in batteries, the network tariff needs to increase in order to recuperate all network costs which remain the same. Thus, the business case of batteries (and solar PV) improves with increasing DER adoption. Saturation occurs when it becomes very costly to lower individual network charges, e.g. further reduce the individual peak demand when it is already significantly lowered due to a certain investment in batteries. This ''race-to-the-bottom'' effect or non-cooperative behaviour is captured by the modelling formulation.[15] On the other hand, if grid costs are assumed to be driven by the aggregated peak demand and the network tariff in place adequately targets the network cost driver, an investment in batteries by active consumers can decrease the value of additional investment in DER. This effect is however ambiguous. Namely, each additional investment in batteries can lower the total grid costs. But at the same time, the grid charges paid by the active consumers will decrease as well. If the decrease in grid charges paid by the active consumer due to the adoption of batteries is lower in magnitude than the decrease in the total grid costs caused by their investment in batteries, all grid costs can be recuperated with a lower network tariff. In that case, an investment in batteries will decrease (''cannibalise'') the incentive to install additional battery capacity.[16] On the other hand, if the decrease in grid charges paid by the active consumer due to the adoption of batteries is higher than the magnitude of the decrease their investment caused on the total grid costs, the network tariff needs to increase to recuperate all grid costs. In this case, the same but weakened ''race-to-the-bottom'' effect as under the sunk grid assumption occurs.

The second observation is that not only batteries are under-invested in; active consumers also do not operate batteries in a way that their operation would lead to the lowest grid costs possible given the installed battery capacity. This is illustrated in the example shown in Figure 4; the results are shown for the run in which we assume that 5 kWp solar PV is installed by the consumer and batteries cost 100 €/kWh. It is clear that under capacity-based charges, the active consumers flatten their profile in order to lower the grid charges to be paid (2nd row - left graph). However, it is the aggregated demand profile of both active and passive consumers that drives the grid costs. The aggregated profile is also shown in Figure 4 (2nd row –right graph). It could be said that active consumers operating their battery under capacity-based charges are uninformed about the aggregated demand.[17] As such, the reduction of the aggregated peak demand is limited. Under the central planner approach, the active consumers significantly lower their demand at the time that the passive consumers have their peak. As a result, the aggregated peak, the one that really matters, is minimised.

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

[15] Its significance is mostly a function of the proportion of active consumers and the attractiveness of DER investments relative to the network tariff structure and the magnitude of its coefficients.

[16] Similarly, as each investment in solar PV lowers the price of energy around noon and thus decreases the incentive to install more solar PV as described in Hirth (2013).

[17] Capacity-based network charges would have the same outcome as the central planner in the case that all consumers are active and they all have exactly the same electricity demand profile. This is also verified with the model.

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

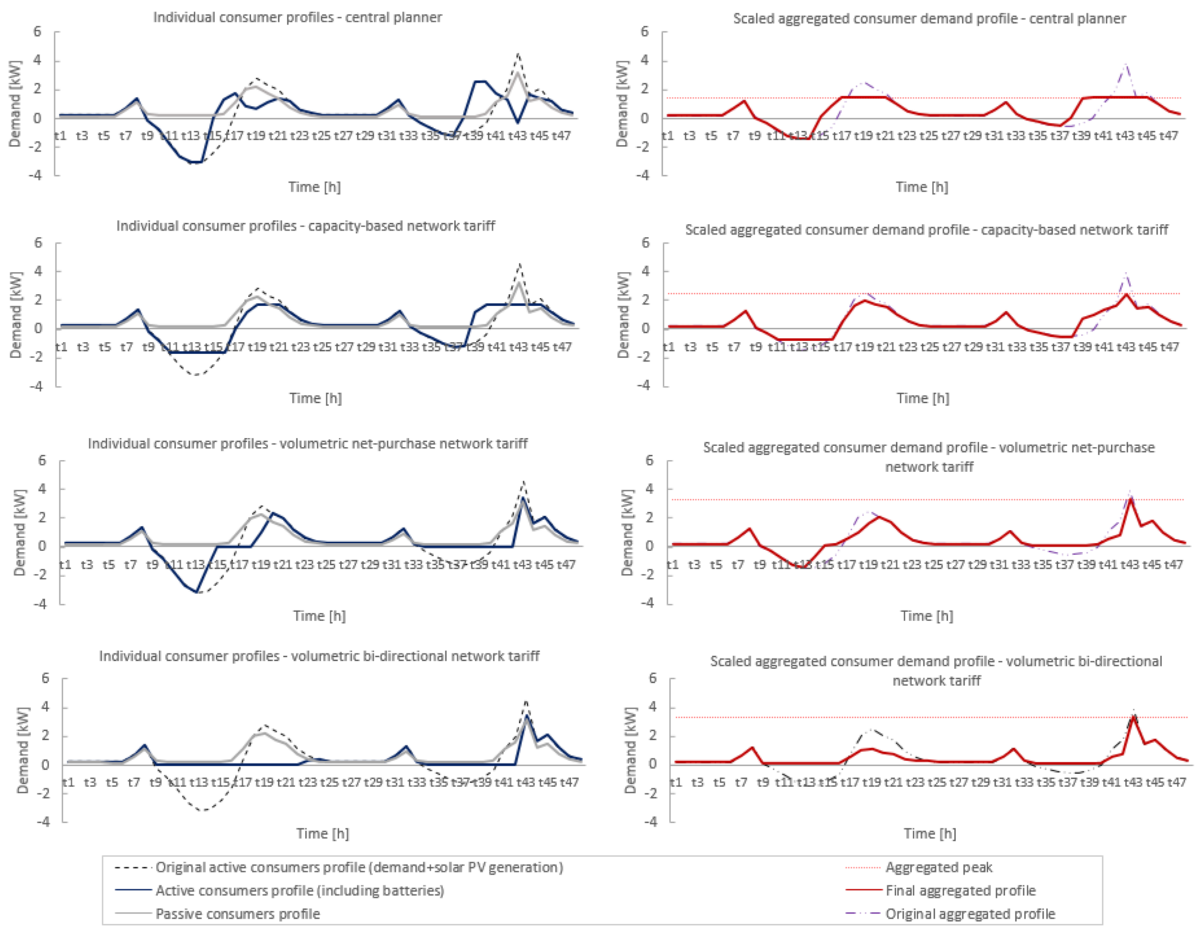

Figure 4: Reactions of active consumers to the different network tariff design and their impact on the aggregated load profile and peak. Assumption: 5 kWp solar PV already installed by the active consumer and battery investment cost of 100 €/kWh.

The third observation is that the two network tariff designs that incentivise self-consumption do not lead to investment in batteries if there is no solar PV installed by the active consumer or when there is solar PV installed, but batteries are relatively expensive. In other words, these network tariff designs block the business case of storage when not coupled with electricity generation behind the meter. Figure 3 shows that because of the fact that no batteries are installed, the system costs are significantly higher than in the central planner case.

Similar as in the case grid costs are assumed sunk, the fourth observation is that the two network tariff designs that incentivise self-consumption are shown to lead to significant investment in batteries if there is solar PV installed by the active consumer and batteries are relatively cheap. However, the investment in batteries does not result in a lower system cost as can be seen from Figure 3. Instead, the opposite occurs. The system cost increases relative to the benchmark. Figure 4 illustrates what happens. Indeed, the active consumers use the battery to increase self-consumption; under volumetric network charges with net-purchase 57.8 % of the electricity generated by solar PV is self-consumed for this example. This percentage increases further for bi-directional volumetric charges as also can be deducted from Figure 4, the self-consumption rate attained is 80.8 %.[18] However, the batteries are not operated in a way that their functioning leads to a lower aggregated peak demand. Instead, the batteries are used to store as much as self-produced electricity as possible until it is fully charged. After, the battery is used to fulfil the demand of the active consumers instead of grid supplied electricity. The discharging goes on until a point in time that the batteries are fully discharged. Looking at Figure 4, for this example, the batteries are fully discharged just before the time steps when aggregated peak demand is near its maximum. As a result, the aggregated peak demand decreases only very slightly.

Figure 5 summarises observations 1, 2 and 4 and further clarifies what happens regarding the total system cost for the example shown in Figure 4. The first vertical bar represents the baseline scenario, the case that no active consumer invests in DER. The proportions of the grid costs, energy retailer costs and taxes and levies are those as shown in Table 1. The next vertical bar represents the most optimal trade-off between the grid costs, retailer energy costs, solar PV and batteries for the given parameter settings. This optimal trade-off is the result of the central planner. This mix lowers the sum of the interacting components of the electricity bill to a total system cost which is 14 percentage points lower than the baseline.[19] In the example, capacity-based charges, also lead to a mix which lowers the total system costs relative to the baseline, however, not as much as the central planner. Mainly due to an under-incentive to invest in batteries and sub-optimal operational signals, the grid costs are not

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

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

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

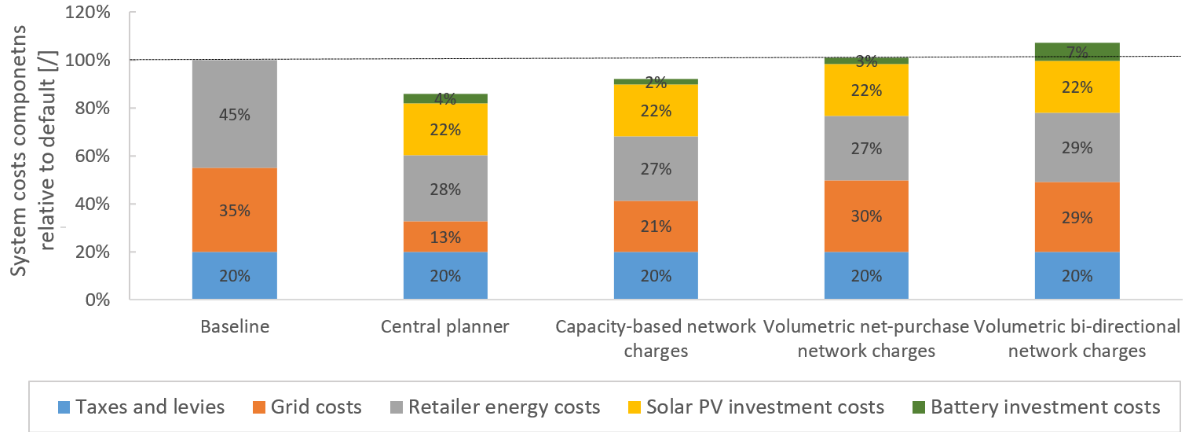

Figure 5: System costs and its components for the different network tariff designs. Assumption: 5 kWp solar PV already installed by the active consumer and battery investment cost of 100 €/kWh.

5.3 The impact of time-varying energy prices

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

In this section, we introduce two TOU energy pricing schemes besides the flat retailer energy prices. In the previous sections, a constant retailer energy price of 0.08 €/kWh is assumed. Figure 6 shows the two newly introduced options. The TOU1 profile is 'solar PV friendly' as during hours that solar PV is producing, an energy price is charged which is slightly higher than the flat energy charge. The TOU2 profile charges relatively high prices during the evening when consumer demand is expected to peak and charges a relatively low price during the hours that solar PV is producing a lot. The TOU2 profile is less 'solar PV friendly' but might induce battery investment due to significant relative changes in the energy price between the different periods. These daily energy price patterns are used as representative for the year. To be able to compare results among the three energy price profiles, the TOU1 and TOU2 profile are scaled to make sure that in the baseline scenario (no DER) the weighted average energy price per consumer type is equal over the different energy price profiles. Also, for the runs for which the PV investment is forced, the difference in avoided energy costs due to solar PV adoption with the different TOU energy price schemes are corrected for to be able to compare the results with flat retailer energy prices.

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

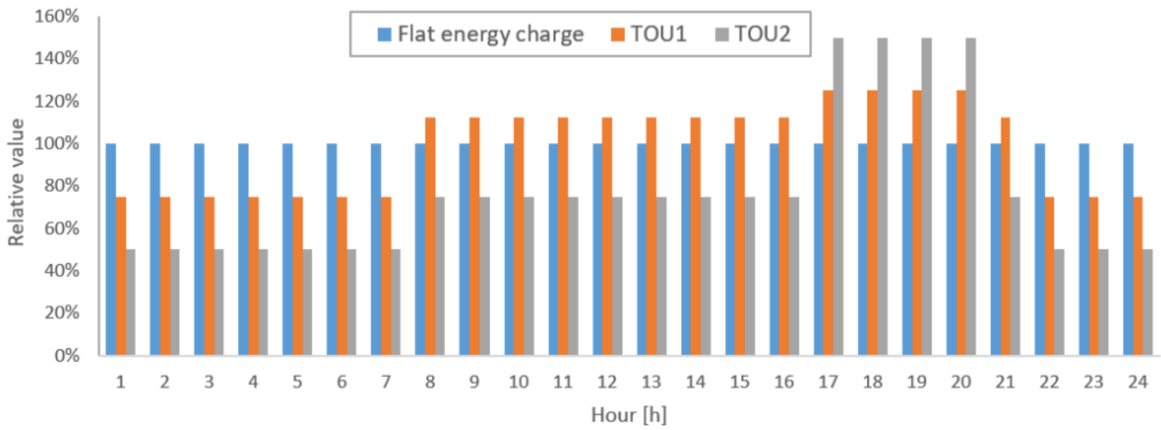

Figure 6: Three energy price schemes.

In Table 5, the results for the battery capacity installed per active consumer are shown for the different battery investment costs, distribution network tariff designs and energy price schemes. We assume that all grid costs are driven by the aggregated peak demand. We do three observations. First, when comparing the results in Table 5 with the results in Table 4, we see that indeed the battery capacity installed by the active consumers remains the same or in most cases increases under the TOU energy prices when compared to flat energy prices. This statement holds for the benchmark and the three evaluated distribution network tariff designs. Second, when comparing the two TOU energy price schemes, the TOU2 energy price scheme results in the highest increase in battery capacity installed for this numerical example. Third, interestingly, still no batteries are installed under the network tariffs that incentivise self-consumption if not combined with the adoption of solar PV. Even though with time-varying energy prices there is the additional opportunity to arbitrage the energy prices.

Table 5: Battery and solar PV investment per active consumer for the different network tariff designs and energy pricing schemes under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated peak demand.

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

By including TOU energy prices, not only the grid costs can be decreased due to battery adoption but also the retailer energy costs for active consumers can be lowered due to gains from arbitrage. Looking at the system-level, energy arbitrage by active consumers can have a significant impact on the wholesale energy market. However, because of the fact that the energy prices are not endogenous in the model, it cannot be easily assessed how the arbitrage actions of the active consumers would affect the wholesale energy prices. An extension of the modelling approach is needed. Whatsoever, what is clear is that imperfect network tariff design obstructs optimal energy arbitrage strategies. A consumer, when deciding about the adoption and operation of storage will look at the possible reduction in her final electricity bill, instead of at each separate cost component (network charges, energy costs and taxes and levies) in isolation. As a result, the interaction between network charges and energy prices has an impact on the business case of storage but also on the potential welfare gains from introducing time-varying instead of flat energy prices to residential consumers.

6. **Peak-coincident network prices: approximating the central planner outcome**

In the previous subsection, it is shown that none of the evaluated distribution network tariffs can replicate the outcome of the central planner. However, the evaluated network tariff designs are rather simple. In the literature, it is discussed that so-called critical peak-pricing or coincident peak-pricing can reproduce ideal incentive properties for consumers (see e.g. Abdelmotteleb et al. (2017), Baldick (2018) and Pérez-Arriaga et al. (2017)). In this work, we test what happens if we allow the upper-level regulator to set such time-varying network charges. Figure 7 shows the resulting peak-coincident network charges for the numerical example with the three energy prices schemes. The results are shown for the case we assume that the active consumers have 5 kWp solar PV installed and the battery investment costs are 250 and 100 €/kWh.

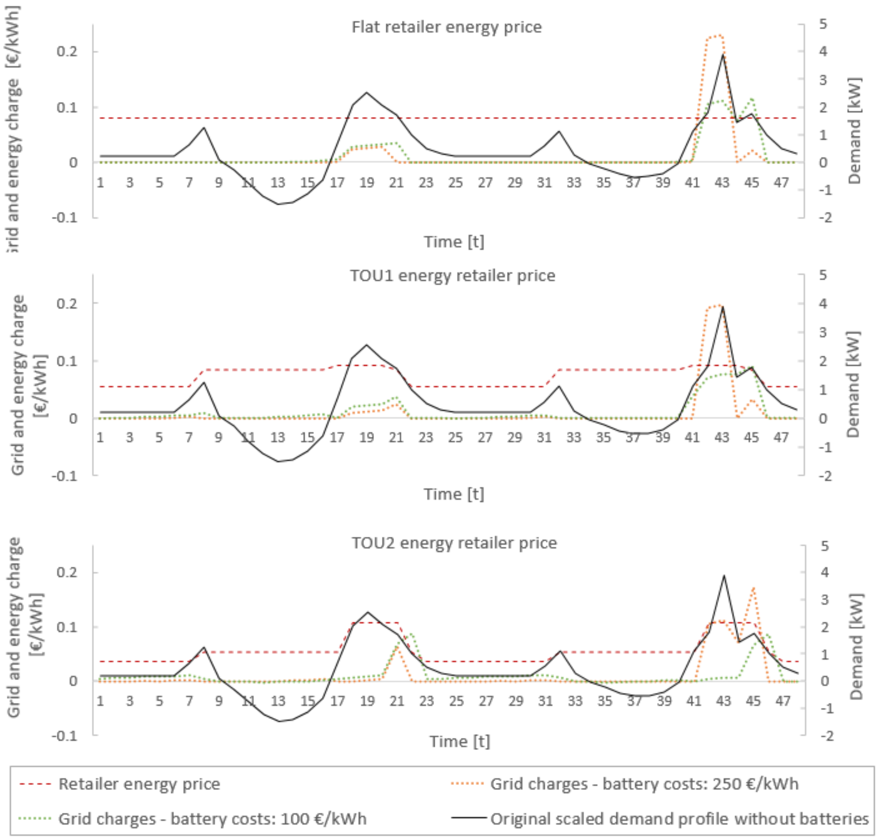

Figure 7: Examples of peak-coincident network prices for the case 5 kWp is installed by the active consumers. Sensitivity for the battery investment costs of 250 and 100 €/kWh.

As expected, it can be seen from Figure 7 that this more advanced network tariff exhibits peak prices at the time steps that the aggregated demand peaks and that network prices are equal to zero when the aggregated demand is rather low.[20] Additionally, it is shown that the network charges are a

[20] The peak-coincident network charges shown in 7 are obtained using a two-step process. First, the MPEC is solved. After solving the MPEC, the lowest possible system costs (the objective of the upper-level) is known. However, the network charges computed are not unique. Namely, the upper-level regulator can arbitrarily increase the time-varying network charge at time-steps that the elasticity of the consumers is very low without changing the obtained value of the objective function.

function of the investment cost of the batteries and the energy price scheme in place. Overall, the lower the battery investment cost, the wider but, the less steep the network peak prices. The width has to do with the fact that if batteries are cheaper and thus higher capacities are adopted, the number of time steps increases in which the aggregated demand reaches its maximum. During all these time steps a network price signal is needed. The decreasing steepness of the peak has to do with the fact that with cheaper batteries a less strong incentive is needed to reaches the optimal outcome.[21] If the peak price would be steeper, too many batteries could be invested in and vice-versa. Further, it can be seen that the network charges adjust with the energy prices scheme in place in order to send an adequate aggregated price signal to the consumers.

For this numerical example, the outcome obtained by these peak-coincident network charges in terms of battery investment and the total system cost is exactly the same or less than 1 % higher than under the central planner.[22] Overall, these results suggest that a more advanced network tariffs as formulated in this paper can approximate the outcome of a first-best outcome closely. A formal proof of how close the approximation is as a function of the parameters is out of the scope of this paper.

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

7. **Conclusion and policy implications**

We use a game-theoretical model to analyse whether different distribution network tariff designs align the business case of residential electricity storage, in the form of batteries, with overall wider system benefits. Three different network tariff designs are evaluated: capacity-based charges, net-purchase volumetric network charges and bi-directional volumetric network charges. Capacity-based

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However, these arbitrary choices for the upper-level do have a distributional impact for the lower level consumers. Therefore, a second solution step was added. The MPEC remains exactly the same except for one constraint and the objective function. One constraint is added which states that the total system cost is forced to be equal to the minimal total system cost obtained in step one. The objective function of the upper-level changed to a minimisation the sum of the coefficients of the network charges. As such, a unique solution is obtained for the network charges without room for arbitrary choices of the upper-level regulator.

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

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

network tariffs incentivise consumers to lower their individual peak demand. The two other network tariff designs result in a difference between the value of on-site generated electricity that is self-consumed and electricity that is directly injected back into the network. As such, these network tariff design incentivise self-consumption. We compare the outcome of the game-theoretical model for the different network tariff designs with a first-best central planner solution. Besides network tariff design, another important driver for battery adoption is time-varying retailer energy prices. Therefore, also the impact of time-varying energy prices on battery adoption and the interaction with distribution network tariff design is investigated.

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

After, the other extreme is investigated; the situation when still many grid investments have to be made, and the future grid costs are driven by the growing aggregated peak demand of consumers. It is shown that in that situation the tested network tariff designs will not only give an inadequate investment signal to the consumers, also will the consumers operate their installed batteries sub-optimally from a grid point of view. If consumer electricity demand profiles are rather homogeneous, batteries are under-invested by capacity-based charges. If consumer electricity demand profiles are heterogeneous, consumers will lower their individual demand which will have little effect on the system peak demand; a similar dynamic as in the sunk grid cost scenario occurs. With a network tariff design that encourages self-consumption, the business case of storage is unrightfully negatively impacted when the batteries are not coupled with onsite generation such as solar PV. Oppositely, when active consumers combine solar PV with cheap batteries or grid costs are high, an over-investment in batteries can result under the network tariff designs that encourage self-consumption. The batteries are fully charged with self-generated solar PV to increase self-consumption, but it can happen that by the time the system peak demand occurs, the batteries are already fully discharged again. In that case, a high capacity of batteries is installed, but they do not contribute to overall grid costs savings. It should be noted that energy losses in the distribution network or the cost of bi-directional flows are omitted in the presented analysis.[23] When self-consumption increases, there is less electricity exchange between the active consumers and the grid and bi-directional flows are reduced. More elaborated grid costs functions could be experimented with in future work.

Time-of-use energy prices instead of flat energy prices are shown to improve the business case for residential storage for all evaluated network tariff designs. With time-of-use energy prices, the active consumers can use their batteries to arbitrage energy prices on top of lowering their network charges. However, imperfect network tariff designs can impact the optimal energy arbitrage strategies from a system point of view. To quantitatively assess this effect, an extension of the presented model with endogeneous wholesale energy prices is necessary. However, what is clear is that distribution network tariff design and different possible retailer energy price schemes should not be evaluated in isolation. Both interact as a consumer reacts to their aggregate. Even more difficulties can be expected when accounting for taxes and levies in the electricity bill which are left out in this analysis.

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

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

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

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

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

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8. **Appendix A: the complete modelling formulation**

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

Sets

i : 1,..,N: Consumers types

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

Parameters

Upper-level

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

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

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

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

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

PC_i : Proportion of consumer type i

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

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

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

Lower level

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

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

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

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

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

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

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 [%]

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

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

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

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

Variables

UL decision variable

vnt : Volumetric network tariff [€/kWh]

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

fnt: Fixed network charge [€/connection]

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

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

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

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

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

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

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

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

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 [€]

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

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

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

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

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

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

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

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

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

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

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

A.2. Original optimisation problems

<u>The upper-level problem for a total system cost minimising regulator</u>

Objective function, the minimisation of total system costs:

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

With its components being:

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

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

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

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

Finding the aggregated peak demand in absolute value:

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

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

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

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

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

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

<u>The lower level problem for an electricity cost minimising consumer</u>

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

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

With:

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

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

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

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

Constraints (including duals):

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A.3. MPEC reformulation as a MILP

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

Newly introduced sets, parameters and variables

Sets

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

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

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

Parameters

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

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

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

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

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

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

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

Variables

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

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

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

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

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

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

Model transformations

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

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

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

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

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

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

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

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

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

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

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

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

It follows that:

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

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

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

with:

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

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

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

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

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

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

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

$$\text{Maximise } \textstyle\sum_{t=1}^T (\mu_{t,i}^a * \mathrm{D}_{t,i}) + \mu_{1,i}^b * \mathrm{SOC}_0 - \sum_{t=1}^T \mathrm{PrDSM_i} * \mathrm{D_{t,i}} * \lambda_{t,i}^e - \mathrm{MS}_i * \lambda_i^m - \mathrm{MB}_i * \lambda_i^n \qquad \text{(A.65)}$$

Thus it follows that:

$$\textstyle\sum_{t=1}^T (\mu_{t,i}^a * \mathrm{D}_{t,i}) + \mu_{1,i}^b * \mathrm{SOC}_0 - \sum_{t=1}^T (\mathrm{PrDSM_i} * \mathrm{D_{t,i}} * \lambda_{t,i}^e) - \mathrm{MS}_i * \lambda_i^m - \mathrm{MB}_i * \lambda_i^n = \sum_{t=1}^{\mathrm{T}} (qw_{t,i} - qi_{t,i} * \mathrm{NM}) * vnt * \mathrm{WDT} + qmax_i * cnt + \sum_{t=1}^{\mathrm{T}} (qw_{t,i} - qi_{t,i}) * cpp_t * \mathrm{WDT} + fnt + is_i * \mathrm{AICS} + ib_i * \mathrm{AICB} + \sum_{t=1}^{\mathrm{T}} \left(qw_{t,i} * \mathrm{EBP_t} - qi_{t,i} * \mathrm{ESP_t}\right) * \mathrm{WDT} + \sum_{t=1}^{\mathrm{T}} \left(dDSM_{t,i}\right) * \mathrm{CDSM_i} * \mathrm{WDT} \qquad \text{(A.66)}$$

We can reformulate A.66 as:

$$\textstyle\sum_{t=1}^{\mathrm{T}} (qw_{t,i} - qi_{t,i} * \mathrm{NM}) * vnt * \mathrm{WDT} + qmax_i * cnt + \sum_{t=1}^{\mathrm{T}} (qw_{t,i} - qi_{t,i}) * cpp_t * \mathrm{WDT} + fnt = \sum_{t=1}^T (\mu_{t,i}^a * \mathrm{D}_{t,i}) + \mu_{1,i}^b * \mathrm{SOC}_0 - \sum_{t=1}^T \left(\mathrm{PrDSM_i} * \mathrm{D_{t,i}} * \lambda_{t,i}^e\right) - \mathrm{MS}_i * \lambda_i^m - \mathrm{MB}_i * \lambda_i^n - \left(is_i * \mathrm{AICS} + ib_i * \mathrm{AICB} + \sum_{t=1}^{\mathrm{T}} \left(qw_{t,i} * \mathrm{EBP_t} - qi_{t,i} * \mathrm{ESP_t}\right) * \mathrm{WDT} + \sum_{t=1}^{\mathrm{T}} \left(dDSM_{t,i}\right) * \mathrm{CDSM_i} * \mathrm{WDT}\right) \qquad \text{(A.67)}$$

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

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

We can see that the left-hand side of Eq. A.68 equals the right hand-side of Eq. A.9. Thus, we replace the bilinear terms in the right hand side of Eq. A.9 with the linear expression on the right-hand side of Eq. A.68.[24]

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

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

$$\mathrm{WDT} * (\mathrm{EBP}_t + vnt + cpp_t) + \mu_{t,i}^a + \lambda_{t,i}^a - \lambda_{t,i}^f = 0 \qquad \forall\, t,i \qquad \text{(A.69)}$$
$$-\mathrm{WDT} * (\mathrm{ESP}_t + \mathrm{NM} * vnt + cpp_t) - \mu_{t,i}^a + \lambda_{t,i}^a - \lambda_{t,i}^g = 0 \qquad \forall\, t,i \qquad \text{(A.70)}$$
$$cnt - \sum_t \lambda_{t,i}^a = 0 \qquad \forall\, i \qquad \text{(A.71)}$$
$$\mu_{t,i}^b - \mu_{t+1,i}^b * (1 - \mathrm{LT} * \mathrm{DT}) + \lambda_{t,i}^b - \lambda_{t,i}^h = 0 \qquad \forall\, t \neq \{\mathrm{T}\}, i \qquad \text{(A.72)}$$
$$\mu_{T,i}^b + \mu_i^c + \lambda_{T,i}^b - \lambda_{T,i}^h = 0 \qquad \forall\, t = \mathrm{T}, i \qquad \text{(A.73)}$$
$$\mu_{t,i}^a + \frac{\mu_{t,i}^b}{\mathrm{EFD}} * \mathrm{DT} + \lambda_{t,i}^c - \lambda_{t,i}^i = 0 \qquad \forall\, t,i \qquad \text{(A.74)}$$
$$-\mu_{t,i}^a - \mu_{t,i}^b * \mathrm{EFC} * \mathrm{DT} + \lambda_{t,i}^d - \lambda_{t,i}^j = 0 \qquad \forall\, t,i \qquad \text{(A.75)}$$
$$\mathrm{CDSM}_i * \mathrm{WDT} + \mu_{t,i}^a - \mu_{t\in day,i}^d + \lambda_{t,i}^e - \lambda_{t,i}^k = 0 \qquad \forall\, t,i \qquad \text{(A.76)}$$
$$-\mu_{t,i}^a + \mu_{t\in day,i}^d - \lambda_{t,i}^l = 0 \qquad \forall\, t,i \qquad \text{(A.77)}$$
$$\mathrm{AICS} + \sum_t \mu_{t,i}^a * \mathrm{SY_{t,i}} + \lambda_i^m - \lambda_i^o = 0 \qquad \forall\, i \qquad \text{(A.78)}$$
$$\mathrm{AICB} - \sum_t \mu_{t,i}^b - \sum_t \lambda_{t,i}^c * \mathrm{BDR} - \sum_t \lambda_{t,i}^d * \mathrm{BCR} + \lambda_i^n - \lambda_i^p = 0 \qquad \forall\, i \qquad \text{(A.79)}$$
$$qw_{t,i} - qi_{t,i} + is_i * \mathrm{SY}_{t,i} + qbout_{t,i} - qbin_{t,i} + dDSM_{t,i} - uDSM_{t,i} - \mathrm{D}_{t,i} = 0 \qquad \mu_{t,i}^a free \qquad \forall\, t,i \qquad \text{(A.80)}$$
$$soc_{1,i} - qbin_{1,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{1,i}}{\mathrm{EFD}} * \mathrm{DT} - \mathrm{SOC}_0 = 0 \qquad \mu_{1,i}^b\ free \qquad \forall\, i \qquad \text{(A.81)}$$
$$soc_{t,i} - qbin_{t,i} * \mathrm{EFC} * \mathrm{dt} + \frac{qbout_{t,i}}{\mathrm{EFD}} * \mathrm{DT} - soc_{t-1,i} * (1 - \mathrm{LR} * \mathrm{DT}) = 0 \qquad \mu_{t\neq 1,i}^b\, free \qquad \forall\, t \neq 1, i \qquad \text{(A.82)}$$
$$soc_{T,i} - \mathrm{SOC}_0 = 0 \qquad \mu_i^c\ free \qquad \forall\, i \qquad \text{(A.83)}$$
$$\sum_{t=1}^{\mathrm{T\in day}}\big(uDSM_{t,i} - dDSM_{t,i}\big) = 0 \qquad \mu_i^d\ free \qquad \forall\, i \qquad \text{(A.84)}$$
$$0 \le qmax_i - qw_{t,i} - qi_{t,i} \quad \perp\ \lambda_{t,i}^a \ge 0 \qquad \forall\, t,i \qquad \text{(A.85)}$$
$$0 \le ib_\mathrm{i} - soc_{t,i} \quad \perp\ \lambda_{t,i}^b \ge 0 \qquad \forall\, t,i \qquad \text{(A.86)}$$
$$0 \le ib_\mathrm{i} * \mathrm{BDR} - qbout_{t,i} \quad \perp\ \lambda_{t,i}^c \ge 0 \qquad \forall\, t,i \qquad \text{(A.87)}$$
$$0 \le ib_\mathrm{i} * \mathrm{BCR} - qbin_{t,i} \quad \perp\ \lambda_{t,i}^d \ge 0 \qquad \forall\, t,i \qquad \text{(A.88)}$$
$$0 \le \mathrm{PrDSM_i} * \mathrm{D_{t,i}} - dDSM_{t,i} \quad \perp\ \lambda_{t,i}^e \ge 0 \qquad \forall\, t,i \qquad \text{(A.89)}$$
$$0 \le qw_{t,i} \quad \perp\ \lambda_{t,i}^f \ge 0 \qquad \forall\, t,i \qquad \text{(A.90)}$$
$$0 \le qi_{t,i} \quad \perp\ \lambda_{t,i}^g \ge 0 \qquad \forall\, t,i \qquad \text{(A.91)}$$
$$0 \le soc_{t,i} \quad \perp\ \lambda_{t,i}^h \ge 0 \qquad \forall\, t,i \qquad \text{(A.92)}$$
$$0 \le qbout_{t,i} \quad \perp\ \lambda_{t,i}^i \ge 0 \qquad \forall\, t,i \qquad \text{(A.93)}$$
$$0 \le qbin_{t,i} \quad \perp\ \lambda_{t,i}^j \ge 0 \qquad \forall\, t,i \qquad \text{(A.94)}$$

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

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

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

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

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

$0 \leq is_i \quad \perp \ \lambda_{i}^{o} \geq 0 \quad \forall\, i \quad$ (A.99)

$0 \leq ib_i \quad \perp \ \lambda_{i}^{p} \geq 0 \quad \forall\, i \quad$ (A.100)

Eq. (A.85-A.100) are complementarity constraints. We linearise these constraints by replacing them with disjunctive constraints using the method described in Fortuny-Amat and McCarl (1981). Alternatively, a transformation using SOS1 variables as explained in Siddiqui and Gabriel (2013) or can be implemented as indicator constraints (GAMS, 2018). In the final formulation, we can also substitute $\lambda_{t,i}^{f}$, $\lambda_{t,i}^{g}$, $\lambda_{t,i}^{i}$, $\lambda_{t,i}^{j}$, $\lambda_{t,i}^{k}$, $\lambda_{t,i}^{l}$, λ_{i}^{o} and λ_{i}^{p} out.

Newly introduced sets, parameters and variables

Parameters

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

Variables

$r_{t,i}^{a}, r_{t,i}^{b}, r_{t,i}^{c}, r_{t,i}^{d}, r_{t,i}^{e}, r_{t,i}^{f}, r_{t,i}^{g}, r_{t,i}^{h}, r_{t,i}^{i}, r_{t,i}^{j}, r_{t,i}^{k}, r_{t,i}^{l}$, r_{i}^{m}, r_{i}^{n}, r_{i}^{o}, r_{i}^{p}: Binary variables used to transform complementarity constraints (A.85-A.100) into disjunctive constraints [-]

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

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

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

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

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

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

$\mathrm{WDT} * (\mathrm{EBP_t} + vnt + cpp_t) + \mu_{t,i}^{a} + \lambda_{t,i}^{a} \leq \mathrm{M^f} * r_{t,i}^{f} \quad \forall\, t,i$ (A.112)

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

$-\mathrm{WDT} * (\mathrm{ESP_t} + vnt * \mathrm{NM} + cpp_t) - \mu_{t,i}^{a} + \lambda_{t,i}^{a} \leq \mathrm{M^g} * r_{t,i}^{g} \quad \forall\, t,i$ (A.114)

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

$qbout_{t,i} \leq \mathrm{M^i} * (1 - r_{t,i}^{i}) \quad \forall\, t,i$ (A.117) and $\mu_{t,i}^{a} + \frac{\mu_{t,i}^{b}}{\mathrm{EFD}} * \mathrm{DT} + \lambda_{t,i}^{c} \leq \mathrm{M^i} * r_{t,i}^{i} \quad \forall\, t,i$ (A.118)

$qbin_{t,i} \leq \mathrm{M^j} * (1 - r_{t,i}^{j}) \quad \forall\, t,i$ (A.119) and $-\mu_{t,i}^{a} - \mu_{t,i}^{b} * \mathrm{EFC} * \mathrm{DT} + \lambda_{t,i}^{d} \leq \mathrm{M^j} * r_{t,i}^{j} \quad \forall\, t,i$ (A.120)

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

and $\mathrm{CDSM_i} * \mathrm{WDT} + \mu_{t,i}^{a} - \mu_{t\in day,i}^{d} + \lambda_{t,i}^{e} \leq \mathrm{M^k} * r_{t,i}^{k} \quad \forall\, t,i$ (A.122)

$uDSM_{t,i} \leq \mathrm{M^l} * (1 - r_{t,i}^{l}) \quad \forall\, t,i$ (A.123) and $-\mu_{t,i}^{a} + \mu_{t\in day,i}^{d} \leq \mathrm{M^l} * r_{t,i}^{l} \quad \forall\, t,i$ (A.124)

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

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

$is_i \leq \mathrm{M^o} * (1 - r_{i}^{o}) \quad \forall\, i$ (A.129) and $\mathrm{AICS} + \sum_t \mu_{t,i}^{a} * \mathrm{SY}_{t,i} + \lambda_{i}^{j} \leq \mathrm{M^o} * r_{i}^{o} \quad \forall\, i$ (A.130)

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

$\mathrm{AICB} - \sum_t \lambda_{t,i}^b - \sum_t \lambda_{t,i}^c * \mathrm{BDR} - \sum_t \lambda_{t,i}^d * \mathrm{BCR} + \lambda_i^k \leq \mathrm{M^p} * r_i^p \qquad \forall\, i \quad$ (A.132)

A.3.4. Final model formulation

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

A.3.5 Including peak coincident network prices

These network charges can be quite easily integrated into the model. The grid cost recovery described by Eq. A.9 in this Appendix becomes Eq. 133 below where cpp_t stands for the (time-varying) network charge in €/kWh. fnt represents the uniform fixed network charge which might complement the time-varying network charge.

$$TotalGridcosts = \sum_{t=1}^{\mathrm{T}} \sum_{i=1}^{\mathrm{N}} \mathrm{PC}_i * cpp_t * (qw_{t,i} - qi_{t,i}) * \mathrm{WDT} + fnt \tag{A.133}$$

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

$$GridCharges_i = \sum_{t=1}^{\mathrm{T}} (qw_{t,i} - qi_{t,i}) * cpp_t * \mathrm{WDT} + fnt \tag{A.134}$$

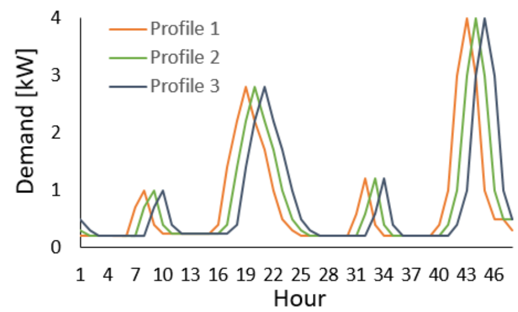
In this case, the regulator has to decide how to set the time-varying network charges in order to minimise the total system costs. Regarding the solution method, it is in this case extremely important that the bilinear products in the upper-level cost recovery constraint (Eq. 1) are efficiently linearised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

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

9. Appendix B: sensitivity analysis

B.1 Data sensitivity analysis

To test the robustness of the results, an additional setup was evaluated. In the numerical example in the body of the text, only two consumer profiles are used. Each consumer type, active and passive, is represented by one profile, and the profiles are coincident. In reality, many individual profiles exist, and these will not be all coincident. In this appendix, three different consumer profiles were used. These profiles are shown in Figure B.1. together with the proportion of consumers per profiles and type.



	Active	Passive
Profile 1	16.7%	0 %
Profile 2	16.7%	50 %
Profile 3	16.7%	0 %

Figure B.1: Profiles and proportions consumers per profile and active/passive

B.2 Results sensitivity analysis

The results for the battery investment costs are shown in Table B.1. All grid costs are assumed to be driven by the aggregated peak demand. Please note that now the average capacity of the batteries installed by the different active consumer groups is shown. Logically, the capacities installed differ to a certain extent from the results in Table 4 but the observations remain the same.

Table B.1: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated peak demand.

	Distribution network tariff design	Benchmark – central planner	Capacity-based [€/kW]	Volumetric Net-purchase [€/kWh]	Volumetric Bi-directional [€/kWh]
	Investment cost batteries	Average battery installed per active consumer [kWh] / PV in brackets [kWp]			
No PV installed, only batteries can be invested in by the active consumers	350 €/kWh	1.9 (0)	1.2 (0)	0.0 (0)	0.0 (0)
	300 €/kWh	1.9 (0)	1.2 (0)	0.0 (0)	0.0 (0)
	250 €/kWh	1.9 (0)	1.2 (0)	0.0 (0)	0.0 (0)
	200 €/kWh	6.2 (0)	3.9 (0)	0.0 (0)	0.0 (0)
	150 €/kWh	10.1 (0)	5.7 (0)	0.0 (0)	0.0 (0)

	100 €/kWh	12.1 (0)	6.9 (0)	0.0 (0)	0.0 (0)
Batteries and PV can be installed in by the active consumers	350 €/kWh	1.9 (0)	1.2 (0)	0 (4.9)	0.0 (0.6)
	300 €/kWh	1.9 (0)	1.2 (0)	0 (4.9)	0.0 (0.6)
	250 €/kWh	1.9 (0)	1.2 (0)	0 (4.9)	0.0 (0.6)
	200 €/kWh	6.2 (0)	3.9 (0)	0 (4.9)	0.0 (0.6)
	150 €/kWh	10.1 (0)	5.7 (0)	0 (4.9)	0.5 (0.6)
	100 €/kWh	12.1 (0)	7.3 (0.7)	3.6 (5)	1.7 (1.1)
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	1.8 (5)	1.0 (5)	0.0 (5)	0.0 (5)
	300 €/kWh	2.1 (5)	1.4 (5)	0.0 (5)	0.0 (5)
	250 €/kWh	2.1 (5)	1.4 (5)	0.0 (5)	0.0 (5)
	200 €/kWh	6.2 (5)	1.8 (5)	0.0 (5)	5.2 (5)
	150 €/kWh	11.0 (5)	6.2 (5)	0.0 (5)	5.2 (5)
	100 €/kWh	12.4 (5)	7.4 (5)	3.6 (5)	11.7 (5)

When comparing the results in Figure 3 and Figure B.2, it can be seen that for expensive batteries, the performance in terms of the reduction of system costs is overestimated with coincident consumer profiles. If batteries are cheaper and thus more batteries are installed, the individual peaks will be flattened over multiple time-steps thus possibly also during the time steps other consumers have their peak demand and as a result the aggregated peak will decrease.

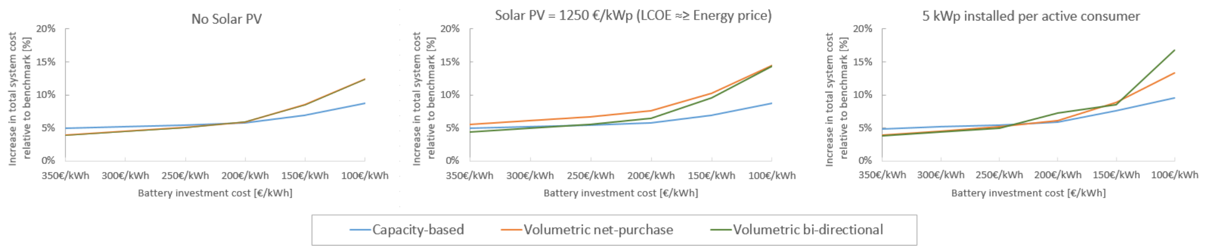


Figure B.2: Increase in total system costs for the three network tariff structures when compared with a central planner. Sensitivity for three different assumptions regarding solar PV adoption and the investment cost of storage.

Table B.2 shows the result for the battery adoption under different TOU energy prices. Again, the capacities installed differ to a certain extent from the results in Table 5 but the observations remain the same.

Table B.2: Battery and solar PV investment per active consumer for the different network tariff designs under different investment cost assumptions for batteries and interaction with solar PV investments. All grid costs are assumed to be driven by the aggregated peak demand.

Distribution network tariff design		Benchmark – central planner		Capacity-based [€/kW]		Volumetric Net-purchase [€/kWh]		Volumetric Bi-directional [€/kWh]	
Energy price		TOU1	TOU2	TOU1	TOU2	TOU1	TOU2	TOU1	TOU2
Investment cost batteries		Battery installed per active consumer [kWh] / PV in brackets [kWp]							
No PV installed, only batteries can be invested in	350 €/kWh	1.9 (0)	8.6 (0)	1.2 (0)	3.7 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	300 €/kWh	1.9 (0)	12.1 (0)	1.2 (0)	6.1 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	250 €/kWh	3.5 (0)	12.7 (0)	2.1 (0)	7.0 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	200 €/kWh	10.0 (0)	13.2 (0)	5.3 (0)	7.5 (0)	0 (0)	0 (0)	0 (0)	0 (0)
	150 €/kWh	12.1 (0)	15.0 (0)	6.6 (0)	8.1 (0)	0 (0)	0 (0)	0 (0)	0 (0)

by the active consumers	100 €/kWh	12.7 (0)	16.3 (0)	7.2 (0)	8.3 (0)	0 (0)	0 (0)	0 (0)	0 (0)
Batteries and PV can be installed in by the active consumers	350 €/kWh	1.9 (0.4)	8.6 (0)	1.2 (0.4)	3.7 (0)	0 (5)	0 (0.7)	0 (0.7)	0 (0.4)
	300 €/kWh	1.9 (0)	12.1 (0)	1.3 (1.4)	6.1 (0)	0 (5)	0 (0.7)	0 (0.7)	0 (0.4)
	250 €/kWh	3.5 (0)	12.7 (0)	1.9 (1.3)	7.0 (0)	0 (5)	0 (0.7)	0 (0.7)	0 (0.4)
	200 €/kWh	10.0 (0)	13.2 (0)	5.2 (0.8)	7.5 (0)	0 (5)	0.1 (0.9)	0 (0.7)	0.1 (0.5)
	150 €/kWh	12.1 (0)	15.0 (0)	6.6 (0.7)	8.1 (0)	0 (5)	1.9 (1.5)	1.0 (0.9)	2.8 (1.4)
	100 €/kWh	12.7 (0.4)	16.3 (0)	7.3 (0.6)	8.3 (0)	4.5 (5)	8.2 (3.1)	6.8 (2.8)	8.2 (3.2)
Active consumer has a 5 kWp solar PV, batteries can be invested in	350 €/kWh	2.1 (5)	8.5 (5)	1.3 (5)	2.6 (5)	0 (5)	0 (5)	0 (5)	5.2 (5)
	300 €/kWh	2.1 (5)	12.4 (5)	1.4 (5)	5.3 (5)	0 (5)	0 (5)	0 (5)	5.2 (5)
	250 €/kWh	4.1 (5)	12.4 (5)	1.5 (5)	6.3 (5)	0 (5)	3.7 (5)	4.8 (5)	5.2 (5)
	200 €/kWh	9.6 (5)	13.0 (5)	4.3 (5)	8.1 (5)	0 (5)	5.2 (5)	5.2 (5)	7.5 (5)
	150 €/kWh	12.4 (5)	14.9 (5)	6.0 (5)	9.2 (5)	0 (5)	5.2 (5)	5.2 (5)	7.6 (5)
	100 €/kWh	12.4 (5)	18.2 (5)	6.7 (5)	10.3 (5)	4.5 (5)	7.6 (5)	7.6 (5)	11.7 (5)