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Abstract

Demand-side flexibility can be incentivised to reduce the need for investment in distribution grids either implicitly or explicitly. Implicit demand-side flexibility is when prosumers react to price signals triggered by network tariffs. Explicit demand-side flexibility is when the DSO can contract flexibility. In this paper, we focus on one contractual arrangement: mandatory curtailment by the DSO for a fixed level of compensation. We develop a long-term bi-level equilibrium model. The upper level (UL) is a regulated DSO deciding on the network investment and/or curtailing consumers for a fixed level of compensation. The lower level (LL) consists of consumers, which can be prosumers or passive consumers. Prosumers can invest in solar PV and battery systems. They react to the network tariffs and to the compensation provided by the DSO for curtailing them. The regulated DSO anticipates the reaction of the consumers when investing in the network and when setting the level of curtailment. Network tariffs are set to recover the network costs and the payments made to consumers that have been curtailed. We find that the economics of explicit demand-side flexibility in distribution grids are positive, and they are more positive when tariffs are cost-reflective. This implies that we cannot avoid redesigning tariffs by using explicit demand flexibility. We also find that setting an appropriate level of compensation is difficult in the presence of prosumers and passive consumers. A level of compensation that is high enough for passive consumers will be gamed by prosumers.

Keywords

Bi-level modelling, Demand-side flexibility, Distribution network investment, Flexibility compensation, Network tariffs, Prosumers.

1. Introduction*

The Clean Energy Package (CEP) Directive (EU) 2019/944 calls on the Member States to develop regulatory frameworks that incentivise distribution system operators (DSOs) to consider the use of flexibility as an alternative to grid expansion. DSOs will have to develop and publish network development plans that make a trade-off between the use of flexible resources and system expansion. There are only a few studies that focus on this trade-off. BMWi (2014), a study for the German energy ministry, finds that allowing DSOs to curtail up to 3% of distributed generation would save about 40% of the network expansion cost. ENEDIS (2017) considers the costs and benefits of six flexibility options, on both the demand side and the supply side, and finds that they may provide important net gains by 2030. Furthermore, an impact assessment report developed by CE and VVA Europe (2016) for the European Commission estimates that the European Union could save up to €5 billion annually by avoiding distribution investments towards 2030.

In the academic literature, Spiliotis et al. (2016) propose a model that assesses the trade-off between grid expansion and demand and DG curtailment. They find that for a congested 24-node radial distribution network all physical expansions could be avoided with 12% flexible demand. Klyapovskiy et al. (2019) consider flexibility from the demand side and in terms of technical solutions using grid assets and compare them to traditional reinforcement over a period of four years. In this paper, we focus on the potential of explicit demand-side flexibility. Regulators typically design different schemes for supply-side and demand-side flexibility. The regulatory framework for demand-side flexibility is less developed and is more controversial. It is more complicated than curtailing consumption because prosumers can invest in other technologies, such as battery storage and solar PV.

The first contribution of this paper is that it assesses the interaction between implicit and explicit demand-side flexibility. Implicit demand-side flexibility is when prosumers react to price signals triggered by network tariffs. Explicit demand-side flexibility is when the DSO curtails consumers' loads for a certain amount of compensation. There are many academic papers on network tariff design (e.g. Burger et al. (2020) and Schittekatte and Meeus (2020)) yet they do not look at the interaction between network tariffs and explicit demand-side flexibility. At the same time, the above-mentioned papers on demand-side flexibility do not include network tariffs in their models, leaving a gap in the literature. The second contribution of this paper is that it discusses the right level of compensation for explicit demand-side flexibility. Many studies focus on the level of compensation for supply-side flexibility but we are not aware of a similar study on demand-side flexibility. The third contribution of this paper is through modelling. We develop a long-term bi-level equilibrium model. The upper level (UL) is a regulated DSO deciding on the network investment and demand-side flexibility levels, and recovering the costs of both via distribution network tariffs. The lower level (LL) consists of consumers, which can be prosumers or passive consumers. Prosumers can invest in solar PV and battery systems. Prosumers react to the network tariffs and to the compensation provided by the DSO for curtailing them. The regulated DSO anticipates the reaction of the consumers when investing in the network and when setting the level of curtailment of passive consumers and prosumers. Network tariffs are set to recover the network costs and the payments made to consumers that have been curtailed.

The paper is structured in four sections. In section 2, we introduce the modelling approach. In section 3, we detail the results of a numerical example. Finally, in the conclusion we summarise our main findings and their policy implications.

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2. Methodology

In this section, we first introduce our modelling approach, picturing the game-theoretical model and summarising the relevant academic literature. We then present the mathematical formulation with the different players' optimisation problems and the underlying assumptions.

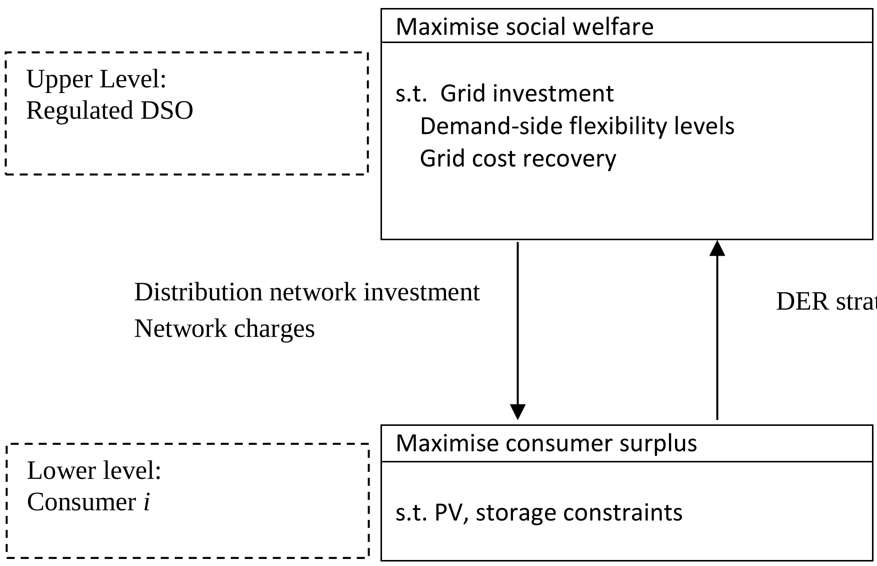
2.1 Modelling Approach

Our stylised model has a so-called bi-level structure. It is formulated as a mathematical program with equilibrium constraints (MPEC) using Karush–Kuhn–Tucker (KKT) optimality conditions. Being a perfectly regulated DSO, the UL maximises system welfare. In the LL we model electricity consumers, passive consumers and prosumers being active consumers, which maximise their respective surpluses or welfare. The UL feasible set is defined by both a set of constraints and the LL optimisation problem, as it anticipates consumers' reactions to its decisions.

Over the past two decades, the use of bi-level programming has received growing attention among academics. It can address many real-world problems, as they can be formulated as MPECs. Many academic papers and books have focused on this kind of programming problem (e.g. Luo et al. (1996) and Dempe (2002)). In the electricity sector in particular, it has also been increasingly applied. The model used in this paper is an extended version of that used in Schittekatte and Meeus (2020), which in turn builds on Schittekatte et al. (2018). It has the same game-theoretical set-up. Schittekatte and Meeus (2020) apply a cost minimisation formulation that only looks at distribution tariffs as an implicit demand-side flexibility solution. In this paper, we include explicit demand-side flexibility in a welfare maximisation context.

The model allows the regulated DSO to calculate the system welfare and the corresponding level of optimal explicit demand-side flexibility. The regulated DSO also decides on the network charges to send the correct signals to consumers, as is schematised in Figure 1. The consumers are divided into prosumers and passive consumers. Prosumers can strategically decide on the optimal level of PV and storage investment to maximise their surpluses.

Figure 1: Schematic overview of the bi-level model setting



The model output can be interpreted as a generalised Nash equilibrium of a non-cooperative game between the aforementioned agents, i.e. the regulated DSO and the electricity consumers. In the next subsection we present the two optimisation problems. Further details about the problem-solving are presented in Annex A.

To solve the MPEC problem, we apply the KNITRO solver in GAMS software (GAMS, 2020). The KNITRO options file allows the user to easily set certain computation options, *inter alia* the multi-start heuristic option, which looks for multiple local solutions in order to locate the global solution. We also include tight variable finite upper and lower bounds to reduce computation time.

2.2 Mathematical formulation

In this subsection, we first introduce the UL optimisation problem and then the LL optimisation problem.

2.2.1 The upper level: the regulated DSO

The UL problem maximises system welfare. It is represented, in Eq. 1, as the difference between the gross system welfare and the total system costs. Gross system welfare, in Eq. 2, corresponds to the gross welfare from electricity consumption to which we add a welfare correction being the potential compensation consumers would receive from the DSO for flexibility services (Eq. 3). Total system costs consist of four components: system grid costs, demand-side flexibility costs, energy costs and DER investment costs (Eq. 4). The regulated DSO decides on: the optimal levels of network investment and demand-side flexibility based on the grid parameters; and compensation. It also anticipates the LL strategy. The trade-off between network investment and the use of flexibility is a topic of growing importance in distribution planning.

$$\text{Maximise} \quad \text{GrossSystemWelfare} - \text{TotalSystemCosts} \tag{1}$$

The electricity demand $\mathrm{d_{i,daytype,t}}$ is equal for consumers, i, regardless of whether they are active or passive. Demand profiles are 24h time series, and t takes a value from 1 to 24. However, it differs according to the $\mathrm{daytype}$: normal days or critical days with higher peaks. Their total weight equals the number of days per year. $\mathrm{PC_i}$ corresponds to the proportion of prosumers and passive consumers. The compensation, comp, is considered uniform for the different hours and consumer types and $\mathrm{wdt_{daytype}}$ is a factor annualising the values.

$$\text{GrossSystemWelfare} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{PC_i} * \sum_{\mathrm{Daytype}=1}^{\mathrm{M}} \sum_{\mathrm{t}=1}^{\mathrm{T}} (\mathrm{d_{i,daytype,t}} - qflex_{i,daytype,t}) * \mathrm{VoLL} * \mathrm{wdt_{daytype}} + \text{WelfareCorrection} \tag{2}$$

$$\text{WelfareCorrection} = \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{PC_i} * \sum_{\mathrm{Daytype}=1}^{\mathrm{M}} \sum_{\mathrm{t}=1}^{\mathrm{T}} \mathrm{comp} * qflex_{i,daytype,t} * \mathrm{wdt_{daytype}} \tag{3}$$

$$\text{TotalSystemCosts} = \text{SystemGridCosts} + \text{SystemFlexCosts} + \text{SystemDERCosts} + \text{SystemEnergyCosts} \tag{4}$$

Eq. 5 represents the system grid costs corresponding to the DSO's investment in network expansion. They are assumed to be driven by the coincident peak, meaning that there is no grid at the beginning of the simulation. No sunk costs are therefore included and neither do they have to be recovered. System grid costs are a function of the coincident peak ($CPeak$) and the original demand, $\mathrm{d_{i,daytype,t}}$, peak, which is DPeak. The extent to which system grid costs are a function of DPeak or $CPeak$ depends on the WF, that is, the weighting factor representing the network cost driver proxy. It has values ranging between 0 and 1. A WF equal to zero means that individual consumer actions adapting their consumption will not impact grid investment. Conversely, a value of 1 means that a consumer demand reduction of 1 kW will reduce the system peak by 1 kW and consequently reduce grid investments. A similar approach to grid cost representation is used in Schittekatte and Meeus (2020).

$$\text{SystemGridCosts} = \text{IncrGridCosts} * (\text{DPeak} - \text{WF} * (\text{Dpeak} - CPeak)) \qquad (5)$$

The $CPeak$ is determined as the maximum of the demand peak ($CPeakDemand$) and injection peak ($CPeakInjection$) and is represented by Eqs. 6 to 8. $CPeakDemand$ is the maximum value of consumers' withdrawals from the grid ($qw_{t,i}$) minus injections ($qi_{t,daytype,i}$). Both $qw_{t,daytype,i}$ and $qi_{t,daytype,i}$ are consumer decision variables. The same logic applies to $CPeakInjection$.

$$\text{CPeak} = \max\,(CPeakDemand, CPeakInjection) \qquad (6)$$

$$\text{CPeakDemand} \geq \sum_{\text{i}=1}^{\text{N}} \text{PC}_{\text{i}} * \left(qw_{t,daytype,i} - qi_{t,daytype,i}\right) \quad \forall \text{t} \qquad (7)$$

$$\text{CPeakInjection} \geq \sum_{\text{i}=1}^{\text{N}} \text{PC}_{\text{i}} * \left(qi_{t,daytype,i} - qw_{t,daytype,i}\right) \quad \forall \text{t} \qquad (8)$$

Eq. 9 represents the demand-side flexibility costs, which are the costs of load curtailment. When volume $\text{qflex}_{\text{i,daytype.t}}$ occurs (in kWh), it is multiplied by its compensation, comp (in €), which is a parameter exogenous to the model. They are then summed for the different time steps and day types and multiplied by the annuity factor.

$$\text{SystemFlexCosts} = \sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} \sum_{\text{i}=1}^{\text{N}} \text{PC}_{\text{i}} * \left(\text{comp} * qflex_{i,daytype.t}\right) * \text{wdt}_{\text{daytype}} \qquad (9)$$

Prosumers can invest in DERs, which are solar PV and battery systems. Eq. 10 represents the total investment costs in DERs. The decision variable is_i is for solar PV investment (in kWp) installed by consumer i, and ib_i is for investment in batteries (in kWh) installed by consumer i. AICS and AICB are the annualised investment costs for solar PV and batteries respectively. No maintenance costs or degradation of the DER technologies are assumed.

$$\text{DERcosts} = \sum_{\text{i}=1}^{\text{N}} is_i * \text{AICS} + ib_i * \text{AICB} \qquad (10)$$

The system energy costs are calculated using Eq. 11. EBP_{t} refers to the fixed purchase price of a kWh of electricity. ESP_{t} is the fixed price received for selling a kWh of electricity.

$$\text{EnergyCosts} = \sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} \sum_{\text{i}=1}^{\text{N}} (qw_{t,daytype,i} * \text{EBP}_{\text{t}} - qi_{t,daytype,i} * \text{ESP}_{\text{t}}) * \text{wdt}_{\text{daytype}} \qquad (11)$$

The cost recovery equation (Eq. 12) allows the regulated DSO to recover both the explicit demand-side flexibility and network investment costs from the network tariffs. Network tariffs are typically composed of three components; a capacity cnt (€/kW), a volumetric vnt (€/kWh) and a fixed component fnt (€/consumer). In our modelling, we only allow capacity-based charges as they are deemed to be the most cost-reflective. The LL decides on $qw_{i,daytype,t}$, $qi_{i,daytype,t}$ and $qmax_i$, where $qmax_i$ is the maximum of $qw_{i,daytype,t}$ and $qi_{i,daytype,t}$ over the time series.

$$\begin{aligned} &\sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} \sum_{\text{i}=1}^{\text{N}} \text{PC}_{\text{i}} * \left(\text{comp} * qflex_{i,daytype,t}\right) + \text{IncrGridCosts} * CPeak \\ &\qquad = \text{vnt} * \sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} \sum_{\text{i}=1}^{\text{N}} \text{PC}_{\text{i}} * \left(qw_{i,daytype,t} - qi_{i,daytype,t}\right) * \text{wdt}_{\text{daytype}} + cnt \\ &\qquad * \sum_{\text{i}=1}^{\text{N}} \text{PC}_{\text{i}} * qmax_i + fnt \end{aligned} \qquad (12)$$

Eq. 13 provides non-negativity constraints for the upper-level optimisation problem.

$$cnt, fnt, vnt, qflex_{t,daytype,i} \geq 0 \quad \forall \text{i}, \text{t}, \text{daytype} \qquad (13)$$

2.2.2 The lower level: consumers

In the LL, we model electricity consumers, which can be passive or active. Passive consumers are assumed not to react to flexibility sourcing or network tariffs, while prosumers can invest in DERs to maximise their surpluses. They can also make a trade-off between being curtailed and receiving the corresponding remuneration or investing in DERs to limit the load reduction volumes. A combination of both is, of course, possible. While flexibility allows network costs to be reduced, it harms the consumers' welfare as they value electricity consumption at the VoLL levels.

Each consumer aims to maximise its surplus expressed in Eq.14, which corresponds to the difference between the gross consumer surplus and the costs incurred.

$$\text{Maximise} \quad \text{GrossConsumerSurplus}_\text{i} - \text{Costs}_\text{i} \tag{14}$$

The gross consumer surplus (Eq.15) corresponds to the value of electricity consumption, that, is every kWh consumed multiplied by the VoLL, to which we add the welfare correction, is the compensation each consumer gets for explicit demand-side flexibility.

$$\text{GrossConsumerSurplus}_\text{i} = \sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} (\text{d}_{\text{t,,daytype,i}} - qflex_{i,daytype,t}) * \text{VoLL} * \text{wdt}_\text{daytype} + \text{WelfareCorrection}_\text{i} \tag{15}$$

$$\text{WelfareCorrection}_\text{i} = \sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} \left(\text{comp} * qflex_{i,daytype,t}\right) * \text{wdt}_\text{daytype} \tag{16}$$

We divide the costs that every consumer has to pay into three components: energy costs, network charges and DER costs, as is shown in Eq. 17. The calculation of each component is given by Eqs. 18 to 20.

$$\text{Costs}_\text{i} = \text{EnergyCosts}_\text{i} + \text{GridCharges}_\text{i} + \text{DERcosts}_\text{i} \qquad \forall \text{ i} \tag{17}$$

$$\text{EnergyCost}_\text{i} = \sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} \left(qw_{t,daytype,i} * \text{EBP}_\text{t} - qi_{t,daytype,i} * \text{ESP}_\text{t}\right) * \text{wdt}_\text{daytype} \qquad \forall \text{ i} \tag{18}$$

$$\text{Gridcharges}_\text{i} = \sum_{\text{Daytype}=1}^{\text{M}} \sum_{\text{t}=1}^{\text{T}} \left(qw_{t.daytype,i} - \text{NM} * qi_{t,daytype,i}\right) * vnt * \text{wdt}_\text{daytype} + cnt * qmax_i + fnt \qquad \forall \text{ i} \tag{19}$$

$$\text{DERcosts}_\text{i} = \text{is}_\text{i} * \text{AICS} + \text{ib}_\text{i} * \text{AICB} \qquad \forall \text{ i} \tag{20}$$

The consumer's demand balance is shown in Eq. 21.

$$qw_{i,daytype,t} + is_i * \text{SY}_{\text{i,daytype,t}} + qbout_{i,daytype,t} - qi_{i,daytype,t} - qbin_{i,daytype,t} + qflex_{i,daytype,t} - \text{d}_{\text{i,daytype,t}} = 0 \qquad \forall \text{ t, daytype, i} \tag{21}$$

In order to solve the problem, the LL optimisation problem is replaced by Karush-Kuhn-Tucker (KKT) optimality conditions. The full sequence of the mathematical process can be found in Annex A.

3. Case study and results

This section is divided into three subsections. First, we present the case study and justify the parameters used. Second, we present the results. Finally, we conduct a sensitivity analysis.

3.1 Case study

In this subsection, we introduce the parameters we consider in our model. First, we introduce the demand-related parameters, including the VoLL values. Second, we present the DER parameters, and third we list the grid parameters together with the flexibility compensation. Finally, we summarise the parameters for the reference scenario.

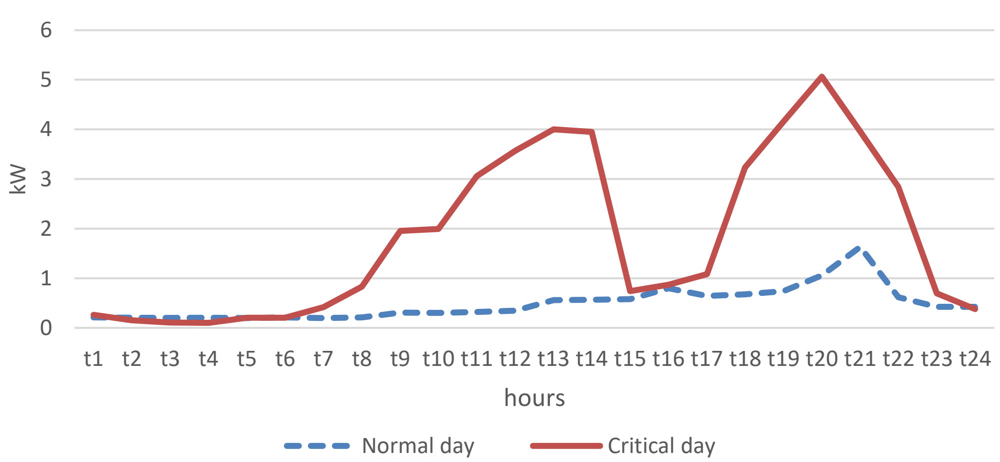
3.1.1 Demand-related parameters

In our model, we consider a 50%-50% distribution between prosumers and passive consumers in the reference scenario. This may seem quite ambitious today. Nevertheless, seeing the current trends in the electricity sector, i.e. decreasing DER investment costs and rising electricity bills together with climate awareness and the movement towards reappropriation of the energy transition, more and more passive consumers may become active.

Both prosumers and passive consumers have similar load profiles. The load profiles we use are divided into two categories: normal days and critical days. The two types of profile are annualised with different weights. In the reference scenario, we use 350 normal days and 15 critical days. The concept of critical days in network planning is analogous to critical peak pricing (CPP) for electricity retail tariffs. For instance, in Australia, CCP tariff schemes assume 10 to 15 days with extreme demand (Norris et al., 2014). In France, 22 days are considered critical in retail tariffs offers within the TEMPO programme (EDF, 2019), while for demand curtailment RTE considers 10 to 15 days critical based on weather forecasts (RTE, 2019a) and 10 to 25 days based on system voltage (RTE, 2019b). Demand-side flexibility schemes can be decoupled from electricity retail offers (EnergyAustralia, (2019) and AGL, (2019)) and operated by system operators to ensure reliable supply in extreme weather events. For instance, CRE (2018) summarises the demand curtailment regulatory framework organised by system operators in France.

We obtain the normal day' load profiles from the 2019 Belgian synthetic load profiles (SLPs) of residential consumers (Synergrid, 2019). SLPs reflect the average load, meaning that the peaks are normalised. They are used as input data in the academic literature, as for instance Govaerts et al. (2019). The maximum peak load is found during a winter weekend and is ~1.6 kW. The maximum peak load during weekdays is also in winter and is slightly lower than the peak load at weekends. On critical days, the two daily peaks are magnified. The maximum peak load on critical days is ~5 kW. The high peaks in the critical day' profiles are due to spikes in consumption resulting from weather conditions or other external factors leading to an extensive use of appliances with higher power requirements. Hayn et al. (2014) present an illustration of the peak demand for selected household appliances, such as a dishwasher ~3 kW, an oven ~2.8 kW and a dryer ~2.7 kW. We distribute their use randomly in terms of time, amplitude and duration, with a concentration of use around the two original peaks of normal days, as is shown in Figure 2. In the future, with the integration of electric vehicles and heat pumps it is likely that these technologies will have a huge impact on household' electricity consumption and the load profile peaks. We use a yearly demand of 4000 kWh, which is in the same range as the average residential electricity consumption in Belgium (ENGIE, 2019).

Figure 2: Profiles for normal and critical days



Our modelling approach values the possible discomfort felt by consumers related to demand-side flexibility sourcing, which is expressed through the VoLL and the value of lack of adequacy (VoLA) parameters. The VoLA corresponds to a VoLL with one day's notice. Its value is about 50% less than the VoLL in the different Member States. Using different values of the VoLL can therefore be linked to the time of the announcement of a load reduction event to consumers, which is the notice factor. ACER (2018) gives estimated VoLL and VoLA values for the different EU Member States. We consider a VoLL equal to 5.33 €/kWh in our reference scenario. According to ACER 2018, this corresponds to the annual average VoLA in Belgium. VoLL values differ across Europe. The lowest domestic value is in Bulgaria, with 1.5 €/kWh, and the highest is in the Netherlands, with 22.94 €/kWh. Similarly, VoLA values vary among the Member States, from 0.83 €/kWh in Bulgaria to 12.73 €/kWh in the Netherlands.

3.1.2 DER parameters

We consider that prosumers can invest up to 4 kW of solar PV. There is no utility-scale PV and neither are there large battery systems. A European Commission (2017) behavioural study assumes 3.87 kW to be the average size of residential solar PV installations in Belgium by 2030. Prosumers can also invest up to 8 kWh in battery system capacity.

The installation cost of PV is assumed to be 1200 €/kWp, with a lifetime of 20 years and a discount rate of 5%. For instance, in Germany a small rooftop PV (5-15 kWp) costs in the range between 1200€/kWp and 1400€/kWp (Kost et al., 2018). Worldwide, PV investment costs are decreasing, as IRENA (2018) and Solar Power Europe (2018) state. This justifies our choice of PV investment cost projection.

Regarding battery storage, we opt for a 100€/kWh investment cost, with a lifetime of 10 years and a discount rate of 5%. We also use 90% efficiency in charging and discharging and a 2% leakage rate. IRENA (2017) includes a projection of battery storage costs in 2030 of around 140 €/kWh, depending on lithium-ion battery technology. In a JRC report, Steen et al. (2017) state that lithium-ion battery prices were under $140/kWh in 2017 according to different sources. In the US, Tesla has announced that it will reach $100/kWh by 2022.

3.1.3 Grid-related parameters

In our analysis, grid costs are assumed to be 100% driven by the coincident peak. No network is assumed at the beginning of the simulation. The aim is to stress the value of the trade-off between grid investment and flexibility, as flexibility contributes to reducing the coincident peak. To obtain the values of the grid cost function parameters (Eq. 5), we first calculate the 'default' network costs of the consumers modelled. In our setting, $IncrGridCosts$ are 400 €/kW. The network tariffs are capacity-based. In the reference scenario, we use a perfect proxy for the accuracy of network cost drivers: WF =1. This means that tariffs are deemed to be cost-reflective of the system state and that prosumers correctly adapt their profiles to price signals. An imperfect proxy, e.g. 0.5, would mean that consumers will lower their demand at a different time to that needed by the DSO. Introducing an imperfect proxy would also relax the assumption of identical consumer demand profiles (Schittekatte, 2019).

Regarding demand-side flexibility compensation, we choose $\text{comp} = 1€/\text{kWh}$ for the reference scenario. As the procurement of flexibility services has only been being tested recently in the electricity sector, there are not many studies that assess demand-side flexibility compensation. Nouicer and Meeus (2019) list the different pioneering flexibility procurement projects at the distribution level in the EU. One of these is the Piclo project, for which a UKPN (2019) post-tender report indicates the price of the accepted bids in its 2018/19 flexibility tender. The values for utilisation payments range between 0.001€ and 1.28 €. The minimum bid of 0.001€ includes an availability payment, while the maximum one of 1.28 € does not. In our model, we only give a utilisation (energy) compensation for demand flexibility.

It should be noted that UKPN flexibility bid prices reflect the prices of a voluntary market-based mechanism.

3.1.4 The reference scenario

Based on the assumptions above, in Table 1, we summarise the main parameters in our reference scenario.

Table 1: Parameters in the reference scenario

Parameter	Value
VoLL	5.33 €/kWh (equal to VoLA of Belgium)
Comp	1 €/kWh
Annual demand	4000 kWh
Frequency of critical days	15
Default Load (normal days)	Synthetic Load Profiles (SLP) - Belgium
Incremental network expansion costs	400 €/kW, no sunk grid costs
WF	1, i.e. cost-reflective tariffs
Network tariffs	cnt, its magnitude is decided endogenously for the entire year (no time differentiation)
Solar PV investment cost	1200 €/kWp
Battery investment cost	100€/kWh
Electricity withdrawal price EBP_t	0.08 €/kWh
Electricity injection price ESP_t	0.072 €/kWh

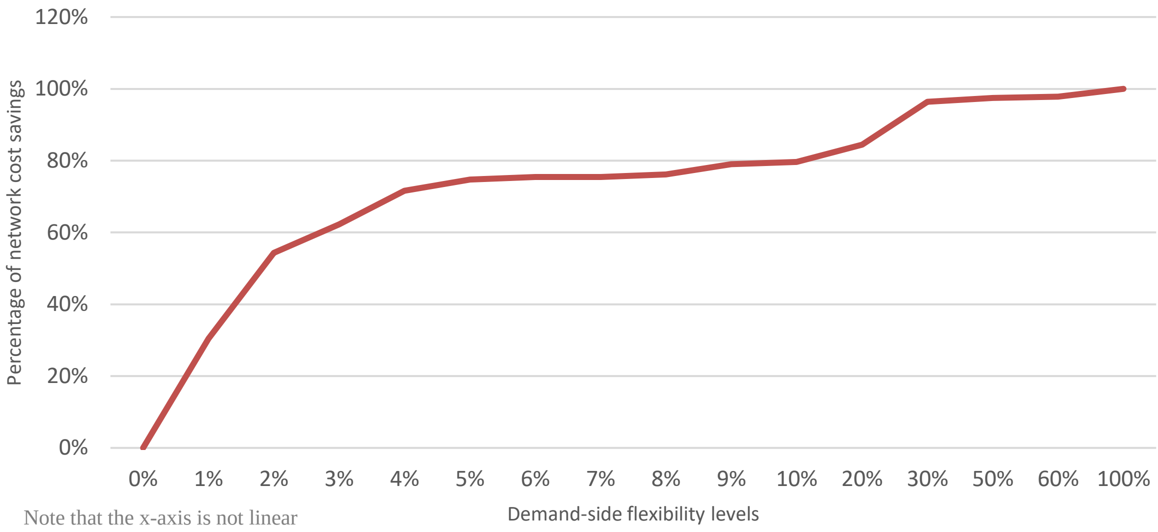
3.2 Results

In this section, we first present the role of demand-side flexibility in saving distribution network investments. We then assess its impact on system welfare in order to find the optimal demand-side flexibility level. Next, we investigate the impact of network tariffs and explicit demand-side flexibility compensation. Finally, we assess the role of some context-related elements in the demand-side flexibility framework.

3.2.1 Distribution network investment savings

In a first step, we run our model to assess the savings in distribution network investments that the DSO can realise by adopting different levels of demand-side flexibility. To do this, we calculate the network investment in the case where no flexibility is procured. In steps, we then integrate the different demand-side flexibility levels, which are calculated as percentages of the annual demand. This forces the model to solve for the flexibility levels indicated. Figure 3 shows the network investment savings for different demand-side flexibility levels that are procured. It resembles the BMWi (2014) system expansion savings curve, which focuses on DG curtailment.

Figure 3: Distribution network investment savings

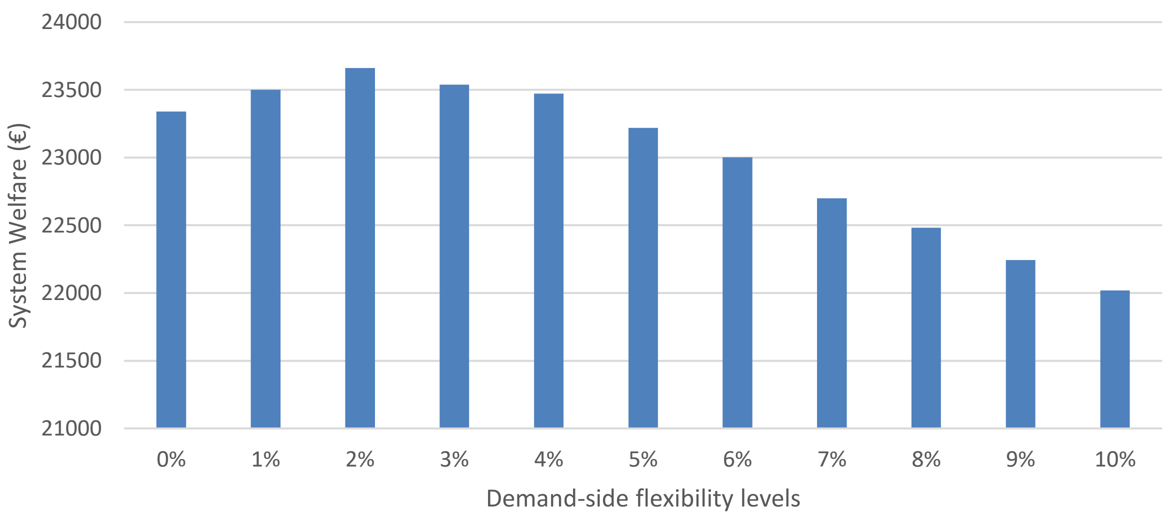


Network cost savings increase rapidly for demand flexibility volumes below 6 %, and then the curve has a less steep incline. We find that a 3% level of demand-side flexibility allows 62% of distribution grid investment and a 5% level allows 75%. The flexibility costs are not taken into account in Figure 3. They are considered as operational expenditures (OPEX), while the savings on grid investment are purely on capital expenditure (CAPEX).

3.2.2 Impact on system welfare

In a second step, we extend our analysis to look at the system welfare (represented in Eq. 1) for different demand-side flexibility levels. This encompasses the introduction of gross welfare, which is measured through the VoLL, valuing the socio-economic loss involved in non-provision of an electricity unit to the consumer (ACER, 2018). In addition, the different system costs (represented in Eq. 4) are considered. The aim is to have a more holistic view of the impact of demand-side flexibility levels on the opportunity costs of electricity consumption and the different associated costs at the system level.

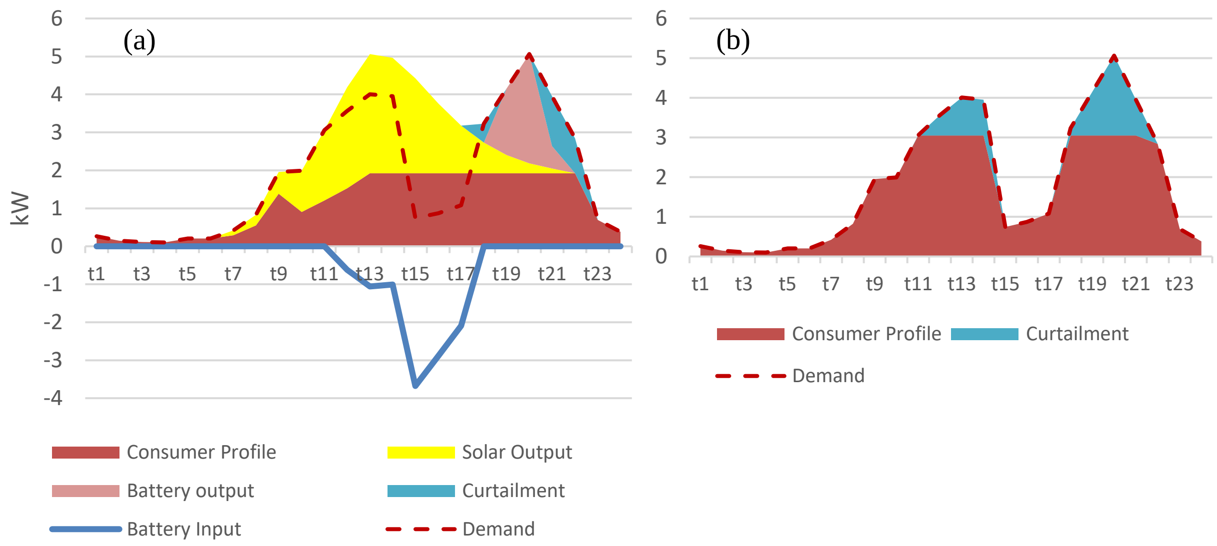
Figure 4: System welfare for different demand-side flexibility levels



As in the previous figure, in Figure 4 we integrate the different demand-side flexibility levels in steps and then plot the system welfare levels. We find that for low levels of demand-side flexibility from 0% to 2% there is an increase in system welfare as demand-side flexibility increases. From 2% onwards, the system welfare starts to decrease. This means that the optimal demand-side flexibility level is between 1% and 3%. The decrease in system welfare for higher demand-side flexibility volumes is driven by two effects: a decrease in gross system welfare and an increase in flexibility costs, and consequently in total system costs.

We then allow the model to decide on the optimal demand-side flexibility level. For the reference scenario, this results in an optimal level of 1.48% demand-side flexibility and €23,816 system welfare, normalised to the (average) consumer. This flexibility allows a €476 annual welfare gain compared to the case where no demand-side flexibility is introduced. Passive consumers are more curtailed than prosumers, with a 65%/35% ratio of the total flexibility level, as is shown in Figure 5. The rationale behind this is that under the reference scenario parameters the DSO relies on implicit demand-side flexibility by transmitting price signals to prosumers to invest in solar PV and batteries, which they use when following the system needs. Passive consumers, in turn, are curtailed more as they do not have alternative ways to generate electricity. However, they are not curtailed to a level that makes their profiles similar to those of the prosumers as this would require higher volumes of curtailment that will severely decrease gross consumer welfare and thus outweigh the savings in total system costs.

Figure 5: Load profiles for the different types of consumers in the reference scenario: (a) prosumers, (b) passive consumers

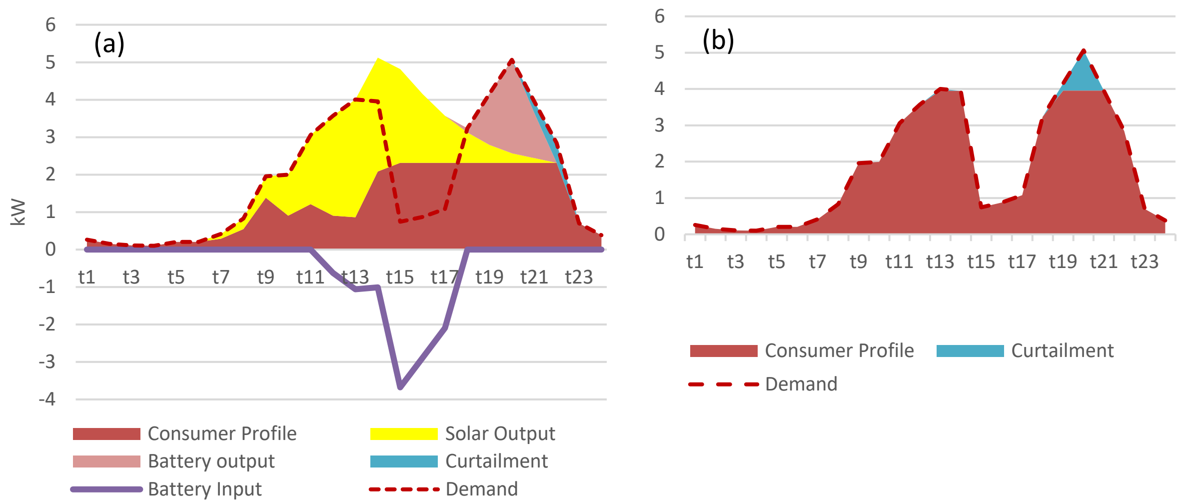


3.2.3 An imperfect proxy for network cost driver, WF=0.5

In order to assess the impact of implicit demand-side flexibility, we introduce partly cost-reflective network tariffs. To do this, we include a 0.5 proxy for network cost drivers, meaning that a 1 kW reduction in the consumer profile peak contributes a 0.5 kW reduction in the system peak. This is also equivalent to having heterogeneous demand profiles among consumers that are optimising their individual profiles. Passey et al. (2017) find that the correlation coefficient between consumer payments under capacity-based tariffs and responsibility for the network peak is very low, at 0.56.

Under this condition, the optimal demand-side flexibility level drops from 1.48% to only 0.35%. The resulting welfare gain drops too, to € 41.8. The rationale behind this is that with an imperfect proxy the potential of explicit demand-side flexibility is limited. Indeed, following their reaction to partly cost-reflective tariffs, the prosumer profile is higher than in the case of a perfect proxy. Therefore, the overall difference between the profiles of prosumers and passive consumers is less pronounced. Consequently, less curtailment is applied to passive consumers. Figure 6 shows the load profiles of both types of consumers for a WF equal to 0.5.

Figure 6: Load profiles for the different types of consumers with WF =0.5: (a) prosumers, (b) passive consumers



3.2.4 The role of prosumers and DER investments

We further expand our assessment by going to extreme cases of prosumer shares: first with 100% passive consumers and second with 100% prosumers, both with cost-reflective tariffs. We find that when all consumers are passive the optimal demand-side flexibility level stands at 1%, while allowing a €313 welfare gain. In the case of 100% prosumers, on the other hand, the optimal demand-side flexibility level is 0.34%, allowing only €124. In Table 2 we present the optimal demand-side flexibility levels and the welfare gains for the different cases.

Table 2: Flexibility levels and welfare gains for different shares of prosumers

	100% Passive consumers	50%-50% Reference Scenario	100% Prosumers
Flexibility level	1%	1.48%	0.34%
Welfare (Welfare gain) (€)	23,111 (313)	23,816 (476)	23,922 (124)

In the case of 100% passive consumers, there is no implicit demand-side flexibility that will change consumer behaviours. The DSO procures 1% of explicit demand-side flexibility. Compared to the reference scenario, the optimal flexibility level is lower. The reason is that in the reference scenario the contribution of implicit demand-side flexibility allows more explicit demand-side flexibility, mainly among passive consumers, and leads to more system cost savings. However, with all passive consumers, this difference between profiles is non-existent. For 100% prosumers, there is 0.34% explicit demand-side flexibility, which is also lower than in the reference scenario. The rationale behind this is that prosumers are able to flatten their consumption profiles in reaction to the network tariff signals sent by the DSO. However, with an already flattened profile there is limited room for further welfare gain, taking into account the effect of the gross consumer welfare loss and the reduction in total system costs. This results in a small welfare gain in the case of 100% prosumers.

3.2.5 Strategic behaviours and the impact of compensation levels

Another parameter that is key in the economics of explicit demand-side flexibility in distribution networks is flexibility compensation. In this part, we run the model for different levels of compensation. We set a low compensation, compared to the reference scenario, at €0.5 and a high compensation equal to the VoLL at €5.33. Table 3 shows the demand-side flexibility levels and the welfare gains for the different compensation levels.

We see that with low compensation the optimal flexibility level decreases, as does the welfare gain, as this compensation is too low for passive consumers. It therefore decreases the optimal flexibility level and the related welfare gain. For a compensation equal to the Voll, the optimal flexibility level remains almost the same. However, the welfare gain is reduced compared to the reference scenario. This is due to strategic behaviour by prosumers, which is shown in their load profiles in Figure 7. We explain this further in the next two paragraphs.

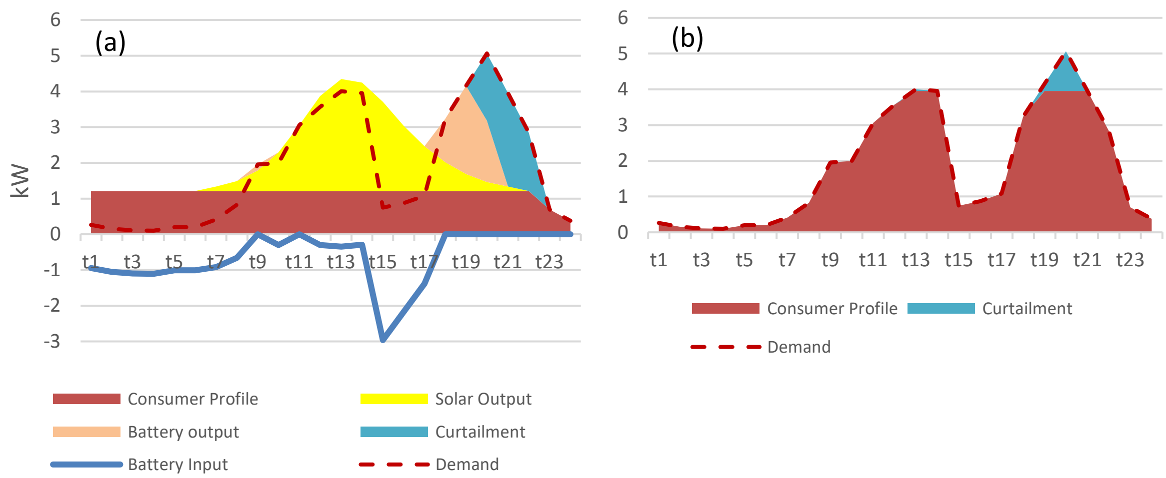
Table 3: Flexibility levels and welfare gains for different compensation levels

Comp	€0.5	€1 Reference scenario	€5.33
Flexibility level	0.8%	1.48%	1.49%
Welfare gain	€239	€476	€152

Compared to the load profile in the reference scenario (in Figure 5(a)), we see in Figure 7(a) that prosumers use their battery output differently. Indeed at t20, which corresponds to the evening peak, prosumers' battery input is 1.7 kW instead of 2.9 kW in the reference scenario. In addition, at t21 there is no battery output from prosumers, compared to 0.6 kW in the reference scenario. Therefore, the DSO has to curtail more prosumers, including at the night peak, even though the network tariffs are cost-reflective. Indeed, with this behaviour prosumers are more curtailed than passive consumers, with a 65%/35% ratio, which is the reverse of the reference scenario.

Another effect that is seen with high compensation is that the prosumer profile has a smaller magnitude in Figure7(a) than in Figure 5(a). We may think that this is as a positive reaction to cost-reflective network charges. However, if we look again at the battery output during and following the night peak we see that with no or little battery output in these hours there is in fact more curtailment of prosumers.

Figure 7: Load profile for the different types of consumers with Comp= €5: (a) prosumers, (b) passive consumers



We may tend to think that compensation set at the VoLL will lead to higher welfare gain. However, we find that this does not happen in the case of prosumers as they value electricity consumption less, which leads to them behaving strategically in order to benefit from the relatively high compensation. The rationale behind this is that prosumers and passive consumers value electricity differently. Therefore, the VoLL for prosumers is lower than for passive consumers. Studies on VoLL estimates segment consumers into different groups based on their economic activity, e.g. domestic consumers and industrial consumers (ACER, 2018). However, there is no differentiation between active and passive consumers in VoLL estimations. For instance, ENW (2019) highlights that vulnerable and low-income electricity consumers have higher VoLLs than average. Further effects of the VoLL will be presented in the next section.

3.2.6 Sensitivity results

In this section, a sensitivity analysis is carried out in order to assess the impacts of three context-specific parameters in the demand-side flexibility framework. These parameters are the VoLL, the frequency of critical days and network investment costs. The sensitivity analysis aims to validate the model results and to highlight the extent to which the potential of demand-side flexibility is context-specific.

A. Impact of VoLL levels

In the first sensitivity analysis, we consider two other VoLL values: 2 €/kWh, which is a low VoLL across the EU Member States, and 9.6 €/kWh, which is high.

Table 4: Flexibility levels and welfare gains for different VoLL levels

VoLL	2 €/kWh	5.33 €/kWh Reference scenario	9.6 €/kWh
Flexibility level	4.4%	1.48%	0.2%
Welfare gain	€334.5	€476	€266.4

First, we observe that VoLL levels are inversely proportional to demand-side optimal flexibility levels. For a low VoLL of 2 €/kWh we observe higher levels of demand-side flexibility: 4.4% of the total demand. This is explained by the fact that consumers value electricity consumption less. The lower welfare gain is due to the decrease in gross system welfare due to higher flexibility levels compared to the reference scenario. In addition, as gross welfare is a product of VoLL multiplication, then a lower VoLL will also lead to lower welfare gain. At a high VoLL of 9.6 €/kWh we see the opposite effect, with a low demand-side flexibility level leading to a relatively high welfare gain.

Another element that impacts the potential of demand-side flexibility is the notice factor. This translates into whether consumers are notified (e.g. via email or SMS) about the curtailment event or not. According to ACER (2018), implementing a notice factor reduces the impact of electricity disruption. It also translates into a reduction of VoLL by about 50%, which is then called VoLA. Indeed, in the case of Belgium VoLL is equal to 9.6 €/kWh and VoLA is equal to 5.33 €/kWh. This means that the effect of introducing a notice factor is the same as moving from the third to the second column in Table 4. It therefore results in higher optimal demand-side flexibility and, more importantly, higher welfare gains.

B. The impact of the frequency of critical days

For the second sensitivity analysis, we choose frequencies of critical days from 5 to 104 days a year. The choice of 104 as the maximum frequency corresponds to the frequency of weekend days a year. This is in order to assess how an optimal flexibility volume interacts with the frequency of critical days, *inter alia* when they become as frequent as weekend days.

Table 5: Flexibility levels and welfare gains for different frequencies of critical days

Frequency of critical days	5	15 Reference scenario	104
Flexibility level	2.1%	1.48%	0%
Welfare gain	€612	€476	€0

We observe that the optimal levels of flexibility are inversely proportional to the frequency of critical days. For low frequencies of critical days, there are higher optimal demand-side flexibility volumes. There are two main reasons behind this observation. First, with low frequencies of critical days the regulated DSO would need fewer flexibility volumes to reduce the peaks on the critical days. Second, as we increase the frequency of critical days the total annual demand volume increases. This is natural since the demand during a critical day is higher than on a normal day. Substituting a normal day with a critical one increases the total demand volume. This could be neutralised by reducing the demand on the other normal days. However, we do not change this for practical reasons as changing the normal day profile may create other unwanted effects'. The two above-mentioned effects happen in opposite directions in the two first columns in Table 5. Indeed, for five critical days there is higher welfare gain and higher optimal levels of flexibility, as it is easier to neutralise the critical day' peaks.

Another observation is that in the case with 104 critical days, meaning that they are as frequent as weekend days, the optimal flexibility level is 0%. This confirms the fact that the variation in demand profiles between weekdays and weekends does not result in the use of explicit demand-side flexibility during weekends. Weekend days usually have different consumption levels and peaks. For instance, in the Belgian SLP of Synergrid (2019), weekend days have slightly higher peaks. With a high frequency of critical days higher volumes are needed to reduce peaks to realise system cost savings, as these peaks are very frequent, which in turn will impact gross system welfare. Therefore, it is better to fully build the distribution network and size it to fit the critical day's demand without procuring any flexibility.

C. The impact of network investment costs

Network expansion costs are particularly relevant in DSOs network planning. High network expansion costs can incentivise DSOs to further use demand-side flexibility. In order to assess the impact of this, we consider three scenarios with different incremental network costs, as is shown in Table 6.

Table 6: Flexibility levels and welfare gains for different network expansion costs

Network expansion costs	200€/kW	400 €/kW	600€/kW
Flexibility levels	0.3%	1.48%	3%
Welfare gain	€55	€476	€464

The results confirm that optimal demand-side flexibility volumes increase with higher network expansion costs. With low expansion costs, reinforcing the network is the most logical pathway. Demand-side flexibility of 0.3% is deemed optimal. This will only allow a €55 welfare gain. With low network expansion costs, the regulated DSO will naturally favour network reinforcement as it is not costly. Only a very small part of the consumer's demand is curtailed.

For high network expansion costs, the optimal flexibility levels increase. The rationale behind this is that with high network expansion costs the contribution of demand-side flexibility to system cost savings is more significant. However, the welfare gain is limited due to higher volumes of demand-side flexibility impacting gross system welfare in comparison with the reference scenario.

4. Conclusions and policy implications

In what follows, we summarise our main findings on the interaction between implicit and explicit demand-side flexibility and the appropriate level of compensation for curtailing demand. In addition, we comment on our sensitivity analysis and indicate the direction of our future research.

First, regarding the interaction between implicit and explicit demand-side flexibility, we found that this interaction strongly depends on the cost-reflectiveness of network tariffs. If network tariffs are cost-reflective, prosumer investments in PV and batteries already take into account the cost of network investments. Explicit demand-side flexibility is then mainly used to target passive consumers that do not respond to tariffs. Passive consumers are typically curtailed during critical conditions when it is cheaper to curtail load than to invest in the network to cover the peak. This, of course, only happens if these critical conditions do not occur frequently. If network tariffs are only partly cost-reflective, explicit demand-side flexibility can also be used to target prosumers to correct their behaviour. However, this correction now comes at a higher cost because the compensation that is provided to prosumers or passive consumers when they are curtailed has to be recovered through the network tariffs. By trying to fix the imperfect signal from the network tariff, we are therefore increasing that signal (and cost). This gives an intuitive explanation of the surprising result that explicit demand-side flexibility is used more in the scenarios with more cost-reflective tariffs. The welfare gains associated with the use of explicit demand-side flexibility are also higher in these scenarios. The policy implication of this result is that we cannot avoid redesigning network tariffs by introducing explicit demand-side flexibility mechanisms.

Second, concerning the appropriate level of compensation to curtail demand, we found that it is very difficult to set an appropriate level of compensation in a context with prosumers and passive consumers. If the compensation is below the VoLL, passive consumers are only partly compensated for their loss. If the compensation is increased towards the VoLL, it becomes so attractive for prosumers that they game the system. They start to use their batteries against system needs, anticipating that they will get curtailed and compensated. They are then generously remunerated at the VoLL, but they only lose load they artificially contributed to. Note that cost-reflective network tariffs cannot stop this behaviour because the signal from the potential compensation can be stronger than the signal from the network tariff in some scenarios. The policy implication of this result is that regulators will have a hard time setting a fixed level of compensation for mandatory load curtailment by DSOs.

Third, we performed a sensitivity analysis. Different countries have different VoLL values. The potential for explicit demand-side flexibility will be higher in countries with a lower VoLL. If consumers know in advance that they will be curtailed, their VoLL is also lower. This implies that explicit demand-side flexibility will have more potential if it can be combined with a notification to consumers to warn them before they are curtailed. Different countries also have different types of critical conditions. The potential of demand-side flexibility is much higher in countries that have critical conditions that are infrequent. If they become as frequent as weekends, it will be cheaper to design the network to handle these conditions. If they are less frequent, it can be cheaper to curtail demand under these critical conditions. This, of course, also depends on the cost of expanding the grid, which can also vary among countries and regions.

Finally, it should be remembered that in this paper we have modelled explicit demand-side flexibility as a mandatory scheme with fixed compensation. The alternative is to let DSOs procure flexibility at a market price. This would allow demand-side flexibility to compete with supply-side flexibility, and would also avoid the difficulty in setting an appropriate level of compensation. It could, however, create new issues with market parties influencing the market price and/or not providing flexibility when the DSO needs it to remedy congestion. This will be the next step in our research and we look forward to analysing it.

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Appendix

Appendix A: The MPEC model resolution

A1. MPEC Model formulation details:

SETS

i : 1,..,N: Consumers types, 1 for active and N for passive
t: 1,..,T: Time steps, hours, T=24h
Daytype: normal, critical

PARAMETERS

Upper level

$\mathrm{PC_i}$: Proportion of consumer type i
VoLL: Value of lost load [€/kWh]
comp: Compensation for flexibility [€/kWh]
IncrGridCosts: Incremental annualised grid cost per kW, scaled per average consumer [€/kW]
$\mathrm{d_{i,daytype,t}}$: Original demand at (t, daytype) of consumer i [kW]
$\mathrm{wdt_{daytype}}$: annuity factors for the different costs [-]

Lower Level

dt: time step, as a fraction of 60 minutes [-]
$\mathrm{MS_i}$: Maximum solar capacity for consumer i [kW]
$\mathrm{MB_i}$: Maximum battery capacity for consumer i [kWh]
$\mathrm{SY_{t,i}}$: PV panel yield at time step t of consumer i [kWh/kWpeak]
$\mathrm{EBP_t}$: Energy price for buying electricity from the grid [€/kWh]
$\mathrm{ESP_t}$: Energy price received for injecting in the grid [€/kWh]
ICS: investment cost solar PV [€/kWp]
AFS: Annuity factor for solar PV investment
ICB : Investment cost battery [€/kWh]
AFB: Annuity factor for battery investment
BDRatio: Ratio of max power output of the battery over the installed energy capacity [-]
BCRatio: Ratio of max power input of the battery over the installed energy capacity [-]
ηout: Efficiency of discharging the battery [%]
ηin: Efficiency of charging the battery [%]

VARIABLES (in italics)

Upper Level

cnt: Capacity component of the network tariff [€/kW]
fnt: fixed component of the network tariff [€/consumer]
vnt: Volumetric component of the network tariff [€/kWh]
$qflex_{i,daytype,t}$: Demand-side flexibility procured by the DSO[€/kWh]
$CPeak$: The coincident peak demand resulting from the model optimisation (the highest value of $CPeakDemand$ and $CPeakInjection$).
$CPeakDemand$: The coincident peak demand resulting from the model optimisation
$CPeakInjection$: The coincident peak injection resulting from the model optimisation
$GrossSystemWelfare$: The gross system welfare created from electricity consumption [€]
$WelfareCorrection$: The welfare correction coming from flexibility compensation [€]
$TotalSystemCosts$: Total annualised system costs, scaled per average consumer [€]
$SystemGridCost$ Total annualised grid costs, scaled per average consumer [€]
$SystemEnergyCosts$: Total annualised energy costs, scaled per average consumer [€]
$SystemDERCosts$: Total annualised DER costs, scaled per average consumer [€]

Lower Level
$qw_{i,daytype,t}$: Energy withdrawn at (t, daytype) by consumer i [kW]
$qi_{i,daytype,t}$: Energy injected at (t, daytype) by consumer i [kW]
is_i: Installed solar PV capacity by consumer i [kW]
ibi: Installed battery capacity by consumer i [kWh]
$qbout_{i,daytype,t}$: Discharge of the battery of consumer i at (t, daytype) [kW]
$qbin_{i,daytype,t}$: Charge of the battery of consumer i at (t, daytype) [kW]
$SOC_{t,i}$: State of charge of the battery [kWh]
$GrossConsumerSurplus_i$: The gross system welfare created from electricity consumption for consumer i [€]
$WelfareCorrection_i$The welfare correction coming from flexibility compensation, for consumer i [€]
$Costs_i$: Annualised costs for consumer i [€]
$EnergyCosts_i$: Annualised energy costs for consumer i [€]
$GridCharges_i$: Annualised grid charges for consumer i [€]
$DERcosts_i$ Annualised DER costs, for consumer i [€]

FULL CONSUMER CONSTRAINTS

1) $qw_{i,daytype,t} + is_i * \mathrm{SY}_{\mathrm{i,daytype,t}} + qbout_{i,daytype,t} - qi_{i,daytype,t} - qbin_{i,daytype,t} + qflex_{i,daytype,t} - \mathrm{D}_{\mathrm{i,daytype,t}} = 0 \quad \forall\, t\,, daytype \quad (\mu 1_{t,i})$

2a.) $SOC_{i,daytype,t} - qBin_{i,daytype,t} * \eta\mathrm{in} * \mathrm{dt} + \frac{qBout_{i,daytype,t}}{\eta\mathrm{out}} * \mathrm{dt} - SOC_{i,daytype,t-1} * (1 - \varphi * dt) = 0 \quad \forall\, t \neq 1\,, daytype \quad (\mu 2_{t,i})$

2$b.$) $SOC_{i,daytype,T} - SOC_{i,daytype,1}$ - $qBin_{i,daytype,1} * \eta\mathrm{in} * \mathrm{dt} + \frac{PBout_{i,daytype,1}}{\boldsymbol{\eta out}} * \mathrm{dt} = 0 \quad (\mu 2_{1,i})$

4.) $-qmax_i + qw_{i,daytype,t} + qi_{i,daytype,t} \leq 0 \quad \forall\, t \quad (\lambda 1_{t,i})$
5.) $SOC_{i,daytype,t} - IB_i \leq 0 \quad \forall\, t \quad (\lambda 2_{t,i})$
6.) $qBout_{i,daytype,t} - IB_i * \mathrm{BDRatio} \leq 0 \quad \forall\, t \quad (\lambda 3_{t,i})$
7.) $qBin_{i,daytype,t} - IB_i * \mathrm{BCRatio} \leq 0 \quad \forall\, t \quad (\lambda 4_{t,i})$
8.) $-qw_{i,daytype,t} \leq 0 \quad \forall\, t \quad (\lambda 5_{t,i})$
9.) $-qi_{i,daytype,t} \leq 0 \quad \forall\, t \quad (\lambda 6_{t,i})$
10.) $-SOC_{i,daytype,t} \leq 0 \quad \forall\, t \quad (\lambda 7_{t,i})$
11.) $-qBout_{i,daytype,t} \leq 0 \quad \forall\, t \quad (\lambda 8_{t,i})$
12.) $-qBin_{i,daytype,t} \leq 0 \quad \forall\, t \quad (\lambda 9_{t,i})$
13.) $IS_i - MS_i \leq 0 \quad (\lambda 10_i)$
14.) $IB_i - MB_i \leq 0 \quad (\lambda 11_i)$
15.) $-IS_i \leq 0 \quad (\lambda 12_i)$
16.) $-IB_i \leq 0 \quad (\lambda 13_i)$
17.) $-qmax_i \leq 0 \quad (\lambda 14_i)$ implied by equations 4 and 10

A2. Model transformation

THE LAGRANGIAN FORMULATION

$$L=$$

$$\sum_{i=1}^{N}\sum\nolimits_{\text{daytype}}^{\text{critical}}\sum_{t=1}^{T}[-\mathrm{PC_i}*\left(\mathrm{d_{i,daytype,t}}-qflex\right)*\mathrm{Voll}*\mathrm{wdt_{daytype}}+\mathrm{PC_i}$$
$$*\sum_{t=1}^{T}\left(\mathrm{comp}*qflex_{i,daytype,t}\right)*\mathrm{wdt_{daytype}}\ +\left(qw_{i,daytype,t}*\mathrm{EBP_t}-qi_{i,daytype,t}*\mathrm{ESP_t}\right)$$
$$*\,\mathrm{wdt_{daytype}}+\ \left(qw_{i,daytype,t}-\mathrm{NM}*qi_{i,daytype,t}\right)*vnt*\mathrm{wdt_{daytype}}+cnt*\ qmax_i+fn\mathrm{t}$$
$$+\ is_i*\mathrm{AICS}+ib_i*\mathrm{AICB}$$
$$+\sum\nolimits_{\text{daytype}}^{\text{critical}}\sum_{t=1}^{T}\mu 1_{i,daytype,t}*(qw_{i,daytype,t}+is_i*\mathrm{SY_{i,daytype,t}}+qbout_{i,daytype,t}$$
$$-\,qi_{i,daytype,t}-qbin_{i,daytype,t}+qflex_{i,daytype,t}-\mathrm{D_{i,daytype,t}})\ +\mu 2_{i,t\neq 1,daytype}$$
$$*\,(SOC_{i,daytype,t}-PBin_{i,daytype,t}*\eta\mathrm{in}*\mathrm{dt}+\frac{qBout_{i,daytype,t}}{\eta\mathrm{out}}*\mathrm{dt}-SOC_{i,daytype,t-1}$$
$$*\,(1-\varphi*\mathrm{dt}))+\mu 2_{i,daytype,1}*(SOC_{i,daytype,1}-\mathrm{SOC0}-qBin_{i,daytype,1}*\eta\mathrm{in}*\mathrm{dt}$$
$$+\ \frac{PBout_{i,daytype,1}}{\eta\mathrm{out}}*\mathrm{dt})+\lambda 1_{i,daytype,1}*\left(-\ qmax_i+qw_{i,daytype,t}+qi_{i,daytype,t}\right)$$
$$+\ \lambda 2_{i,daytype,t}*\left(SOC_{i,daytype,t}-IB_i\ \right)\ +\ \lambda 3_{i,daytype,t}*(qBout_{i,daytype,t}-IB_i*\mathrm{BDRatio})$$
$$+\ \lambda 4_{i,daytype,t}*\left(PBin_{i,daytype,t}-IB_i*\mathrm{BCRatio}\right)+\lambda 5_{i,daytype,t}\ *\left(-qw_{i,daytype,t}\right)$$
$$+\ \lambda 6_{i,daytype,t}*\left(-qi_{i,daytype,t}\right)\ +\ \lambda 7_{i,daytype,t}*\left(-SOC_{i,daytype,t}\right)+\lambda 8_{i,daytype,t}$$
$$*\left(-qBout_{i,daytype,t}\right)+\lambda 9_{i,daytype,t}*\left(-qBin_{i,daytype,t}\right)+\mu 2_{i,daytype,t1}$$
$$*\left(SOC_{i,daytype,t1}-PBin_{i,daytype,t1}*\eta\mathrm{in}*\mathrm{dt}+\frac{qBout_{i,daytype,t1}}{\eta\mathrm{out}}*\mathrm{dt}-\mathrm{SOC0}\right)+\lambda 10_i$$
$$*\,(IS_i-\mathrm{MS_i}\ )+\lambda 11_i*(IB_i-\mathrm{MB_i}\ )+\lambda 12_i*(-\ IS_i)+\lambda 13_i*(-\ IB_i)$$

KKT conditions

$$\frac{\partial\Gamma}{\partial qw_{i,daytype,t}}=\ \mathrm{wdt_{daytype}}*(\mathrm{EBP_t}+VNT)+\mu 1_{t,i}+\lambda 1_{t,daytype,i}-\lambda 5_{t,daytype,i}$$

$$\frac{\partial\Gamma}{\partial qi_{i,daytype,t}}=-\mathrm{wdt_{daytype}}*(\mathrm{ESP}_t+\mathrm{NM}*VNT)-\mu 1_{t,daytype,i}+\lambda 1_{t,daytype,i}-\lambda 6_{t,daytype,i}$$

$$\frac{\partial\Gamma}{\partial qmax_i}=\ cnt-\ \sum\nolimits_{daytype}^{critical}\sum\nolimits_{t=1}^{T}\lambda 1_{\mathrm{t,daytype,i}}$$

$$\frac{\partial\Gamma}{\partial soc_{i,daytype,t}}=\mu 2_{i,daytype,t}-\mu 2_{i,daytype,t+1}*(1-\varphi*\mathrm{dt})+\lambda 2_{i,daytype,t}-\ \lambda 7_{i,daytype,t}\quad\forall\ t\neq\{T\}$$

$$\frac{\partial\Gamma}{\partial soc_{i,daytype,t}}=\mu 2_{i,daytype,1}-\mu 2_{i,daytype,T}+\lambda 2_{i,daytype,T}-\ \lambda 7_{i,daytype,T}\quad\forall\ t=\{T\}$$

$$\frac{\partial\Gamma}{\partial qBout_{i,daytype,t}}=\mu 1_{\mathrm{i,daytype,t}}+\frac{\mu 2_{i,daytype,t}}{\eta\mathrm{out}}*\mathrm{dt}+\lambda 3_{i,daytype,t}-\lambda 8_{i,daytype,t}$$

$$\frac{\partial\Gamma}{\partial qBin_{i,daytype,t}}=-\mu 1_{\mathrm{i,daytype,t}}-\mu 2_{\mathrm{i,daytype,t}}*\eta\mathrm{in}*\mathrm{dt}+\lambda 4_{\mathrm{i,daytype,t}}-\lambda 9_{\mathrm{i,daytype,t}}$$

$$\frac{\partial\Gamma}{\partial IS_i}=\mathrm{ICS}*\mathrm{AFS}+\ \sum\nolimits_{daytype}^{critical}\sum\nolimits_{t=1}^{T}\mu 1_{i,daytype,t}*\mathrm{SY}_{t,i}+\ \lambda 10_{\mathrm{i}}-\lambda 12_{\mathrm{i}}$$

$$\frac{\partial\Gamma}{\partial IB_i}=\mathrm{ICB}*\mathrm{AFB}-\ \sum\nolimits_{daytype}^{critical}\sum\nolimits_{t=1}^{T}\lambda 2_{\mathrm{i,daytype,t}}-\ \sum\nolimits_t\lambda 3_{\mathrm{i,daytype,t}}*\mathrm{BDRatio}\ -\ \sum\nolimits_t\lambda 4_{\mathrm{i,daytype,t}}*\mathrm{BCRatio}+\lambda 11_{\mathrm{i}}-\lambda 13_{\mathrm{i}}$$

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