Comparison of Priority Service with Multilevel Demand Subscription

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***Abstract*—Priority service and multilevel demand subscription have been proposed as two alternative methods for the mobilization of residential demand response. Whereas priority service relies on the differentiation of electricity service according to reliability, multilevel demand subscription further differentiates electricity service according to duration. Despite its increased complexity, multilevel demand subscription promises increased operational efficiency, as it permits a finer differentiation of consumer classes by the utility. It also allows households to reduce their electricity bills relative to priority service. This paper proposes a framework for quantifying these effects. We design a modeling approach for evaluating the performance of these different aggregator service offerings in a system with utility-scale renewable supply, residential renewable supply, and residential storage. We compare priority service to multilevel demand subscription, and discuss the implications of these different residential demand response options on operational efficiency and consumer expenditures for electricity service on a realistic model of the Belgian power market. We show how the comparison between the two schemes is affected by the adoption of a different time resolution in a detailed case study.**

***Index Terms*—Demand response, priority service, multilevel demand subscription, nonlinear pricing, stochastic programming.**

I. Introduction

RECENT developments in electricity markets indicate the increasing engagement of demand-side flexibility in power system operations [1], [2]. Apart from the traditional participation of price-responsive consumers in day-ahead operations [3], flexible consumers have recently been enlisted for more crucial roles in power system operations, notable among which is the provision of operating (automatic and manual frequency restoration) reserve for balancing [4]. Moreover, recently, the proliferation of storage and renewable resources at the medium and low-voltage grid has placed an increasing need for improved coordination between transmission and distribution systems. Residential flexibility may be exploited in order to enable the integration of distributed renewable supply without imposing the need for exorbitant investment costs in distribution network infrastructure [5]. Poor judgement in the pricing of residential flexibility is best exemplified through the recent backlash against net metering [6]. Net metering was introduced in a number of US States, including Arizona, Hawaii and California, in recent years. It has recently been retracted due to adverse distributional effects [7] and due to the inability of the existing distribution infrastructure to support the roll-out of solar panels that has been induced by net metering.

Whereas the engagement of demand-side flexibility in the commercial and industrial sector has been increasing steadily, the mobilization of residential consumers lags behind [8]. This is despite increasing evidence of residential flexibility in a number of pilot projects [9]–[13], and despite the fact that the residential sector is characterized by higher levels of flexibility than the commercial and industrial sector [14]. A crucial feature of residential consumers is their limited attention span. Therefore, it is essential for aggregator business models which aim at mobilizing residential demand response to respect the needs of residential consumers for control over their equipment, privacy, and simplicity in the pricing of electricity.

Service differentiation in the power industry has offered a perspective on the offering of electricity which inspires aggregator business models that respect the aforementioned requirements for privacy, simplicity and control. Service differentiation moves away from the golden standard of real-time pricing, which is a best-case coordination scenario, but which is confronted with significant informational overhead and institutional barriers. Instead, product differentiation adopts the point of view that residential consumers treat electricity as a service with attributes that can be differentiated. This point of view has inspired various levels of differentiation in electricity delivery [15]–[19], some of which have been widely used in practice (including time of use pricing and demand charges [3]).

In this work we focus on multilevel demand subscription [20]. Multilevel demand subscription is a generalization of priority service [21]. In priority service, flexible consumers procure electricity at different levels of reliability, with higher reliability implying a higher price. Multilevel demand subscription further differentiates the electricity service of a certain level of reliability according to its duration. We discuss priority service and multilevel demand subscription in detail in section II. The contribution of our paper lies in the quantification of the trade-offs between the increased operational efficiency of multilevel demand subscription relative to priority service. The challenges in quantifying the benefits of multilevel demand subscription relate to the co-existence of local distributed renewable supply (rooftop solar) as well as local flexibility in the form of storage at the household level. This requires a careful modeling framework, which we discuss in section III. This framework is then applied to a realistic model of the Belgian power market for two different time resolutions. By comparing these two time resolutions, this study also demonstrates the importance of using a more refined time scale in order to quantify the benefits of demand response more accuraltey in production simulation models.

The paper is organized as follows. Section II provides details

about both approaches compared in this work, namely priority service and multilevel demand subscription. Subsequently, section III describes the modeling framework that we propose in order to compare these two demand response paradigms. The case study examined in this work is detailed in section IV. Section V presents and discusses the results of the case study. Finally, section VI concludes our analysis.

II. Overview of Priority Service and Multilevel Demand Subscription

In this section, the two studied demand response schemes are explained and their functioning is detailed. The first part is devoted to priority service, while the second part is dedicated to its generalization, multilevel demand subscription.

A. Priority Service

Under priority service pricing, households engage in long-term (e.g. annual) contracts for electricity service, much like our current subscription to cell phone services. By engaging in priority service, residential consumers can choose among options with different quality. A higher quality implies a higher price. In the particular case of priority service, quality is measured according to electricity service reliability.

The process of subscribing to and using priority service for a consumer is presented in Fig. 1 for a particular offering of priority service represented by the ColorPower concept [8] which is used as the basis for our case study. Under ColorPower, three options represented by colors are considered: (i) green indicates cheap power that can be interrupted frequently; (ii) yellow indicates power that can only be interrupted under emergency conditions; (iii) red represents expensive power that cannot be interrupted.

Under priority service, the aggregator designs a price menu by assigning a price to each option. An example of a priority service price menu can be found in Table III of section IV. This price menu is then proposed to consumers so that they can subscribe by selecting a particular strip of power for each option. In the example shown in the figure, the consumer subscribes to 1.6kW of green power, 1.8kW of yellow power and 1kW of red power.

Based on the price menu for the case study with 4-hour resolution which is presented in Table III, the consumer subscription to red would cost 91.94€ for the month. A home energy router, at the consumer premises, registers the procured electricity service and allocates individual devices within the home to different colors[1]. Note that the colors will only be available to the consumer (and its router) when the service is not interrupted. For example, in Fig. 1, the dishwasher and washing machine are scheduled under the green color during time period 2, because they are both quite flexible. However, the consumer would like for the washing machine to finish earlier, therefore the washing machine is scheduled under the red color at time period 4, in order to accelerate the completion of its duty cycle. This allocation respects the

[1] Alternatively, consumers can assign their plugs to a specific color manually [8].

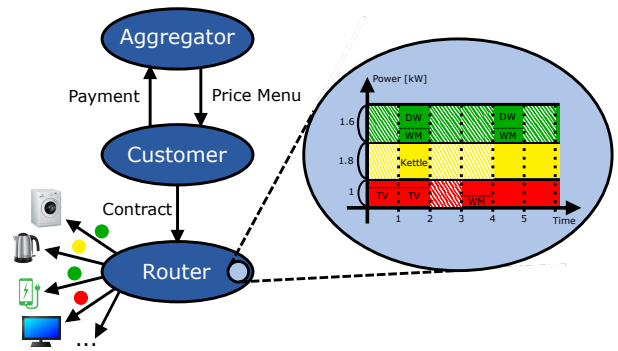

Fig. 1. Setup of home energy router in priority service pricing.

requirement that the average consumption of power within a real-time balancing interval (e.g. 5 or 15 minutes) for the aggregate of home devices under a certain color should not exceed the total amount of kW procured for that color.

The home energy router can gain knowledge, through repeated experience, about the consumption patterns of households, the interruption patterns of different colors, as well as the discomfort of consumers from different interruption events. This allows the home energy router to continuously improve by gradually learning how to best serve the needs of the household. This creates a scope for the application of learning in home energy scheduling, for which an increasing body of literature is currently being developed [22], [23]. In this work we consider a relatively simple home energy management problem, and focus instead on the macroscopic implications in terms of market equilibrium and household cost.

The utility which offers priority service to residential consumers commits to a certain level of reliability for each service option. This level of reliability needs to be respected on average over an extended period of service (e.g. annually) even if certain periods may be characterized by fluctuations around this average [24]. In a setting of vertical integration, the utility interrupts colors in order of decreasing reliability, since higher-valuation consumers will prefer higher levels of reliability. In a market setting, the utility can map the reliability level of different colors to wholesale market bids through the price duration curve of the market. The utility must design the menus carefully, so as to ensure that households are segmented adequately. This can be achieved by utilizing aggregate statistical information about the consumer population [21], [24] in the form of demand functions typically available to utilities.

Note that, in this paper, we develop priority service under a strict interpretation as a pure capacity-based service. Concretely, we assume that 1 kW of service, once procured, is bought for the *entire* service horizon, whether the consumer shows up for consuming the service or not. This assumption implies in practice that a portion of the household subscription is not used entirely at every time period, due to time-varying consumption profiles. This leads to potential energy consumption that is procured but never used, and renders priority service pricing expensive for consumers, as shown in [25] with a simple example. For this reason, an alternative implementation of priority service is presented in [26] where

the total price of the priority service menu is separated into a reservation and an energy service charge. This allows the aggregator to alleviate the impact of the capacity charge, and thus reduces the overall cost of priority service for households. In this work, we investigate a generalization of priority service, namely multilevel demand subscription, which extends the priority service scheme by integrating an energy component related to the duration of a given strip of procured capacity, and thus allows reduction in the overall bill of consumers.

B. Multilevel Demand Subscription

Multilevel demand subscription generalizes the priority service model of the previous section. From the point of view of consumers, kilowatts of different priority levels (i.e. colors) are "topped up" with credits. More credits entitle customers to use more hours of power of a certain quality, but cost more. Thus, the energy router within the home needs to respect not only the power limit of each color, but also the total number of credits over the service period (e.g. over the year).

An example of a multilevel demand subscription price menu is provided in Table IV of section IV. The consumer now has the opportunity to subscribe to the green color but for a third of the horizon. Let us assume that the consumer chooses a strip of 1kW of green color for a third of the horizon. This will cost 21.52€ for the month. In this case, the consumer will only be able to use this green power strip of 1 kW for a third of the day each day during the month. Priority service is therefore a special instance of multilevel demand subscription for which only one duration level is considered which is equal to the full service horizon.

Note that multilevel demand subscription is similar to duration-differentiated energy services presented in [16] insofar as duration is concerned, with an added component given by the reliability of service. Choosing between priority service and multilevel demand subscription is equivalent to a trade-off between simplicity and operational efficiency. Indeed, this service offering presents increased complexity from the point of view of the household since more options are available in the price menu which imply a more complex choice for households. However, as we demonstrate in the results section, this allows households to reduce their electricity bills by subscribing to shorter durations, while also empowering the utility to better discriminate among consumer types, thereby increasing efficient allocation of power to flexible demand.

Accordingly, the utility commits not only to honoring the reliability of each service option, but also to honoring the duration of that option. The task of pricing the menu also becomes more challenging. Although the utility can still rely on aggregate statistical information about the population, the utility is now required to estimate a load duration curve for the population, parametric on a retail price. This set of information is more rich, and therefore harder to obtain than the demand curves for priority service pricing.

III. Simulation Framework

In order to simulate the performance of different residential pricing methods, we need to account for the interplay between utility-scale and distributed rooftop solar uncertainty. Concretely, a realization of a sample path of uncertainty over the horizon is a realization of $(\omega^U, \omega^H) \in \Omega^U \times \Omega^H$. Here, Ω^U is the set of sample paths of renewable supply from utility-scale renewable resources, whereas Ω^H is the set of sample paths of renewable supply from rooftop solar resources.

The interface between the utility and the household is the service contract. The service contract allows the utility and the household to decentralize their decision-making according to locally observable information related to uncertainty. This decentralization is represented in the left part of Fig. 2. More specifically, from the point of view of the utility, the uncertainty in the system comprises utility-scale renewable supply and *net residential demand*. The net residential demand is driven by rooftop solar supply at the households; however the utility meters and reacts to net demand. Similarly, from the point of view of the household, a realization of uncertainty comprises of rooftop solar power supply as well as the *interruption of different service options*. The interruption patterns are of course driven by utility-scale renewable supply, however the household does not observe or react to this information. Essentially, the residential service contracts can be viewed as a way of decentralizing a dynamic optimization problem under uncertainty (that of dispatching the *entire* system against *system-level* uncertainty) between the utility and the household.

The pricing and design part of priority service and multilevel demand subscription in our case are developed in [27], whereas the main focus of the current paper is to create a methodology for assessing the performance and efficiency of both service options in a system simulation model which features two layers of uncertainty (at the wholesale level and at the local level). Indeed, in [27], three optimization programs are solved in order to design a multilevel demand price menu and in order to quantify the subscription of different consumer types under different service options. The results of these models are provided as inputs for the present work in which the performance of the two demand response schemes is compared in a real-time simulation framework that uses the price menu and subscription computed in [27] as *input*. Note that the aforementioned literature that is cited in the introduction [15]–[19] is mainly focused on the design and pricing of the service contract, as in the case of [27].

In this section, we describe our proposal for simulating this decentralized decision-making process, to quantify the efficiency of priority service and multilevel demand subscription via a rolling-horizon approach. This proposal bears similarities with the hierarchical coordination of transmission and distribution system operations proposed in [28], [29]. Our rolling optimization approach is depicted in Fig. 2 and is discussed in further detail in the following paragraphs. At each period, there is an interaction between the utility and households after the local uncertainty of each sub-system (ω^U, ω^H) is revealed.

First, households (indexed by $h \in \mathcal{H}$) estimate their consumption for the present period by optimizing their behaviour until the end of the horizon, based on the household decision problem ($H_{h,t}$), given (i) the previous energy state of their residential storage (if any is available), indicated by e^h_{t-1}, (ii)

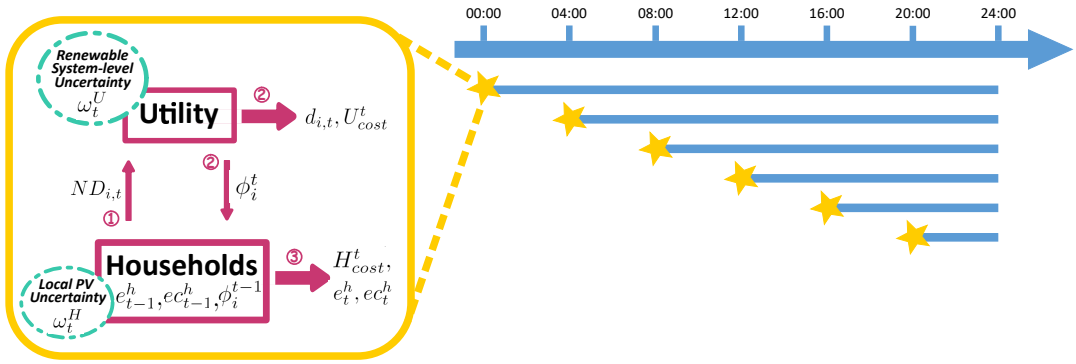

Fig. 2. Illustration of the rolling optimization approach used to assess the performance of priority service and multilevel demand subscription for a model with 4-hour resolution. The stepsize is adjusted correspondingly for the model with 15-minute resolution.

the amount of energy left to consume based on their contract subscription, indicated by ec_{t-1}^h, and (iii) the interruption pattern of options faced at time period $t-1$, indicated by ϕ_i^{t-1}. This step results in the computation of a residential aggregated net demand ($ND_{i,t}$) for time period t, which is observed by the utility for each option $i \in \mathcal{I}$. Note that households use the information of the previous time period concerning the interruption of options because it corresponds to their best forecast of the interruption for the upcoming balancing interval.

Generators are then dispatched at system level in order to meet the net demand of all households in the population, with consideration of the system-level renewable uncertainty using the mathematical program (U_t). During this second step, the utility reacts to the net demand of households by only supplying a certain portion of that demand ($d_{i,t}$). This leads to a new interruption pattern of colors ϕ_i^t, and to a certain production cost U_{cost}^t for the current time period.

Finally, households adapt their originally planned behaviour in response to the actual supply that is provided by the system at the current time step (represented by the new interruption pattern of options ϕ_i^t). This third step leads to the computation of the shortage cost that the household actually experiences at the present time step (H_{cost}^t). We can further compute the new energy state of the battery, e_t^h, as well as the remaining energy credits left on the contract until the end of the horizon.

In the remainder of this section, we describe the problems solved by the utility (U_t) and households ($H_{h,t}$). The simpler utility model is discussed first as it amounts to a simple economic dispatch model. We then define the multi-stage optimization that drives household consumption.

A. Rolling Optimization for the Utility

The decisions of the utility are depicted by means of a single-period optimization problem. The inter-temporal unit commitment constraints (startup costs, and min up/down time constraints, ramp constraints), and pumped hydro constraints are ignored here since the focus of this study is on the benefits that can be achieved as a result of household flexibility. In future research, it could be interesting to extend this formulation in order to account for the intertemporal constraints of the utility.

Concretely, the utility solves the following problem[2]:

$$(U_t): \quad \max_{d_{i,t}, p_{g,t}} \sum_{i \in \mathcal{I}} \bar{V}_i \cdot d_{i,t} - \sum_{g \in \mathcal{G}} h_g(p_{g,t}) \tag{1}$$

$$s.t. \; f_g(p_{g,t}) \leq 0, \; g \in \mathcal{G} \tag{2}$$

$$d_{i,t} \leq ND_{i,t}, \; i \in \mathcal{I} \tag{3}$$

$$\sum_{i \in \mathcal{I}} d_{i,t} = \sum_{g \in \mathcal{G}} p_{g,t} + \omega_t^U \tag{4}$$

$$d_{i,t}, p_{g,t} \geq 0, \; i \in \mathcal{I}, g \in \mathcal{G} \tag{5}$$

The objective function of the utility is expressed in (1). Here, $h_g(p_{g,t})$ represents the cost incurred by the utility for producing $p_{g,t}$ from generator g. The valuation $\bar{V}_i$ corresponds to the estimate of the average valuation that the utility assigns to priority class i, based on how households decide to subscribe to the multilevel demand service. Equation (2) expresses the production constraints of the utility. Equation (3) implies that the utility may not offer more than the net demand that a certain priority class actually decides to consume at any given time period. The variable $d_{i,t}$ represents the demand served by the utility for reliability class i. Equation (4) expresses the power balance constraint for the utility. The renewable supply ω_t^U in (4) is the utility-scale renewable production, which is sampled during the procedure described above. The net demand $ND_{i,t}$ in (3) is obtained as the solution of the household rolling optimization which is presented in the following section.

B. Rolling Optimization for the Household

In contrast to the utility model which has been simplified in order to relax inter-temporal dependencies, the household rolling optimization is a problem of dynamic decision-making under uncertainty. The household faces uncertainty related to the supply of rooftop solar power at its premises (ω_t^H) and the interruption history of the service tiers (ϕ_i^t) in the home. This uncertainty is depicted in Fig. 3 in the case of only two solar panel production possibilities per time period. The nodes of the scenario tree are named according to the realization of renewable supply (with 'L' indicating *low* solar supply, and 'H'

[2]We describe the problem for the case of multilevel demand subscription, of which priority service is a special instance.

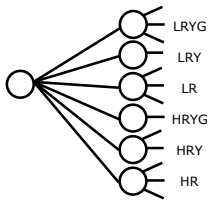

Fig. 3. Scenario tree for the household model $(H_{h,t})$ of section III-B in the case of only two solar panel production possibilities per time period.

indicating *high* solar supply) as well as the service interruption (with 'R' indicating that only the red color is served, 'RY' indicating that only the red and yellow color are served, and 'RYG' indicating that all colors are served).

In this rolling optimization, the household reacts to a history of realizations that have transpired up to stage t. For each stage t, given a stage uncertainty realization of solar production ω_t^H and interruption of services ϕ_i^t, we can describe the household model in terms of future stage costs until the end of the horizon, which is represented by the end of the day in our case study (see section V). The future costs are captured by $\mathcal{H}_{h,t+1}(e_t, ec_{i,t}, \omega_t^H, \phi_i^t)$, namely the value function of the problem. The household model is therefore expressed as:

$$H_{h,t}(e_{t-1}, ec_{i,t-1}, \omega_t^H, \phi_i^t) =$$

$$\min_{\substack{bd_t, bc_t, e_t, ec_{i,t}, \\ nd_{i,t}, \widetilde{nd}_{i,t}}} V_{cut} \cdot ls_t + \mathcal{H}_{h,t+1}(e_t, ec_{i,t}, \omega_t^H, \phi_i^t) \tag{6}$$

$$s.t.\ 0 \leq bd_t \leq BD_h \tag{7}$$

$$0 \leq bc_t \leq BC_h \tag{8}$$

$$0 \leq e_t \leq E_h \tag{9}$$

$$e_t = e_{t-1} - \frac{bd_t \cdot \Delta t}{\eta_h^d} + bc_t \cdot \eta_h^c \cdot \Delta t \tag{10}$$

$$DP_{t,h} - ls_t - PV_h \cdot \omega_t^H \tag{11}$$

$$+ bc_t - bd_t = \sum_{i \in \mathcal{I}} nd_{i,t} \tag{12}$$

$$nd_{i,t} \leq \sum_{j \in \mathcal{J}} \Theta_{h,i,j} \cdot \phi_i^t,\ i \in \mathcal{I} \tag{13}$$

$$\widetilde{nd}_{i,t} \leq \sum_{j \in \mathcal{J}} \Theta_{h,i,j} \cdot \phi_i^t,\ i \in \mathcal{I} \tag{14}$$

$$nd_{i,t} \leq \widetilde{nd}_{i,t}\ i \in \mathcal{I} \tag{15}$$

$$ec_{i,t} = ec_{i,t-1} - \widetilde{nd}_{i,t} \tag{16}$$

$$ls_t, \widetilde{nd}_{i,t}, ec_{i,t} \geq 0 \tag{17}$$

Unserved load in the household is denoted as ls_t. Home battery charge and discharge are denoted as bc_t and bd_t respectively. The energy level of the home battery at the end of time stage t is denoted as e_t. The net demand of the household from the grid is denoted as $nd_{i,t}$, and is differentiated by reliability class $i \in \mathcal{I}$. Note that the net demand can be negative, meaning that the household is injecting excess rooftop solar supply back to the grid but receives no payment or benefit from this action. The non-negative part of the net demand is indicated by the variable $\widetilde{nd}_{i,t}$. This variable is useful for computing the value of variable $ec_{i,t}$ which represents the amount of energy credits left to be used by the household at the end of time stage t.

The objective function given by Eq. (6) describes the goal of the household, which is to minimize its expected cost of interruption. Note that the bill of the household is already accounted for when the household chooses its menu (see [27]). The focus, here, is rather on optimally managing the consumption patterns within the household, *given* a certain choice of contract. The parameter V_{cut} quantifies the discomfort encoutered by consumers when a portion of their load is not served. The value of this parameter in this work is estimated in [30], which presents a case study of the Belgian market. Note that V_{cut} is not differentiated by priority class i, since it only accounts for the disutility that a consumer faces for not being able to satisfy part of its demand.

Equations (7) and (8) represent the battery discharge and charge constraints respectively, with BD_h and BC_h corresponding to the battery discharge and charge limits of household $h \in \mathcal{H}$ respectively. Equation (9) corresponds to the energy limit constraint of the battery, with E_h the energy storage limit of household h. Equation (10) represents the charging dynamics of the home energy battery, where e_{t-1} is a parameter that has been determined in the previous step of the rolling optimization. The charge and discharge efficiency of the battery are denoted as η_h^c and η_h^d for household h, respectively. Note that household batteries are assumed to be empty at the beginning of the day, i.e. $e_0 = 0$.

Equation (12) expresses the power balance constraint of the household. The parameter $DP_{t,h}$ is the inflexible demand of household h in stage t, while PV_h corresponds to the rooftop solar capacity installed in the household. The parameter $PV_h \cdot \omega_t^H$ indicates the rooftop solar supply sampled during the rolling procedure given in Fig. 2.

Equations (13) and (14) express the upper limit on net demand that a household is entitled to based on its chosen contract. The parameter ϕ_i^t indicates whether a certain reliability level i is being served at a given stage of a sample path or not. This parameter is output by the utility model (U_t) which is developed in section III-A. Moreover, the parameter $\Theta_{h,i,j}$ in the right-hand side represents the subscription that the household chooses for each reliability option i and each duration j.

Equation (16) expresses the energy limit of option $i \in \mathcal{I}$. Note that $ec_{i,0}$ is set to be equal to the sum of energy subscribed for under each duration option with the same reliability. Therefore, this constraint enables us to track the amount of energy that remains for a particular reliability option i in the household subscription by the end of time period t. This allows us to account for the maximum duration that a consumer is afforded under a certain option.

The solution of $(H_{h,t})$ yields a net demand decision for each reliability option i for the current period, $nd_{i,t}^\star$, which we denote as $ND_{h,i,t}$ for every household $h \in \mathcal{H}$. The parameter $ND_{i,t}$ which is used in (4) is then the sum of this net demand over all household types:

$$ND_{i,t} = \sum_{h \in \mathcal{H}} N_h \cdot ND_{h,i,t}, \tag{18}$$

where N_h is the number of households of type $h \in \mathcal{H}$ in the population.

Note that the implicit assumption in Eq. (18) is that the realization of uncertainty at every household of the same type is identical. Note that the two household decision steps at each time period use the same optimization program, but with different interruption patterns. The first step uses the interruption pattern of the previous time step, ϕ_i^{t-1}, while the second uses its updated version, ϕ_i^t. The interruption pattern ϕ_i^t is computed by the utility as the portion of demand that is actually served compared to the requested total household net demand ($d_{i,t}/ND_{i,t}$). In case the requested demand is zero, the interruption pattern is assumed to be equal to 1. The interruption pattern can asssume any value between 0 and 1. This represents the fact that the utility has the possibility to curtail a fraction of the households under a particular option, instead of curtailing this option completely.

C. A Dynamic Programming Algorithm for Solving the Household Model

The present section aims at describing a customized solution strategy for the household model ($H_{h,t}$). This model is represented as a multistage stochastic program where the uncertainty is given by a set of finite outcomes and thus forms a scenario tree [31]. The value function of the household model is denoted as $H_{h,t}(e_{t-1}, ec_{i,t-1}, \omega_t^H, \phi_i^t)$, while the expectation of the value functions is denoted as

$$\mathcal{H}_{h,t+1}(e_t, ec_{i,t}, \omega_t^H, \phi_i^t) = E\Big[H_{h,t+1}(e_t, ec_{i,t}, \omega_{t+1}^H, \phi_i^{t+1})\Big|\omega_t^H, \phi_i^t\Big]$$

Note that, as expressed by Eq. (6), the value funcion is then just the current period cost plus the expectation of value functions of the next stage. The dynamic programming algorithm approximates $\mathcal{H}_{h,t+1}$ by supporting hyperplanes around the set of states, which are given by $e_t, ec_{i,t}$. Once a collection of supporting hyperplanes has been found, the expectation of the value function can be approximated as follows:

$$\mathcal{H}_{h,t+1}(e_t, ec_{i,t}, \omega_t^H, \phi_i^t) = \max_{k=1,\ldots,K} \Big\{A_k + B_k \cdot e_t + C_k \cdot ec_{i,t}\Big\}$$

where A_k is the intercept and B_k, C_k are the supporting hyperplane coefficients. With such an approximation, ($H_{h,t}$) can be approximated by replacing $\mathcal{H}_{h,t+1}(e_t, ec_{i,t}, \omega_t^H, \phi_i^t)$ with an auxiliary variable θ followed by the constraints:

$$\theta \geq A_k + B_k \cdot e_t + C_k \cdot ec_{i,t} \;\; \forall k = 1, \ldots, K \tag{19}$$

The procedure to find the supporting hyperplanes can be described as follows. Let Γ_t denote a discretization of the state space at stage t.

(1) For $t = T, \cdots, 2$

(1.1) For $\widehat{e}_{t-1}, \widehat{ec}_{i,t-1} \in \Gamma_{t-1}$

(1.1.1) For all $\xi_t = (\omega_t^H, \phi_i^t)$ at stage t:

Solve the linear problem associated to $H_{h,t}(\widehat{e}_{t-1}, \widehat{ec}_{i,t-1}, \omega_t^H, \phi_i^t)$ and store the dual multipliers $\pi_{\xi_t,t}$ of Eqs. (7)-(16) of the household model.

(1.1.2) Use the dual multipliers $\{\pi_{\xi_t,t}\}_{\xi_t \in \Omega_t}$ to build a supporting hyperplane that approximates $\mathcal{H}_{h,t}(e_{t-1}, ec_{i,t-1}, \omega_{t-1}^H, \phi_i^{t-1})$ around the trial state $\widehat{e}_{t-1}, \widehat{ec}_{i,t-1}$, for all uncertainty realizations $\omega_{t-1}^H, \phi_i^{t-1}$. Further details on how to build a supporting hyperplane can be found in [31].

(1.2) In problem $H_{h,t-1}$, replace the expected value function $\mathcal{H}_{h,t}(e_{t-1}, ec_{i,t-1}, \omega_{t-1}^H, \phi_i^{t-1})$ by an auxiliary variable θ and add the supporting hyperplanes as expressed by Eq. (19).

As the algorithm evolves backwards in the number of stages, supporting hyperplanes are built around states in the set Γ_t, in order to approximate the value functions of the preeceding stages. This approach is in the spirit of other common algorithms such as SDDP [32]. Nevertheless, as opposed to the sampling-based scheme of SDDP, the dynamic programing scheme uses a discretization of the state space in order to ensure that the performance evaluation of our module can characterize the optimal policy of the household at non-optimal parts of the state space, which may occur in the simulation.

IV. Data Used for the Case Study

This section is dedicated to the description of the datasets that are used for populating the case study. This data includes household parameters, renewable supply scenarios, and system parameters for the Belgian system in a forward-looking scenario of the year 2050. We consider two simulations with differing levels of temporal resolution. We work with representative days, each of which is split into (i) either six 4-hour time steps in the first simulation or (ii) 96 15-minute time steps in the second simulation. Section IV-A is dedicated to the computation of the renewable production scenarios. Household parameters are then detailed in section IV-B. The parameters linked with the operation of the system along with details on generators are provided in section IV-C. Finally, section IV-D specifies the data of both demand response schemes.

The considered case study accounts for two types of uncertainty: long-term and short-term uncertainty. Long-term uncertainty corresponds to seasonal variations and is depicted by 8 reference day types consisting of weekdays and weekends for each season of the year. Then, for each scenario, short-term uncertainty is represented by the real-time production of solar panels, wind farms and a pattern of interruptions via a scenario tree. For each day type we use different profiles for households, industrial load, and so on.

A. Renewable Supply Scenarios

As explained previously, two types of uncertainty are accounted for in this study. Therefore, for each day type, a scenario tree representing real-time renewable supply is created, in order to account for short-term uncertainty. Only seasons are taken into account at this stage, because renewable production is not influenced by weekends and weekdays. In order to construct these scenario trees, we collect data from the website of the Belgian TSO Elia [33] for years 2013 to 2017,

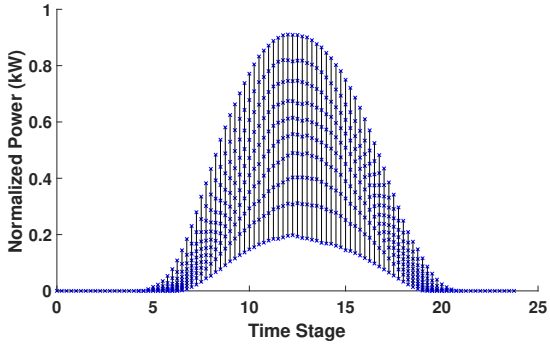

Fig. 4. Scenario tree for solar production with 15-minute resolution.

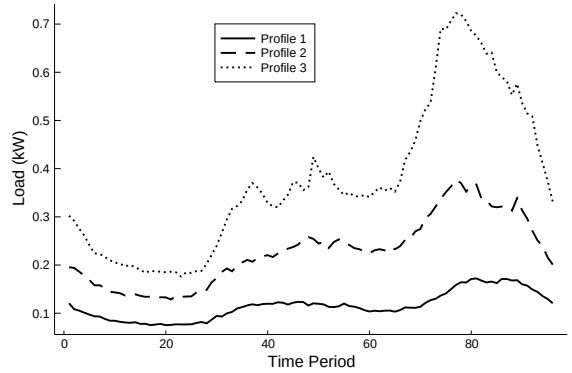

Fig. 5. Household profiles, averaged over day types, that we consider in the case study. The data is bsed on Fluvius [36].

which are then scaled up based on the EU 2050 reference scenario [34].

In order to build these scenario trees for each season, we implement a methodology developed by [35] which aims at capturing inter-temporal uncertainty. For the 4-hour case study, a scenario tree with 2 different outcomes per time stage is considered for both wind and solar power, i.e. a total of 4 outcomes per stage. For the 15-minute case study, we examine a more detailed version of the scenario tree, by allowing ten possible realizations of both wind and solar for each time stage, i.e. a total of 100 outcomes per stage. This growth explains the need to use the dynamic programming algorithm detailed in section III-C. Fig. 4 presents the solar supply lattice for a typical spring day for the case study with 15-minute resolution.

B. Household Parameters

In order to represent the different household types that are present in Belgium in terms of demand profiles throughout the day, we use data from Belgian DSO Fluvius [36]. The data includes injection and production for approximately 100 households with a resolution of 15 minutes for the year 2016. The dataset includes households that are subject to a flat tariff, as well as others that subscribe to a two-part tariff (day/night tariff). Our goal is to group household profiles present in this dataset, in order to create three representative load profiles for Belgian households. However, household profiles in this dataset are influenced by the tariff that they are subscribed to during the time when the data is collected. Therefore, we create a procedure in order to recover only the inflexible part of the load profile of each household. The steps used in order to obtain these three profiles are detailed hereafter:

1) Keep only households with daily load consumption between 2.5 and 40 kWh, so as to remove outliers [37]
2) For each day of a household under a flat tariff, find a day of a household under a two-part tariff with a comparable daily consumption and with a similar temporal profile. Compute an inflexible load profile from the minimum of the two daily profiles. This step enables us to approximate the part of the household consumption that is not dependent on the tariff, and can therefore be interpreted as being inflexible.
3) Cluster the resulting inflexible profiles in order to obtain 3 groups of households for each day type.

The mean profiles of each cluster are kept as the three representative load profiles for each day type. The averaged representative household daily load profiles are presented in Fig. 5. Profile 1 (F1) corresponds to 67.78% of the population, profile 2 (F2) to 25.38%, and profile 3 (F3) to 6.84%.

In order to account for the behaviour of households with batteries and local production (e.g. rooftop solar panels), we assume that (i) 16% of the households is equipped with a PV panel[3], (ii) one third of the households with a PV panel is equipped with a large battery, (iii) one third of the households with a PV panel is equipped with a smaller battery, and (iv) one third of the households with a PV panel is not equipped with a battery. Only types F2 and F3 are assumed to own PV panels. The installed capacity of PV panels is dimensioned so as to allow households to cover 100% of their annual consumption. Since 1kW of PV panels produces 1000kWh on average per year [40], profile F2 is assumed to have an installed capacity of 2kWc, while profile F3 is assumed to have an installed capacity equal to 3.2kWc. We assign no PV to profile F1, because rooftop solar providers typically do not serve apartment owners, who are represented by profile F1. The technical specifications of household batteries are presented in Table I. In total, we model nine types of households. Their characteristics are presented in Table II[4].

C. System Parameters

We now proceed by detailing the configuration of the Belgian system. The fleet of conventional generators consists of 55 units. The installed capacity of each technology follows

[3]This percentage is computed by accounting for the fact that residential solar accounts for 64% of the total installed solar capacity in Belgium in 2018 [38]. Moreover 50% of the new installed PV capacity up to 2030 will be residential [39]. Therefore, in the foreseen scenario of 2050, residential solar production is projected to account for 56.94% of the total solar supply.

[4]Despite the fact that household types 2 to 7 represent a small fraction of the Belgian population, their contribution to system flexibility is not negligible. Moreover, our analysis aims at analyzing the impact of demand response not only on the system but also on individual household types (see section V-B), therefore we are interested in household heterogeneity (e.g. different load profiles, and possible ownership of solar and/or storage), even if certain types of households constitute a relatively small fraction of the total population.

TABLE I
TECHNICAL SPECIFICATIONS OF HOUSEHOLD BATTERIES.

Battery Type	Large [41]	Small [42]
Energy Storage Limit (E, kWh)	13.5	3.84
Power Limit (BD/BC, kW)	5	0.85
Efficiency (η^c/η^d, %)	95	95

the projected capacity of the year 2050, according to the EU 2050 reference scenario [34]. Our forward-looking scenario is motivated by the high penetration of renewable generation that motivates the mobilization of demand response. The technical and economic specifications of the units (maximum power production, marginal cost, heat rates, ...) are available from the website of the Belgian TSO Elia [33]. The installed capacity of conventional generators, which totals 15784 MW, can be broken down as follows: gas (14965 MW), oil (10 MW), biomass (542 MW), and waste (267 MW). The long-term maintenance schedule of units is accounted for by derating their maximum capacity with a certain availability ratio. The availability ratio follows the hourly profiles of 2015 [33]. Import profiles for the year 2015 with hourly resolution are collected from [33]. These profiles are scaled up based on the projected value of the year 2050 [34]. The total load profile of year 2015 is available from [33]. The industrial and commercial load is extracted from the total load profile according to *Synthetic Load Profiles (SLPs)* [43]. The load profile is then scaled up according to the EU 2050 reference scenario [34].

Pumped hydro storage in Belgium is assumed to have a pumping capacity amounting to 1200 MW, while its energy storage capacity amounts to 5700 MWh. Pumped hydro resources are presumed to have a roundtrip efficiency of 76.5% [44]. We assume that pumped hydro storage follows a profile that is fixed exogenously for the producer model of section III-A, and which is assumed to be the same for both demand response schemes that we compare. Our goal in fixing this schedule exogenously is to isolate the effect of residential storage on system operations.

D. Demand Response Parameters

In order to simulate the efficiency of both priority service and multilevel demand subscription, we must determine the menu proposed by the utility under each demand response scheme as well as the subscription of each household type to each service. The menu design problem of the utility is formulated as a Stackelberg equilibrium using an MILP reforulation in [27]. This paper describes this reformulation for both multilevel demand subscription, as well as priority service as a special case. It further presents the optimization problem that households solve when subscribing to a menu, so as to balance their comfort with the cost of electricity. We implement the models presented in [27] with the data introduced in the previous sections. In this paper, we are focusing on the simulation of the system *after* households have subscribed to demand response contracts.

As we describe in section IV-A, the lattice considered for the model with 15-minute resolution is large. Therefore, the three models presented in [27] are solved using dynamic programming for the case of 15-minute resolution [32], [45]. The menus proposed by the utility for both case studies are presented in Table III and in Table IV for priority service and multilevel demand subscription respectively.

Note that 3 duration options are used for multilevel demand subscription. Running the menu design and menu selection models with 4-hour resolution indicates that more duration options than 3 leads to incremental gains in terms of social welfare, while burdening consumers with a more complex menu of options. This empirical finding is consistent with analytical results which exist in the literature (see Proposition 6 of [21]). These results indicate that the additional welfare that can be achieved from additional options declines quadratically with respect to the number of options in a priority service menu. Based on these observations, we limit our case studies to 3 duration options.

Fig. 6 presents the capacity subscription of each household type under the case study with 4-hour resolution for priority service and multilevel demand subscription. The corresponding information for the 15-minute case study is shown in Fig. 7. Note that, for multilevel demand subscription, the capacity procured under each duration option for a particular reliability level is summed in order to allow a comparison to priority service. It is observed in [27] that a household under priority service tends to subscribe to less capacity but more energy than with multilevel demand subscription. The same observation holds in the present model.

V. RESULTS

Using the simulation framework that is described in section III and the data presented in section IV, we are able to compare the performance of priority service (PSP) with multilevel demand subscription (MDSP). The simulation results are obtained using 1000 sample paths for each case study.

A. System-Wide Results

Table V presents key economic indicators for the different pricing policies that have been considered in the simulations for the case study with 4-hour resolution. The corresponding values under 15-minute resolution are indicated in Table VI. The residential shortage cost is calculated according to the household rolling horizon model in the performance evaluation process that is described in section III-B. The supply quantity and the production cost are computed from the producer model that is described in section III-A. The total system cost is given as the sum of the residential shortage and production cost.

Compared to priority service, multilevel demand subscription is able to supply slightly more power to households and therefore reduces their load shortage cost. Indeed, since multilevel demand suscription better discriminates consumers by means of the load duration curve, this paradigm is able to better infer the supply needed at certain time periods within the day. Consumers subscribe to less energy while adapting the timing of their consumption in order to better match the inflexible portion of their consumption profile.

TABLE II
CHARACTERISTICS OF DIFFERENT TYPES OF HOUSEHOLDS.

Type	1	2	3	4	5	6	7	8	9
Category	F1	F2	F3	F2	F3	F2	F3	F2	F3
PV Panel	No	Yes	Yes	Yes	Yes	Yes	Yes	No	No
PV Installed [kW]	0	2	3.2	2	3.2	2	3.2	0	0
Battery Size	No	Large	Large	Small	Small	No	No	No	No
Proportion [%]	67.8	1.35	0.365	1.35	0.365	1.35	0.365	21.32	5.74

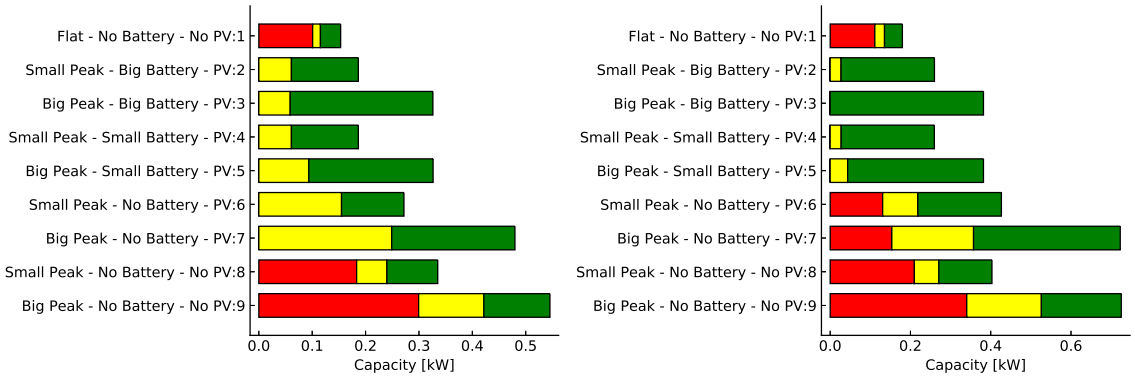

Fig. 6. Capacity subscription of each household type under priority service (left) and multilevel demand subscription (right) for the 4-hour case study.

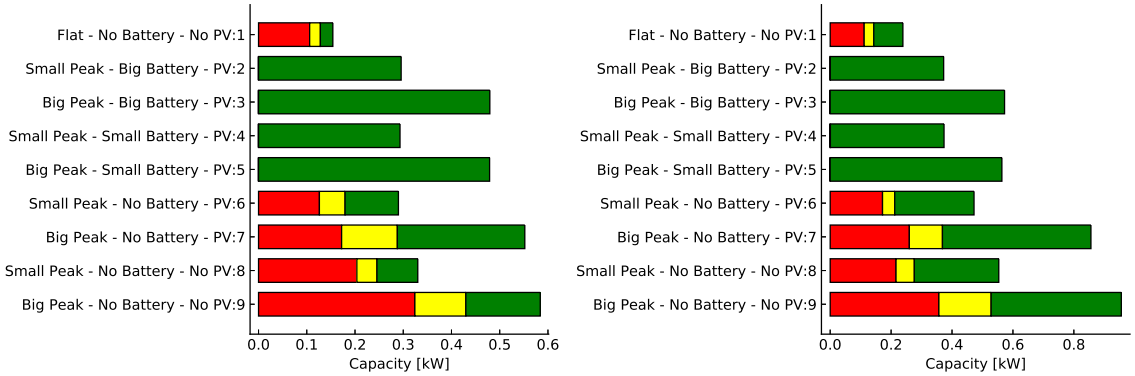

Fig. 7. Capacity subscription of each household type under priority service (left) and multilevel demand subscription (right) for the 15-minute case study.

TABLE III
PRIORITY SERVICE MENU FOR BOTH CASE STUDIES.

Option	Reliability [%]		Price [€/kW-month]	
	4-hour	15-minute	4-hour	15-minute
Green	66.49	58.37	37.79	31.39
Yellow	90.32	89.38	69.93	66.78
Red	100	100	91.94	87.08

TABLE IV
MULTILEVEL DEMAND SUBSCRIPTION MENU FOR BOTH CASE STUDIES.

Option	Duration [%]	Reliability [%]		Price [€/kW-month]	
		4-hour	15-minute	4-hour	15-minute
Green	33.33	66.49	58.37	21.52	17.69
	66.66			33.10	27.21
	100			37.79	31.39
Yellow	33.33	90.32	89.38	41.41	43.04
	66.66			63.14	61.72
	100			69.93	66.78
Red	33.33	100	100	53.43	52.64
	66.66			82.19	80.98
	100			91.94	87.08

TABLE V
COMPARISON OF SYSTEM-LEVEL PERFORMANCE FOR THE 4-HOUR CASE STUDY. VALUES ARE IN M€/MONTH.

	PSP	MDSP
Total Production Cost [M€]	237.16	237.42
Estimated Industrial/Commercial Cost [M€]	157.78	157.78
Estimated Residential Cost [M€]	79.38	79.64
Shortage Cost Industrial Load [M€]	0	0
Total Residential Supply [TWh]	1.54	1.54
Total Residential Load Shortage Cost [M€]	166.55	165.27
Total Residential Payment [M€]	292.03	283.96
Total System Cost [M€]	403.7	402.69

We observe a reduction of 0.25% in system cost compared to priority service for the 4-hour case study. This value increases to 1.98% when the considered resolution is 15 minutes. Note that this gain underscores the importance of a more detailed model (finer resolution with a more detailed scenario tree) in accurately quantifying the efficiency of multilevel demand subscription.

TABLE VI
COMPARISON OF SYSTEM-LEVEL PERFORMANCE FOR THE CASE STUDY WITH 15-MINUTE RESOLUTION. VALUES ARE IN M€/MONTH.

	PSP	MDSP
Total Production Cost [M€]	237.44	239.01
Estimated Industrial/Commercial Cost [M€]	156.87	156.87
Estimated Residential Cost [M€]	80.57	82.14
Shortage Cost Industrial Load [M€]	0.7823	0.7823
Total Residential Supply [TWh]	1.48	1.51
Total Residential Shortage Cost [M€]	209.43	199.91
Total Residential Payment [M€]	285.36	272.53
Total System Cost [M€]	447.65	438.8

B. Households

Fig. 8 compares the total cost (subscription and interruption cost) between multilevel demand subscription and priority service under the case with 4-hour resolution. The figure also details the portion of the cost that is attributed to subscription. Fig. 9 presents the same indicators for the case with 15-minute resolution.

We can observe from the case study with 15-minute resolution that all homes with multilevel demand subscription tend to face a lower total cost, a lower shortage cost and a lower subscription cost. However, this improvement is reduced with the introduction of batteries. This is due to the fact that batteries contribute to reducing the peak net demand of households, which implies that the benefits that are achieved by the options with shorter duration in multilevel demand subscription decrease for households with large consumption.

Multilevel demand subscription is especially beneficial compared to priority service when a household owns rooftop solar panels but no battery. Indeed, options with shorter duration are especially helpful in this context because they enable households to use these options when rooftop solar panels are not producing. For these households, multilevel demand subscription reduces total cost by more than 20%, whereas this reduction amounts to 10% when a battery is added.

Instead, the total costs of households are very close under priority service and multilevel demand subscription for the case study with 4-hour resolution. The maximum reduction that is achieved by multilevel demand subscription in this case study is limited to 6.5%. Moreover, we can observe that the subscription cost for multilevel demand subscription is not always lower than for priority service, as is the case for the case study with 15-minute resolution. This is due to the fact that the case study with 4-hour resolution fails to capture the economic savings that a household achieves by subscribing to options with very short duration (e.g. 1 hour). As we already observe in the discussion of the system-wide results of the previous section, the additional detail of the higher-resolution 15-minute model is justified since it allows for a more precise assessment of the impact of the two contracts on individual types of households.

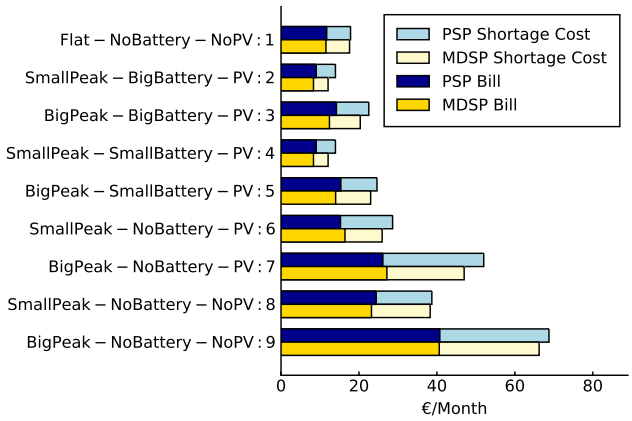

Fig. 8. Comparison of the total cost and the subscription cost for different types of households under priority service and multilevel demand subscription (4-hour resolution).

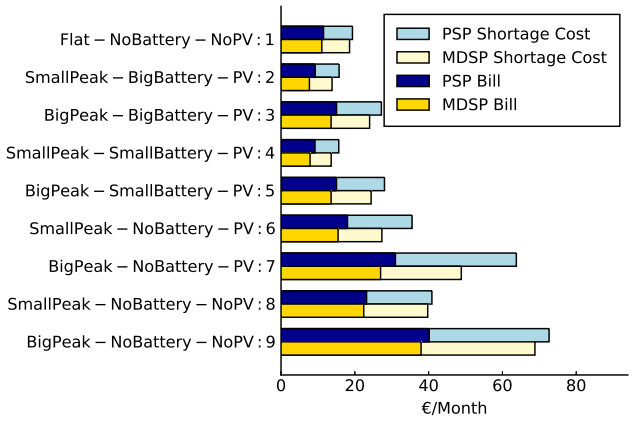

Fig. 9. Comparison of the total cost and the subscription cost for different types of households under priority service and multilevel demand subscription (15-minute resolution).

VI. CONCLUSION

In this study we compare priority service and multilevel demand subscription as two alternative means of mobilizing demand response in the residential sector. A framework is developed for modeling the system-wide effects of residential flexibility under both schemes. Multilevel demand subscription is a generalized form of priority service. As such, it increases implementation complexity from the side of both the utility as well as the residential consumer because of the added differentiation in terms of duration. Indeed, it requires the utility to use a load duration curve of the system instead of a demand function for designing and pricing the menu. In addition, it also necessitates the use of more complex equipment in order to monitor consumer energy credits. Consumers face a more complex decision among a larger set of service options. On the upside, as observed in the results of the present paper, multilevel demand subscription improves operational efficiency by allowing the utility to better discriminate flexible consumers, since it reduces system and household operational costs.

We have examined this trade-off between simplicity and operational efficiency in a case study of the Belgian market. The ability of multilevel demand subscription to better discriminate consumers results in a total cost reduction of about 2% relative to priority service, which represents about 10 M€/month for

the case study with 15-minute resolution. Moreover, multilevel demand subscription allows households to reduce their costs compared to priority service because capacity strips that are procured under priority service remain idle for a significant portion of the service horizon. This reduction amounts to 20% for households that only own solar panels and is limited to 10% when they also own a battery.

The consistency of these results is also observed in an experiment with a lower resolution even though the improvement is smaller. Indeed, the lower resolution model underestimates system cost benefits of multilevel demand subscription along with household subscriptions to options with shorter durations. This underscores the value of an accurate model with finer time resolution at the level of 15 minutes.

On the basis of these observations, we conclude that it may become challenging to engage flexible households with installed renewable supply and storage using pure capacity tariffs. In future markets with distributed flexibility and storage, a mix of energy and capacity charges are likely to be necessary in order to increase the efficiency of operations and keep electricity service charges of households at acceptable levels.

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