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Effective demand response for smart grids: Evidence from a real-world pilot

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ABSTRACT

We show how an electricity customer decision support system (DSS) can be used to design effective demand response programs. Designing an effective demand response (DR) program requires a deep understanding of energy consumer behavior and a precise estimation of the expected outcome. Excessive demand shifting or a high price responsiveness might create new peaks during low-demand periods. We combine insights from a real-world pilot with simulations and investigate how we can design effective DR schemes. We evaluate our pricing recommendations against existing economic approaches in the literature and show that targeted recommendations are more beneficial for customers and for the grid. Furthermore, we conduct robustness tests in which we apply our methods on two independent datasets and observe differences in peak demand and electricity cost reduction, dependent on individual characteristics. In addition, we examine the role of energy policy, as it varies across countries, and we find that the presence of competition in the electricity market creates lower prices and more cost savings for individuals. Finally, we measure the economic value of our DSS and show that our DSS can result in up to 38% savings on household electricity bills. Our results exhibit how the design of effective DR can be achieved and provide insights to energy policymakers with regard to understanding consumers' behavior and setting regulatory constraints.

1. Introduction

Electricity markets are currently experiencing a fundamental change, transitioning from a traditional centralized structure to a decentralized formation, where renewable sources produce a significant share of electricity [27,30]. The restructured electricity grid, where all components are connected with an ICT infrastructure, is known as *smart grid* [3,6]. According to [19] "the smart grid can be defined as an electric system that uses information, two-way, cyber-secure communication technologies, and computational intelligence in an integrated fashion". From a regulatory and policy-making point of view, grid reliability and quality have been identified as the main challenges in the smart grid [18]. One way to support the grid's reliability is to mitigate peak demand and prevent exposure of its infrastructure to critical strains [37,43]. Smart grid capacity should be able to serve the peak demand at each point in time. However, most electricity customers are inclined to consume during peak hours when they return home in the evening (e.g., 6 pm), as shown in their daily household consumption curves [14,20,31]. Therefore, key drivers are incentives to electricity consumers (equipped with smart meters and smart appliances[1]), who can schedule electricity consumption more efficiently than in the past [11,37,42]. According to IEEE, smart meters "are featuring two-way communications between consumers and power providers to automate billing data collection, detect outages and dispatch repair crews to the correct location faster" and smart appliances are "capable of deciding when to consume power based on pre-set customer preferences".[2] In our analysis, we assume as consumers to be the retail household electricity customers that engage only in electricity consumption processes. We do not account for *prosumers* who also engage in small-scale production processes or for commercial and industrial customers (C&I). Electricity consumers are now a cornerstone of a balanced grid, since they can be incentivized via pricing signals to shift part of their consumption to off-peak hours, supporting grid stability (customer-driven process [37]).

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[1] EPRS — European Parliamentary Research Service: http://www.europarl.europa.eu/RegData/etudes/BRIE/2015/568318/EPRS_BRI\T1\textbackslash.%282015\T1\textbackslash%29568318_EN.pdf [Date Accessed: May 24, 2016].

[2] https://www.ieee.org/about/technologies/emerging/emerging_tech_smart_grids.pdf [Date Accessed: May 24, 2016].

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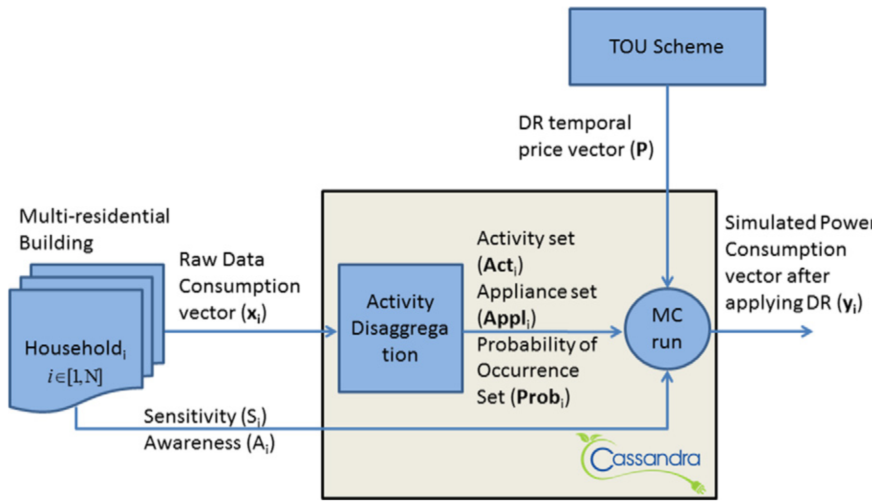

Fig. 1. Individual household analysis model overview.

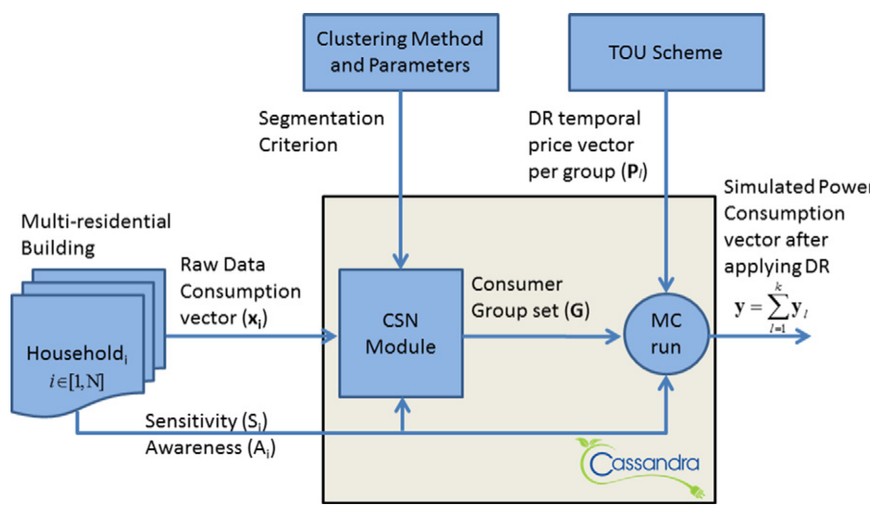

Fig. 2. Energy consumer group analysis model overview.

Demand response (DR) [2,37,42] has been proposed as a set of tools for shifting or curtailing consumer demand so that it adapts to supply, creating a more balanced smart grid.

DR programs can bring numerous benefits to both the distribution grid and to individual consumers. However, designing a successful DR program is challenging. Firstly, consumers might show low willingness to participate, affecting the effectiveness of the program [42]. Secondly, DR benefits are frequently not competitive compared to the traditional capacity expansion solutions. Practically, DR schemes must be designed carefully to achieve the desired outcome (peak reduction or demand curve reshaping). This approach might not be as cost effective as a traditional solution based on grid infrastructure expansion. Grid operators have considerable experience with capacity expansion methods, whereas DR schemes are new and highly dependent on human behavior and acceptance [24,42], which can make them costly and less effective than traditional approaches. Finally, DR pricing schemes might lead to herding behavior and avalanche effects on shifting power demand [20,29,33,44]. This can happen when energy consumers simultaneously react to price signals and change their consumption pattern, creating an avalanche effect. Therefore, instead of having a flat demand curve, there might be situations that demand is more volatile, yielding new peaks.

Increased consumer sensitivity can result in herding, since all consumer strive to minimize electricity costs and tend to shift consumption to low-price periods. We examine how consumer price sensitivity influences the effectiveness of a DR program. Our data-driven approach is rooted in evidence from real-world data, rather than theoretical assumptions, which may not always reflect reality. Data-driven methods might be powerful in situations when exploratory investigation is required [21]. Our results are based on simulations and real-world experiments.[3] We see that each consumer type responds differently to the same DR schemes. We provide insights to energy policymakers about designing effective DR schemes, targeting heterogeneous consumer populations. The main data comes from a multi-residential building in Sweden, comprising 33 apartments where we account for both individual households and the building as an aggregate power consumption unit. However, in the Robustness Tests Section we apply our methods on two independent datasets (from the Netherlands and the USA) to show generalizability of results.

[3] Conducted within the EU Project "Cassandra" https://cassandra.iti.gr:8443/cassandra/app.html [Date Accessed: May 24, 2016].

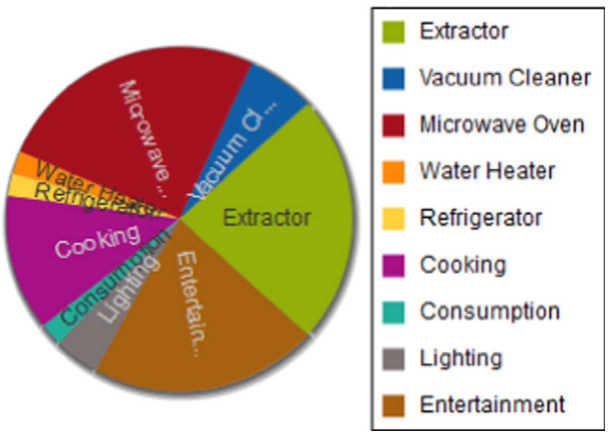

Fig. 3. Appliances of Household W as identified by our platform.

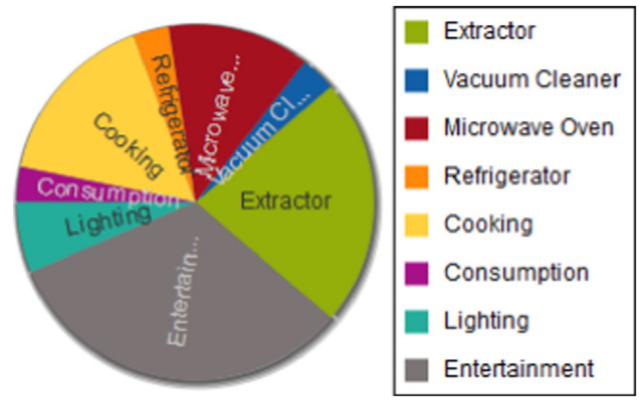

Fig. 5. Appliances of Household Y as identified by our platform.

Designing effective DR schemes in the smart grid is a rather challenging task, since many parameters need to be taken into account. First, in the electricity grid, unlike any traditional supply chains, there is a lot of volatility (on the supply and consumption side) which has increased with the introduction of renewable energy sources that are highly weather dependent. Second, electricity is a perishable good which needs to be consumed at the moment it is produced, otherwise it gets lost. Unlike other perishable goods (fish, flowers [34], etc.), electricity cannot last even a moment without being consumed or stored. Effective DR schemes must be able to match demand and supply, minimizing electricity losses. This makes electricity pricing different than pricing in other capacity allocation domains. In traditional supply chains, any intermittency on the supply side can be overcome by warehousing. However, in smart grids storage is not available on a large scale, and wherever it is available (EVs, cold storage, etc.), it is used mostly for industrial purposes, and is quite expensive. In addition to all these factors, consumer responsiveness to prices is a key factor for creating pricing incentives that can shift electricity consumption. This price responsiveness needs to be examined thoroughly in each consumer portfolio, since prices designed for different types of consumer responsiveness might not be effective in other portfolios (we observe this effect in the Benchmarks Section). In many capacity allocation problems, this price responsiveness or human acceptance might not be as predominant as in electricity markets [7,9,41]. This makes the smart grid a different domain than traditional supply chains, and therefore it requires different treatment. The presented problem has been identified as one of the "wicked problems" [26] which poses major societal challenges, such as the sustainability challenge. Finally, measuring the actual price responsiveness of electricity consumers can be difficult, mainly because of the privacy legislation. Therefore, having an indication of how electricity consumers react to pricing schemes and markets [4,25] can be very helpful for electricity policymakers.

Creating wrong pricing incentives in the electricity grid, can threaten its stability and quality of service [42]. Having uninterrupted electricity supply on the grid and high quality service is an important factor that goes beyond the availability of any other commercial product and influences energy policy overall. Therefore, there is the need to examine thoroughly how we can design effective DR schemes. What makes the DR design even more challenging is the need for combining real-world data with simulations. The Cassandra software platform is the first large scale DSS implementation for the smart grid aiming to service energy policymakers. It has involved multiple research institutions across Europe and was one of the first projects that obtained permission from the EU to perform real-world pilots on electricity consumers (conducting pilots on electricity consumers and having access to their raw consumption data is challenging due to strict privacy legislation). We combine insights from this pilot with simulations and investigate how we can design effective DR schemes. We evaluate our pricing recommendations against existing approaches in the literature and show that targeted recommendations are more beneficial for customers and for the grid. We then conduct robustness tests in which we apply our methods on two independent datasets and we show how the results change. In addition, we demonstrate the role of energy policy, as it varies across countries, in providing successful pricing recommendations. Finally, we show the economic value of our DSS and the recommendations it provides to electricity customers, before and after adjustments for energy policy compliance. Our results show how the design of effective DR can be achieved and provide insights

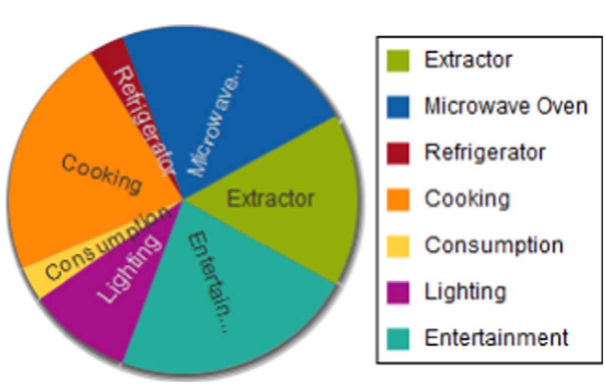

Fig. 4. Appliances of Household X as identified by our platform.

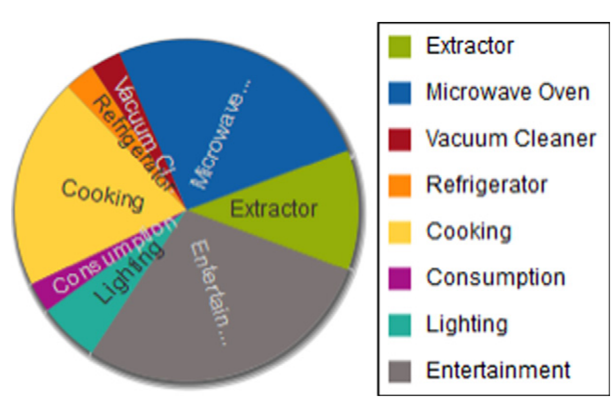

Fig. 6. Appliances of Household Z as identified by our platform.

Table 1
Average peak reduction.

	Household W	Household X	Household Y	Household Z
$S_i = 100\%, A_i = 10\%$	−1.75%	15.53%	11.59%	5.84%
$S_i = A_i = 100\%$	−33.04%	9.92%	23.10%	−41.74%
$S_i = 10\%, A_i = 100\%$	−1.75%	14.36%	11.59%	5.84%
$S_i = A_i = 10\%$	−5.04%	6.69%	4.82%	5.28%
$S_i = A_i = 50\%$	23.41%	10.48%	28.60%	14.23%

Table 2
Energy cost savings.

	Household W	Household X	Household Y	Household Z
$S_i = 100\%, A_i = 10\%$	6.64%	5.26%	1.09%	2.01%
$S_i = A_i = 100\%$	51.77%	38.35%	33.70%	46.98%
$S_i = 10\%, A_i = 100\%$	6.64%	5.26%	1.09%	2.01%
$S_i = A_i = 10\%$	1.77%	2.26%	1.63%	1.34%
$S_i = A_i = 50\%$	18.58%	12.03%	9.78%	12.08%

to energy policymakers with regard to understanding consumers' behavior and setting regulatory constraints.

2. Background on demand response

The term demand response is used to reflect changes in power consumption behavior as a result of a certain intervention. Palensky and Dietrich [37] and the US Department of Energy [43] present a general taxonomy of DR, which lists all measures that reduce or modify power consumption behavior. The most common DR schemes are clustered into two main categories [2,13,17,37,43]:

Price-based DR

- *Time-of-Use (TOU)*: different unit prices over different blocks of time
- *Real Time Pricing (RTP)*: hourly fluctuating electricity prices, reflecting changes in the wholesale electricity price
- *Critical Peak Pricing (CPP)*: combination of TOU and RTP, using TOU as basic price structure

Incentive-based DR

- *Direct load control*: the grid operator remotely turns off electrical equipment to support grid's stability
- *Interruptible/curtailable service*: rate discounts offered to customers for curtailing their consumption
- *Demand bidding/buyback programs*: customer bids for curtailment based on wholesale prices (mostly applicable to large customers)
- *Emergency demand response*: incentive payments offered to customers for reducing their load during high demand periods
- *Capacity markets*: customers offer to provide generation services to the grid in exchange for up-front payments
- *Ancillary services market*: customers bid for offering load in the market as a means of operating reserves.

We refer to the price-based DR schemes offered to the customers as TOU tariffs and to the real-world pilot as *incentive-based* DR. We make this distinction because our pilot does not include variable pricing schemes (due to legislative constraints). Instead consumers

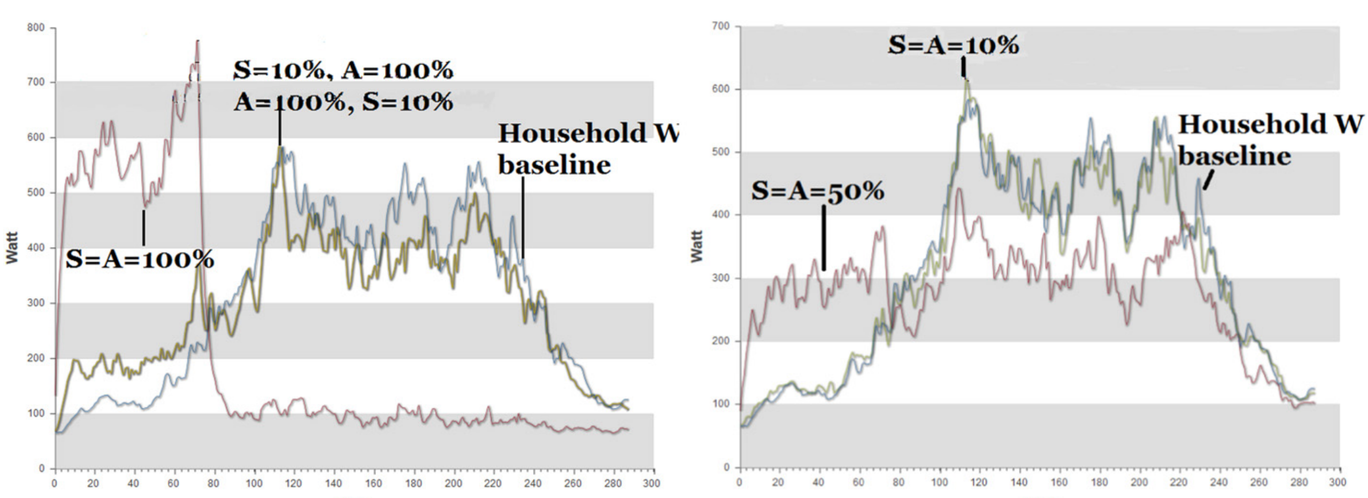

Fig. 7. Consumption curve of Household W with different sensitivity and awareness parametrizations.

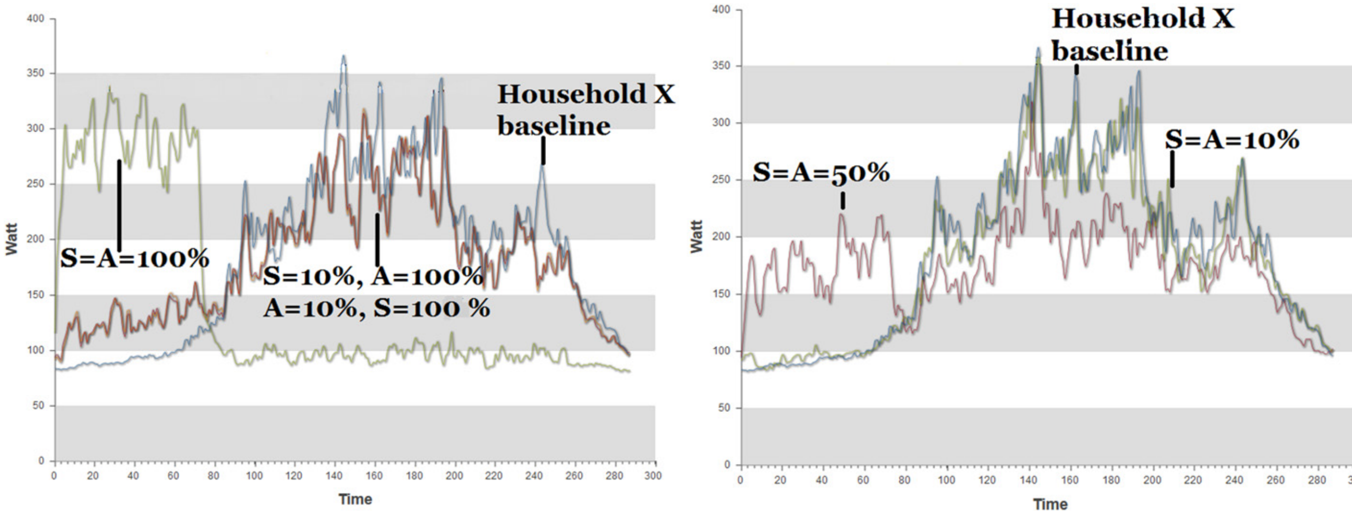

Fig. 8. Consumption curve of Household X with different sensitivity and awareness parametrizations.

received incentives for achieving certain goals related to peak demand reduction (see Section 3.2).

DR has been a key factor for allocating peak demand to low-demand periods, increasing capacity utilization of the existing infrastructure [42]. Aalami et al. [1] propose a model that selects DR programs depending on consumer portfolio. Rodrigues and Linares [39] present a computational model to quantify the benefits of DR programs. Strbac [42] provides a thorough analysis of the benefits and challenges of DR schemes. The main benefits are related to the distribution and transmission grid that face peak demand reduction as a result of power consumption shifting. The challenges are related to the low benefits for participants and policymakers. The low benefit assumption is also confirmed by [20,29] where the authors approach the issue from two different angles.

Price responsiveness is identified as an important factor for successful DR overcoming the low benefits barrier [7,24,41]. Different responsiveness to prices brings versatile outcomes and policymakers should account for this parameter when designing DR programs [9]. This manuscript examines how this responsiveness varies across consumers (also found as sensitivity) learning from data and presents tariff recommendations to consumers. Our price recommendations aim at expanding the consumer's choice spectrum by tailoring electricity tariffs to their behavioral profiles.

3. Methods

3.1. Energy stakeholders' decision support

Firstly, we analyze household consumption behavior after adopting a TOU tariff. TOU tariffs are chosen since they have easily measurable outcomes [23], that can be explained to the consumers, and they generally discourage inefficient consumption.

The model used for the individual household analysis is illustrated in Fig. 1. First, we collect (using smart meters) minute-by-minute consumption data from the households. For each household $i \in [1, N]$, $N = 33$ we get a raw consumption vector $\mathbf{x}_i = \{x_{i,t}\}$ and identify sensitivity ($S_i \in [0\%, 100\%]$) and awareness ($A_i \in [0\%, 100\%]$) toward price changes. These two parameters reflect the extent to which an energy consumer is sensitive and aware of price changes.

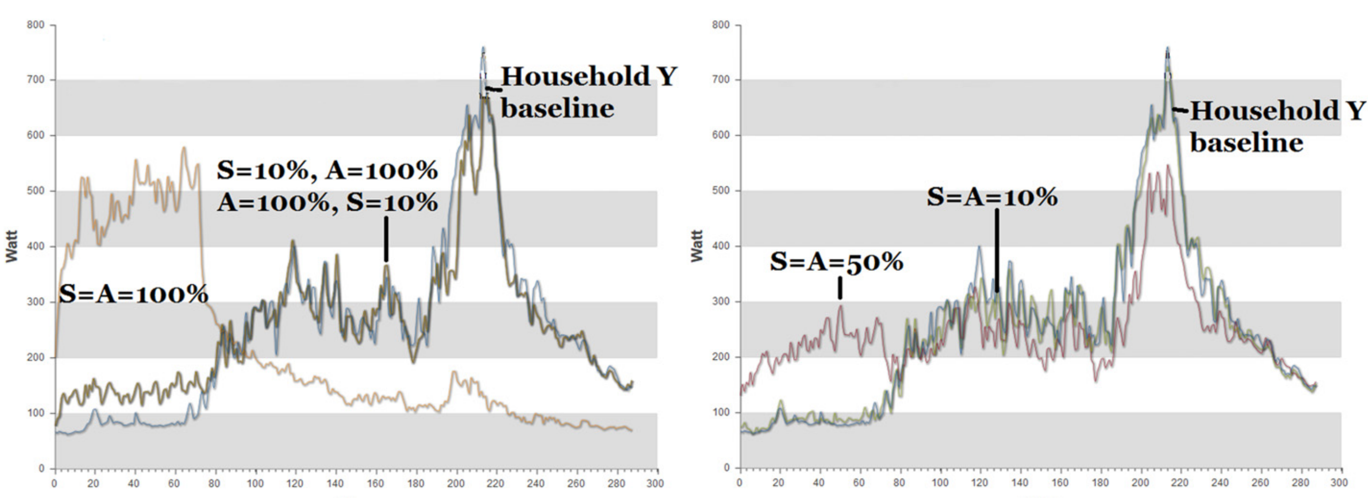

Fig. 9. Consumption curve of Household Y with different sensitivity and awareness parametrizations.

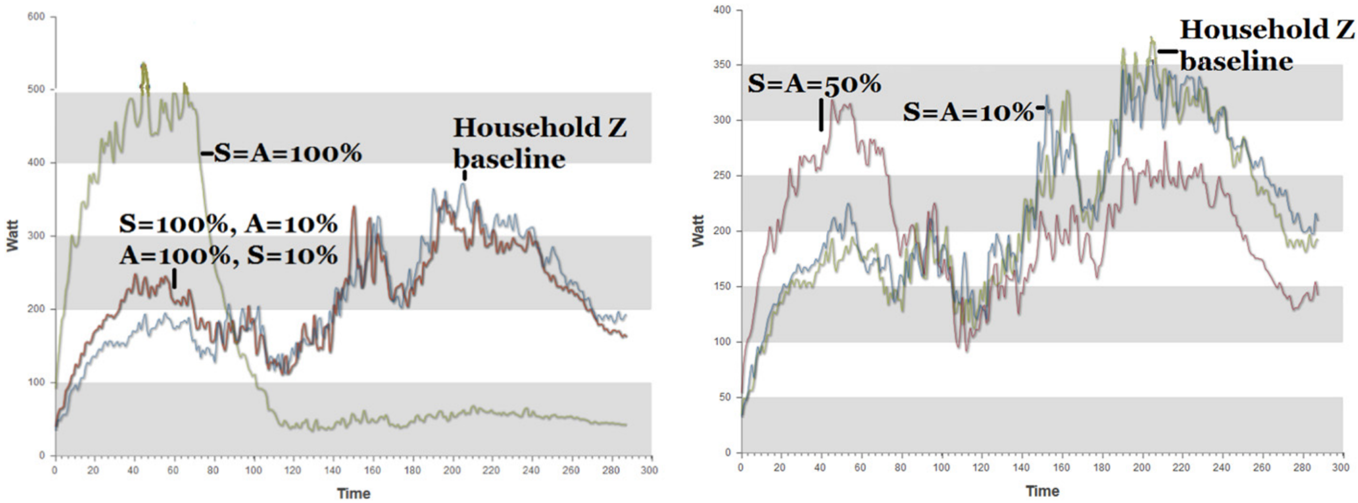

Fig. 10. Consumption curve of Household Z with different sensitivity and awareness parametrizations.

The combination of these two parameters serves as a proxy for consumer responsiveness to prices, which has been identified as one of the important factors for a successful DR scheme [7,24,41]. We argue that besides being price sensitive, consumers must also be aware of price changes, otherwise they will not change their consumption behavior. Therefore, we chose the combination of awareness and sensitivity to model price responsiveness.

The values of sensitivity and awareness were collected through direct interviews with the tenants of the 33 households. More specifically, the tenants were asked to answer the questions displayed in [22] (pages 76–83), which are designed by a team of behavioral researchers and demand response professionals. Holst et al. [22] conducted a behavioral survey, aimed at eliciting customers' sensitivity and awareness. We use the outcome of the behavioral survey to calibrate the sensitivity and awareness parameters of the tenants, since it makes the results more realistic than using arbitrary calibrations. After the pilot, we conducted an accuracy analysis and calculated the errors for these sensitivity and awareness values. To evaluate the accuracy of those values, we gave the behavioral survey to the tenants before and after the DR pilot presented in Section 3.2. The difference in the values they indicated as answers to the questionnaires provides an indication of potentially wrong values for sensitivity and awareness. The error of this analysis lies in the interval [2%–14%]. Sensitivity and awareness are assumed to be independent. If the probability of shifting for a household i at a time step t is $PS_{i,t}$, then it can be expressed by Eq. (1), where $\alpha \in [0,1]$ is a fixed coefficient. Increasing α values yields a higher probability of shifting.

$$PS_{i,t} = \alpha \cdot S_i \cdot A_i \tag{1}$$

After importing the raw data vector $\mathbf{x}_i = \{x_{i,t}\}$, the software platform decomposes this vector into separate activities and identifies related appliances. The disaggregation method used is an event detection approach as described by [35]. This method uses a form of *supervised learning* [36] and can identify which appliances are switched on at each point in time, based on training with real consumption patterns of all household appliances. In Section 3.3.1, the accuracy of the disaggregation approach is evaluated (~66.4% accurate). The goal of this method is to produce accurate disaggregation of the consumption vector $\mathbf{x}_i$ so that distinct activities are identified. The disaggregation process gives as output a discrete set ($\mathbf{Act}_i = \{Act_{i,j}\}$) with all the activities $j \in \mathbb{N}$ and a discrete set ($\mathbf{Appl}_i = \{Appl_{i,m}\}$) with all the appliances $m \in \mathbb{N}$ of each household i. It also returns a set $\mathbf{Prob}_i = \{Prob_{i,j}\}$ with all the probabilities of occurrence for each activity j. All these sets together with the S_i and A_i values are the inputs of the Monte Carlo (MC) optimization [8].

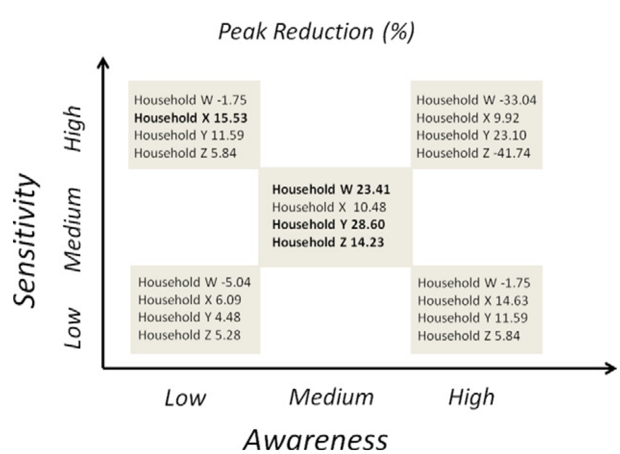

Fig. 11. The impact of sensitivity and awareness on average peak reduction (households with highest peak reduction in bold).

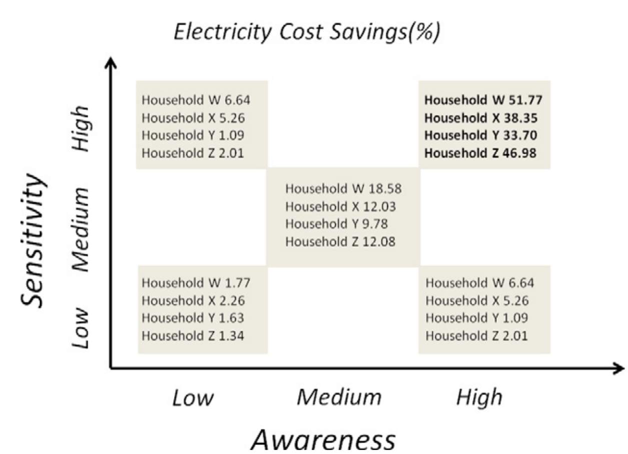

Fig. 12. The impact of sensitivity and awareness on electricity cost savings (households with highest cost savings in bold).

Table 3
TOU tariffs.

	Off-peak price (€/kWh)		Peak price (€/kWh)	
Tariff 1	[00:00–06:00] 0.15	[06:00–00:00] 0.32		
Tariff 2	[00:00–08:00] 0.15	[08:00–16:00] 0.30	[16:00–00:00] 0.37	
Tariff 3	[00:00–06:00] 0.16	[06:00–12:00] 0.26	[12:00–18:00] 0.32	[18:00–00:00] 0.37

Other inputs for the MC module include various pricing schemes in the form of a temporal price vector ($\mathbf{P} = \{P_t\}$). Combining all these inputs, the MC module optimizes the electricity costs of each household and schedules the activities accordingly. MC optimization is the most suitable approach for solving the consumer's cost minimization problem. Due to the high volatility of the electricity consumption curve, there might be situations where the global optimum is not achieved, and the algorithm might give a local optimum as global. With the MC optimization we have the advantage of multiple iterations with different starting points, making sure that the algorithm converges to the global optimum.[4]

The simulated output ($y_i = \{y_{i,t}\}$) is the expected power demand of this particular household i, benefiting the most from the offered TOU tariff, and is determined by Eq. (2). Using the vector y_i after each experiment, we provide recommendations for suitable TOU tariffs for particular households and for the building as a whole. A highly volatile y_i requires different pricing incentives than a more constant and predictable consumption vector y_i.

$$\mathbf{y_i} = \arg\min_{y_{i,t}} \sum_{t=1}^{T} y_{i,t} \cdot P_t \tag{2}$$

T is the time horizon and P_t the prices offered for each time step $t \in [1, T]$. These prices are the designed TOU tariffs in the simulation experiments.

Next, we analyze consumer group behavior, using the model in Fig. 2. We observe that now the price vector (P_l) can be different per group G_l and the output of the model is the summation of the outputs ($\mathbf{y}_l$) of each group ($\mathbf{y} = \sum_{l=1}^{k} \mathbf{y}_l$). The clustering module in the software platform [45], receives as inputs the raw consumption vector $\mathbf{x}_i = \{x_{i,t}\}$ of each household, together with the values for S_i and A_i, produces clusters of consumers and analyzes their similarities. We tested different clustering methods with similar results and selected k-means clustering [5] as it gave the most robust results. The basic logic of k-means clustering in our particular problem is summarized by Eq. (3).

$$\mathbf{G} = \arg\min_{G_l} \sum_{l=1}^{k} \sum_{\mathbf{u}_i \in G_l} \| \mathbf{u}_i - \mu_l \|^2 \tag{3}$$

Here $\mathbf{G} = \{G_1, \ldots, G_k\}$ is the set of the created clusters and $l \in [1, k]$. The vector $\mathbf{u}_i$ is d-dimensional and represents each household consumer i. Each dimension d represents one attribute of the consumer. One example can be $\mathbf{u}_i = \{\mathbf{x}_i, S_i, A_i\}$ with d = 3. The variable μ_l stands for the mean of the points in G_l. This algorithm practically strives to minimize the within-clusters variation. Selecting the value of k in k-means clustering might influence the results. Therefore, in Section 4 we experiment with various values and select the one with the most robust results. The online Appendix (http://xlarge.rsm.nl/DSS/Appendix.pdf) presents a table of the notation used throughout the paper.

[4] Another way to solve the problem would be to use hill-climbing or simulated annealing methods [40], but they would need to be restarted manually many times and would require random starting points to ensure convergence.

Table 4
Cost reduction resulting from the adoption of each tariff.

	Tariff 1	Tariff 2	Tariff 3
Household W	6.64%	22.62%	29.68%
Household X	5.26%	5.34%	4.58%
Household Y	1.63%	2.14%	1.09%
Household Z	1.34%	1.32%	−0.01%

3.2. Real-world pilot

To compare the recommendations provided by the simulations, we conducted a real-world pilot. As part of this pilot, smart meters were installed in each apartment in a multi-residential building in Sweden. We focus on the apartments as individual consumers as well as, on groups of them, and on their dynamics.

The building consists of 33 apartments with different appliances, and consumption activities. Therefore, we examined all apartments and compared tenants' reactions to DR. The pilot consists of three phases: the baseline, the feedback, and the demand response phase. During the baseline phase, which lasted from January 1, 2013 to May 31, 2013, smart meters were installed and measurements about each household's consumption were recorded (raw consumption data $\mathbf{x}_i = \{x_{i,t}\}$). During the feedback phase, which lasted from June 1, 2013 to October 31, 2013, we provided feedback to the consumers about their peak consumption and about the periods that they tend to consume the most. This feedback phase was intended to make household customers aware of their actual energy consumption as well as the time intervals in which they tend to create peaks so that they can make conscious decisions about shifting during the final phase (DR phase). In other words, once customers know when they create peaks, they can consciously reduce them by not consuming at a certain time of day. Therefore, this feedback together with the actual incentive is captured in our results and is tightly coupled to a successful pilot. Finally, during the demand response phase, which lasted from November 1, 2013 to February 28, 2014, we gave consumers incentives to reduce their peak demand in exchange for financial rewards. More specifically, they would receive €1500 if they reduced their average consumption by 7% or more, during the demand response phase, €1000 if they reduced their average consumption by 5%–7% and €500 if they reduced it by 3%–5%. The consumption reduction bounds of $>$7%, 5%–7% and 3%–5% were selected based on previous real-world pilots as the most commonly used and as realistic goals for this region of Sweden. This pilot offers financial incentives to electricity consumers for shifting or curtailing their demand. Hence, it can be categorized under incentive-based DR, which is defined as a program that "gives customers load-reduction incentives that are separate from, or additional to their retail electricity rate" [43].

Table 5
Average peak reduction resulting from the adoption of each tariff.

	Tariff 1	Tariff 2	Tariff 3
Household W	−2.52%	22.92%	21.16%
Household X	14.36%	17.27%	16.22%
Household Y	4.82%	4.72%	4.56%
Household Z	5.28%	−2.81%	5.00%

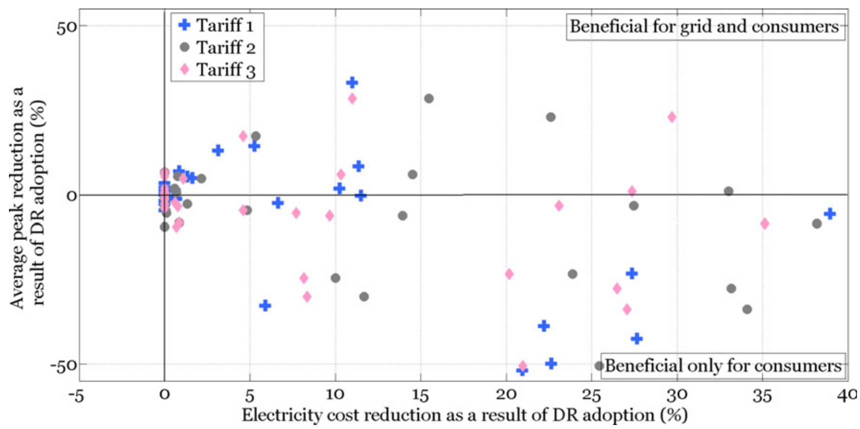

Fig. 13. Peak demand reduction and electricity cost savings for Tariffs 1, 2, and 3.

3.3. Data description

In this section we first describe the individual household observations used in our analysis and then examine the multi-residential building, as an aggregation of individuals.

3.3.1. Individual households

We analyzed all 33 households in the multi-residential building and provided personalized feedback about their energy consumption. Due to space limitations four households were selected for detailed results demonstration. The selection was based on diverse characteristics (sensitivity, awareness, appliances, reaction to incentive-based DR, etc.) and their interest to receive personalized recommendations and put them in practice. For confidentiality reasons, we refer to the households in question as Households W, X, Y, and Z. The online Appendix presents the detailed analysis of all 33 households (http://xlarge.rsm.nl/DSS/Appendix.pdf).

Household W. Household W provided us with the list of appliances, which we use to evaluate the accuracy of the disaggregation. After importing the raw consumption data $\mathbf{x}_w$, we get appliance list $\mathbf{Appl}_w$ shown in Fig. 3. Comparing it to the actual list of appliances, we observe that 12 out of 17 appliances were predicted correctly, which makes the accuracy of the disaggregation module 70%. Fig. 3 shows that the largest portion of energy consumption comes from the cooker hood fan (cooking extractor), the microwave, and the entertainment appliances.

Household X. Household X also provided us with the appliance list. After importing the raw consumption data $\mathbf{x}_x$, we get appliance list $\mathbf{Appl}_x$ shown in Fig. 4. In this household, 12 out of 18 appliances were predicted correctly (accuracy around 67%). We conducted the same analysis for 17 (out of 33) households that agreed to provide their appliance list and found that the average disaggregation accuracy across 17 households is 66.4%. This accuracy rate is quite common in the energy disaggregation literature. Kolter et al. [32] have an electricity disaggregation accuracy of [47%–59%]. Parson et al. [38] have a disaggregation accuracy which differs across appliances with a minimum of 22% for the air-conditioning units and a maximum of 77% for the refrigerator. Kim et al. [28] find that their disaggregation accuracy lies in the interval of [65%–75%]. The disaggregation method predicts all appliances correctly except freezers and dryers. This will be improved as more data are fed into the platform and the method is better trained. Furthermore, the largest part of consumption comes from cooking appliances (including microwave oven) and entertainment devices (Fig. 4).

Household Y. Household Y did not provide a list of appliances, and therefore we had to rely on the software's disaggregation to identify appliances and activities. Given the previous record of 66.4% accuracy in detecting activities, the outcome is expected to be similarly accurate. From the pie chart in Fig. 5, we observe that entertainment devices consume the largest portion of power, whereas cooking activities are also consumption-intensive.

Household Z. Similarly, Household Z did not provide a list of appliances, and therefore we had to rely on the outcome of the software. The pie chart of activities of this household is comparable with Household Y, but here entertainment devices have a slightly smaller portion of the total power demand and cooking activities a slightly higher portion (Fig. 6). Overall, the examined households so far, show large portions of consumption on cooking and entertainment activities (TVs, PCs, etc.).

3.3.2. Multi-residential building

Next we analyzed the multi-residential building, as an aggregation of individuals. This analysis provides insights to energy brokers that want to manage their energy consumer portfolio effectively, since the multi-residential building acts as a small consumer portfolio. In such a group, the energy provider can create sub-groups with similarities in consumption behavior and create pricing schemes targeting different groups. This way, the provider can benefit from the heterogeneity in energy consumption and create a less volatile portfolio, and consumers can save on their electricity bills.

Table 6
Peak demand reduction and cost savings as a result of demand response pilot.

	Household W	Household X	Household Y	Household Z
Peak demand reduction (%)	−19.69	−15.04	18.98	4.39
Cost savings (%)	−18.14	−13.53	25.00	−5.37

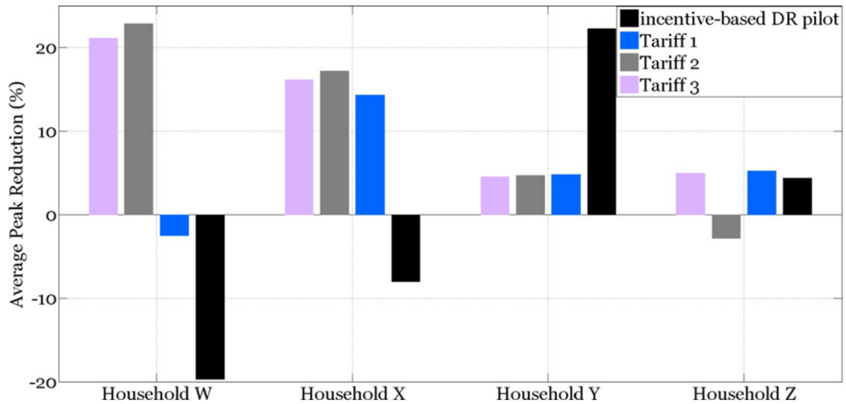

Fig. 14. Benchmarking of all proposed TOU schemes with DR incentives: average peak reduction.

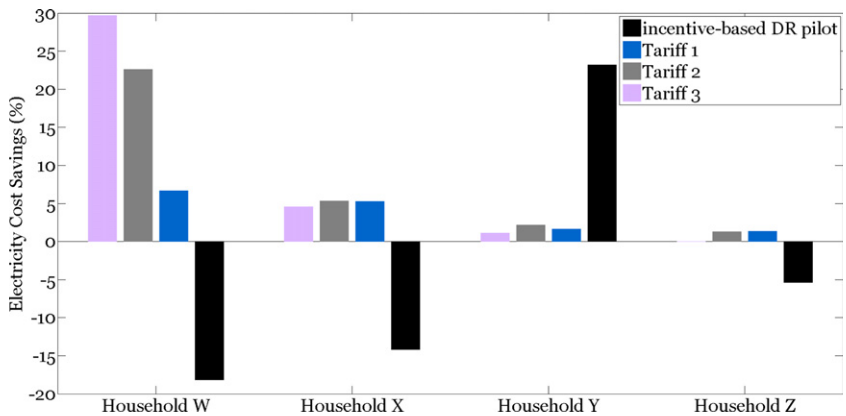

Fig. 15. Benchmarking of all proposed TOU schemes with DR incentives: electricity cost savings.

4. Results

In order to provide energy tariff recommendations to individual customers, we use the models presented in Figs. 1 and 2 to analyze the data collected from the real-world pilot. To ensure convergence of the result, we run a large number of MC simulations (300)[5] for each experiment.

4.1. Sensitivity and awareness analysis

We simulate the response of the four household consumers presented in Section 3.3.1, to different types of pricing schemes, for a range of response parameters (and sensitivity and awareness), so that we can provide personalized recommendations. We contrast the results to the observed values of sensitivity and awareness and provide suggestions for becoming more sensitive or aware, in cases that it can be beneficial. Furthermore, we show how sensitivity and awareness influences peak demand and can be used by energy providers and building managers to reduce peaks.

The sensitivity (S_i) and the awareness (A_i) of the residents in Households W, X, Y, and Z ($i \in \{W, X, Y, Z\}$) are adjusted within a range of $S_i \in [10\%, 100\%]$, $A_i \in [10\%, 100\%]$. We display results for combinations of low sensitivity and low awareness ($S_i = A_i = 10\%$) (this is the lowest parametrization we can have besides 0% which will not affect the simulation), low sensitivity and high awareness ($S_i = 10\%$, $A_i = 100\%$), high sensitivity and low awareness ($S_i = 100\%$, $A_i = 10\%$), high sensitivity and high awareness ($S_i = A_i = 100\%$), and a median solution with $S_i = A_i = 50\%$. Tables 1 and 2 summarize all the response results for each household and for all the combinations of sensitivity and awareness calibration. The two metrics used to evaluate the impact of sensitivity and awareness are average peak reduction, which indicates the benefits for the distribution grid and energy cost savings, which captures the benefits for the customers.

The energy cost after adopting a TOU tariff, C_{TOU} is calculated using the product of simulated response $y_{i,t}$ (Eq. (2)) and the price/kWh (P_t) for each point in time t ($C_{TOU} = \sum_{t=1}^{T} y_{i,t} \cdot P_t$). $C_{initial}$ is the energy cost for the consumer during the same time period without DR adoption. Assuming the initial profile is $y'_{i,t}$, then we have: $C_{\text{initial}} = \sum_{t=1}^{T} y'_{i,t} \cdot P_t$. The cost savings are: $\pi = C_{initial} - C_{TOU}$. This calculation assumes that the household consumers know the

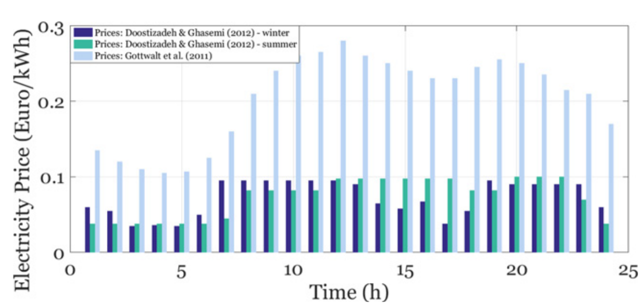

Fig. 16. Variable electricity prices from [16,20].

[5] We experimented with run numbers in the spectrum [10, 1000] and 300 is the number that achieves convergence with negligible error in the produced results.

Table 7
TOU tariffs from [15].

	Off-peak price (€/kWh)	Peak price (€/kWh)	Off-peak price (€/kWh)
2-Tier	[00:00–08:00] 0.1675	[08:00–19:00] 0.2122	[19:00–00:00] 0.1675
3-Tier	[00:00–08:00] ∪ [19.00–00.00] 0.16752	[08:00–16:00] ∪ [18:00–19:00] 0.2122	[16:00–18:00] 0.12

prices in advance and they shift their consumption accordingly. Thus, this calculation includes demand response behavior. We calculate the results assuming a TOU pricing scheme. As an example, we impose a two-part tariff with charges: 0.15 €/kWh for the time period [00:00–06:00] (night tariff) and 0.32 €/kWh for the time period [06:00–00:00] (day tariff) and we compare it to the baseline scenario where the consumer is enrolled to the TOU tariff but does not shift her consumption. The baseline scenario is equivalent to a flat tariff that brings the same cost as the TOU tariff if no shifting is involved (selected so that it satisfies the principle of cost neutrality according to which there will be no changes on the electricity bill, if the customer does not shift behavior).

We identify the S_i and A_i parametrization that gives both positive average peak reduction and substantial energy cost savings. In Tables 1 and 2 we observe medium values for sensitivity and awareness bring both peak reduction and energy cost savings, for all households. Households W and Z have high levels of sensitivity and awareness which makes them over-responsive to prices, creating peaks instead of reducing them. Consequently, energy policymakers should examine their consumer portfolio carefully before imposing DR schemes, because a high responsiveness to prices might yield negative results.

The S_i and A_i parametrization that brings the highest benefits for consumers is the $S_i = A_i = 100\%$. In other words, consumers with the highest sensitivity and awareness toward price changes, make the highest savings in their electricity bill. Consequently, policymakers should examine their consumer portfolio carefully before imposing DR schemes. Consumers with high sensitivity and awareness do not need extra financial incentives for DR participation. However, policymakers will need to add more customers to the portfolio with lower sensitivity and awareness, so that on aggregate level they avoid excessive price responsiveness and peak increase.

In Fig. 7, we see how the consumption curve of Household W changes under different sensitivity and awareness parametrizations with a TOU pricing scheme. The parametrizations $S_w = 100\%, A_w = 10\%$ and $S_w = 10\%, A_w = 100\%$ have identical consumption curves, since the reaction to prices is analogous to the product of $S_w \cdot A_w$. Furthermore, we see that excessive reaction to price changes increases the peaks for $S_w = 100\%, A_w = 100\%$.

The behavior of Household X reacting to the same prices is similar (Fig. 8). The only difference is that the shifting with high awareness and high sensitivity does not yield higher peaks than the initial curve, leading to benefits for the grid and for the individual household. This difference depends on each household's consumption pattern and shifting behavior.

For Household Y, the peak created from shifting for $S_y = A_y = 100\%$ is significantly lower than the actual peak during the baseline case, creating benefits for the distribution grid and for consumers. In contrast, for low sensitivity and awareness the shifting is so little, yielding no significant benefits (Fig. 9).

In Fig. 10, we see that Household Z becomes over-responsive to prices for $S_z = A_z = 100\%$ and the peaks created from shifting are higher than the initial ones. The parametrization of $S_z = A_z = 50\%$ gives the best results in lower peaks and in electricity cost savings for the individuals.

A schematic summary of the previous results is presented in Figs. 11 and 12. The households that either have the highest peak reduction or the highest cost savings for the respective sensitivity and awareness parametrization are marked in bold. Figs. 11 and 12 show how changes in sensitivity and awareness affect the benefits households can achieve. For all households, medium sensitivity and awareness achieves incentive alignment, creating the most benefits for the grid (peak reduction) and for customers (lower electricity bills).

4.2. Pricing schemes

After examining the impact of sensitivity and awareness on peak demand reduction and electricity cost savings across households, we impose TOU schemes to observe changes in the household consumption curve. First, we start with a two-tier TOU tariff (Tariff 1) with prices shown in Table 3. As this tariff only has two tiers, it does not benefit the most from potential shifting behavior. Therefore, we create TOU tariffs with more tiers that have the potential to achieve both electricity cost savings and peak demand reduction. In this way, energy policymakers do not need to provide extra financial incentives and customers will get higher rewards for participating in DR schemes. Gottwalt et al. [20] and Strbac [42] confirm that DR schemes that only focus on peak reduction do not give significant benefits for individuals. Therefore, we propose two DR schemes described by Tariffs 2 and 3 in Table 3. These two schemes have more than two tiers and our goal is to examine if they are more effective in achieving peak demand reduction and cost savings. The detailed results are presented in Tables 4 and 5 (the online Appendix presents the full tables for all 33 households, http://xlarge.rsm.nl/DSS/Appendix.pdf). These results are not dependent on the prices of

Table 8
Peak demand reduction and cost savings — benchmarks.

		Hous. W	Hous. X	Hous. Y	Hous. Z
[20]	Peak demand red. (%)	4.15	2.34	1.35	−0.79
Variable	Cost savings (%)	1.52	1.22	0.00	0.00
[15]	Peak demand red. (%)	5.93	3.73	−10.53	−18.43
2-Tier	Cost savings (%)	0.59	1.41	−5.36	−14.46
[15]	Peak demand red. (%)	0.04	3.10	0.48	2.03
3-Tier	Cost savings (%)	0.63	1.12	0.00	1.09
[16]	Peak demand red. (%)	−0.71	−6.36	3.03	−1.30
Winter	Cost savings (%)	1.49	3.57	0.00	0.00
[16]	Peak demand red. (%)	7.11	10.66	3.66	1.34
Summer	Cost savings (%)	2.74	0.00	0.00	0.00

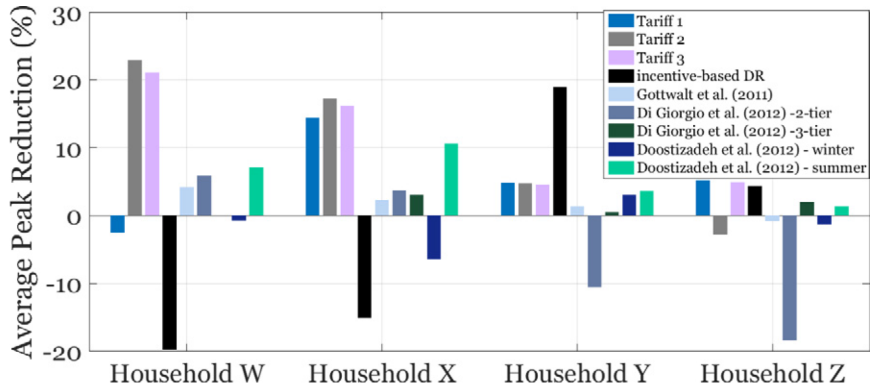

Fig. 17. Benchmarking of the presented TOU tariffs: average peak reduction.

each tier per se, but on the structure of the tariff and the relative difference between the tiers. Practically, the absolute numbers used for the prices do not influence the structure of the results, but they serve as an indication of what the results will look like. Increasing the tiers of the tariffs yields higher peak demand reduction and higher electricity cost savings for households. We compare the outcome of adopting a TOU tariff to the baseline scenario where the consumer is enrolled to the tariff but does not shift consumption (which is equivalent to a flat tariff which brings the same cost as the TOU tariff without shifting — cost neutrality). All compared tariffs presented in Table 3 are constructed so that the average price per kWh is the same in all pricing schemes.

We are interested in tariffs that bring both electricity cost savings for individual customers and peak demand reduction. Fig. 13 (for all 33 households) shows peak demand reduction on the vertical axis and individual cost savings on the horizontal axis. In order to have a win–win situation for smart grid and individual households, we need to look for tariffs in the first quadrant of the axes. Tariffs located in the fourth quadrant are beneficial for individuals but not for the distribution grid. The tariffs in these schemes target consumers with high sensitivity and awareness, who become over-responsive to price changes and create new peaks in demand. At least one of the three tariffs achieves incentive alignment for 72% of the consumer population, creating both peak reduction and cost savings. The remaining 28% comprises high sensitivity and awareness consumers who are over-responsive to price changes. This different behavior to price changes and differences in consumption profiles can be tackled by creating consumer groups with similar characteristics so that demand shifting becomes more effective. Negative peak reductions resulting from high price sensitive consumers can be overcome by reducing the price difference between the tiers of the tariff, so that their reaction to price differences becomes milder. Finally, energy policymakers can create a more diversified consumer portfolio where high price sensitive consumers offset the consumption profile of low price sensitive consumers and create flatter aggregate demand curve. Fig. 13 confirms our initial assumption that DR schemes have different outcomes depending on individual consumer characteristics. Therefore, it is important to examine these characteristics in depth before designing a DR scheme.

4.3. Personalized recommendations

The results of the previous tariffs are compared to the outcome of the incentive-based DR pilot described in Section 3.2. Comparing an incentive-based DR with a simulated price-based DR cannot, of course, provide a thorough comparison between the two methods. It can only provide an indication of how these two techniques can affect the customers and the grid. Incentive-based and price-based DR (TOU tariffs) use different methodology, and we can therefore only compare their outcome.

The demand response phase of the pilot lasted from November 1, 2013 to February 28, 2014. Since the baseline measurements were gathered during different periods over the year, we apply daylight correction in order to have a fair comparison. More specifically, we normalize all the results on the daylight hours of the year to prevent seasonal bias in our comparisons. The impact of this normalization is that the results can now be comparable on the same basis. A shortcoming of this normalization is that it does not account for different usage of appliances depending on the season. However, in our particular case, this shortcoming does not influence the results significantly, since most of the appliances (Figs. 3–6) do not have high dependencies on the season. The lighting devices are most dependent on the season and daylight hours, but they have a small share of the total consumption (see Figs. 3–6).

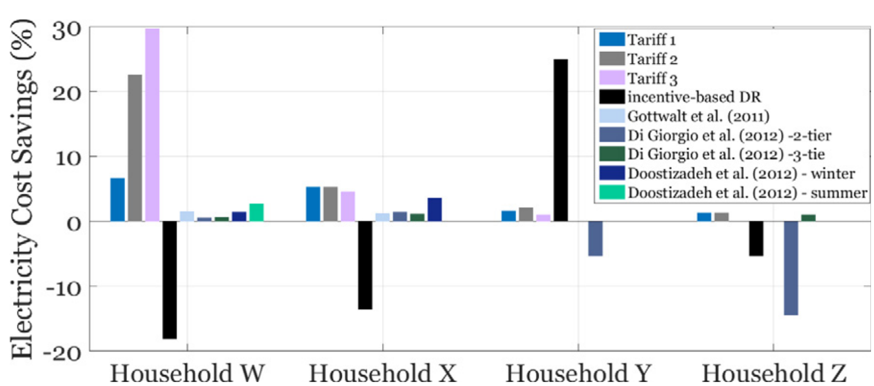

Fig. 18. Benchmarking of the presented TOU tariffs: electricity cost savings.

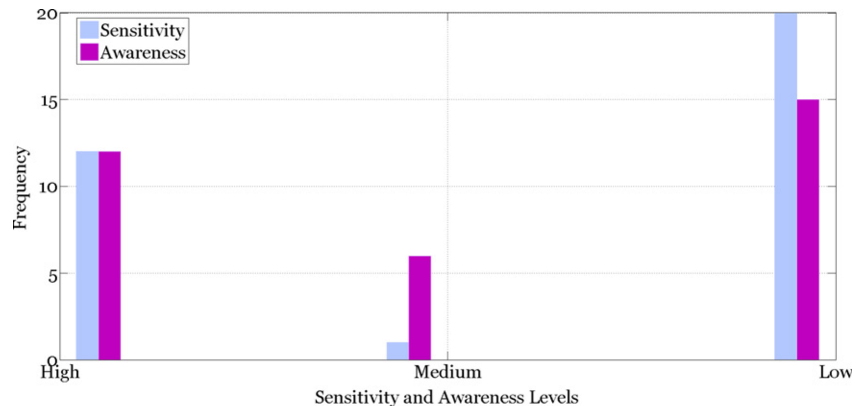

Fig. 19. Sensitivity and awareness histogram in the multi-residential building.

Table 6 presents the results of the DR pilot on the four households in question. For Households W and X, demand actually increased instead of decreased. The residents were either not willing to participate and continued to consume as normal, or they were trying to reduce peak demand in the common areas of the building, shifting a lot of activities in their apartments. This apartment building has communal areas where tenants can do their laundry or other household activities. Therefore, trying to reduce consumption in the common areas might have led to an increase in the demand of some individual households. In other households, such as Y and Z, peak demand decreased significantly, leading to cost savings for Household Y. Although Household Z reduced its peak consumption, it increased total energy consumption and, therefore, had higher electricity costs than before the DR pilot.

Having examined the effect of these three TOU pricing schemes and the DR pilot, we present the most suitable option for each household with regards to: a) average peak reduction and b) cost savings. Figs. 14 and 15 show the average peak reduction and cost savings of the four households, respectively.

For Household W, all recommendations, apart from the incentive-based DR, bring peak demand reduction. However, only Tariff 2 and Tariff 3 yield both peak demand reduction and individual savings on the electricity bill. For Household X, all tariffs besides the incentive-based pilot bring cost savings and average peak reduction. However, the absolute value of peak reduction is lower than this of Household W. For Household Y, the incentive-based DR is clearly the most effective, achieving both peak demand reduction and lower electricity costs. For Household Z, the incentive-based DR leads to peak demand reduction but also to an increase in the total energy consumption and thus to higher electricity costs. Instead, Tariffs 1 and 3 bring peak reduction but small cost savings. This is attributed to the low consumer price sensitivity and awareness.

4.4. Benchmarks

To evaluate our approach against existing ones in the literature, we use a set of benchmarks that has been used in the context of household electricity consumption. All these benchmarks use the same assumptions as we do (target household owners, aim at peak demand reduction and electricity bill savings) and have been effective on the datasets they have been applied to. Each of these benchmarks reveals a new aspect in the comparison (multi-tiers vs. single tiers, low price variation vs. high price variation, etc.). First, we use a variable pricing scheme proposed by [20] and has different tiers for each hour of day (24 tiers, variable pricing). The prices are depicted in Fig. 16 and come from the wholesale prices of the European Energy Exchange (EEX). This benchmark is helpful for examining how a multi-tier tariff performs in our particular population. In addition, we use two other benchmarks from [15]. They are a two-tier and three-tier tariff, and are displayed in Table 7. These benchmarks help us understand how TOU tariffs designed for other populations perform on our population. Finally, we used two benchmarks by [16]. These are multi-tier tariffs (24 tiers, variable), designed for winter and summer, respectively. These two benchmarks (Fig. 16) have lower price tiers than the other three benchmarks and our tariffs, and will therefore be useful to show how our population reacts to lower price tariffs.

The benchmark results are shown in Table 8. Adding the results from the presented benchmarks in Fig. 14, we get Fig. 17. We see that our tariffs have a better peak demand reduction, compared to the benchmarks. This is mostly attributed to the personalization of the tariffs to our portfolio, having examined their price responsiveness. Similarly, adding the results from the presented benchmarks in Fig. 15, we get Fig. 18. We see that the tariffs used in the literature perform worse both in terms of average peak and electricity cost reduction. The three-tier tariff proposed by [15] performs better than the two-tier one. We observed the same in our tariff structures. Furthermore, the tariffs presented by [16] do not perform well in our population because they have quite low prices, and our customers do not shift their behavior enough to create essential peak demand reduction. Finally, we see that multi-tier tariffs (like the ones proposed by [16,20] are not effective in our consumer group, mostly because of the peak and off-peak hours and price differences.

Table 9
TOU tariffs in the multi-residential building for number of clusters k=3.

	Off-peak price (€/kWh)	Peak price (€/kWh)
Cluster 1	[00:00–08:00] 0.18	All other time 0.27
Cluster 2	[08:00–16:00] 0.18	All other time 0.27
Cluster 3	[16:00–00:00] 0.18	All other time 0.27

Table 10
TOU tariffs in the multi-residential building for number of clusters k=4.

	Off-peak price (€/kWh)	Peak price (€/kWh)
Cluster 1	[00:00–06:00] 0.15	All other time 0.27
Cluster 2	[06:00–12:00] 0.15	All other time 0.27
Cluster 3	[12:00–18:00] 0.15	All other time 0.27
Cluster 4	[18:00–00:00] 0.15	All other time 0.27

Table 11
TOU tariffs in the multi-residential building for number of clusters k=5.

	Off-peak price (€/kWh)	Peak price (€/kWh)
Cluster 1	[00:00–05:00] 0.14	All other time 0.27
Cluster 2	[05:00–10:00] 0.14	All other time 0.27
Cluster 3	[10:00–15:00] 0.14	All other time 0.27
Cluster 4	[15:00–20:00] 0.14	All other time 0.27
Cluster 5	[20:00–24:00] 0.14	All other time 0.27

Our consumer population shows, overall, substantial peak demand reduction when there are prices differences, sufficient to create cost savings from shifting. In other words, the residents will not shift their consumption a lot without big price differences, mostly because of their medium price responsiveness. The variable tariffs used by [16,20] do not meet these criteria, and therefore do not create substantial peak demand reduction.

4.5. Consumer group identification within a multi-residential building

After examining the effect of sensitivity and awareness of each individual, we expand the analysis to the whole building. All 33 households belong to a multi-residential building managed by an administrator, who is responsible for paying the aggregate electricity bills. Our recommendations are useful for the building administrator and for the energy provider of these 33 households.

We measured the consumption data of these households from January 1, 2013 to May 31, 2013. We collected their baseline household consumption profiles and imported them into the software platform. Using the CSN module as presented in Fig. 2, we identified various consumer groups based on different segmentation criteria. We selected the two criteria that have the highest variation among the household consumers: total energy consumption and maximum power consumption. We used real data from interviews with tenants to calibrate the sensitivity and the awareness of each household. The histogram in Fig. 19 summarizes the values of the parameters sensitivity (S_i) and awareness (A_i) of the household customers i in the multi-residential building of our pilot.

We demonstrate scenarios with three, four and five numbers of clusters ($k \in [3,5]$) and apply the TOU pricing schemes in Tables 9–11. Since there is no clear rule for selecting the number of clusters in k-means algorithm [5], the parameter k is selected based on domain knowledge or by judging the quality of the produced clusters. We selected these numbers of clusters ($k \in [3,5]$) because we noticed that even when we increased the number of clusters, the observations were mostly concentrated in 3–5 clusters. The rest of the clusters were not sufficiently populated, creating no real insights about the consumer groups. In addition, in some cases (e.g., Fig. 25, right pane) the clusters are very close to each other, indicating that these customers could belong to the same group. Furthermore, given that we have 33 households, a number of clusters $k \in [3,5]$ is expected to create fairly populated clusters. We evaluate the effect of these consumer clusters and their TOU tariffs on peak demand and compare them to a flat tariff scenario where the whole building faces a uniform pricing scheme of 0.24 €/kWh. This uniform pricing scheme is selected to reflect the average electricity price in northern Europe in 2013.[6]

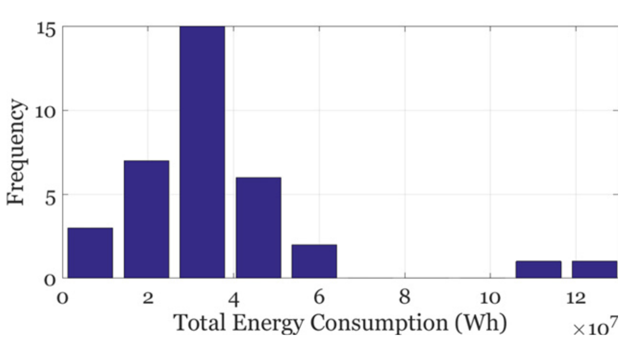

Fig. 20. Histogram for segmentation criterion: total energy consumption.

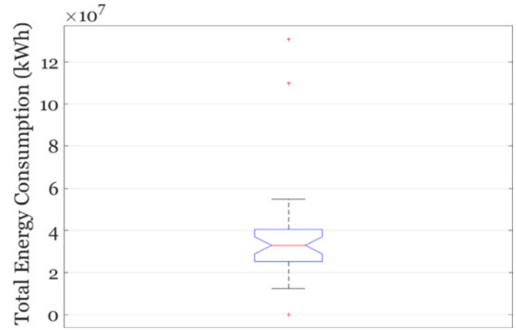

Fig. 21. Boxplot for segmentation criterion: total energy consumption.

In terms of consumer segmentation, we selected the two main differentiating criteria: total energy consumption and maximum power consumption. Typically, electricity consumers have similarities in terms of electricity consumption. The main differences include the overall consumption during a certain time horizon, which is dependent on the number and type of household appliances they possess and the maximum power at which they consume, which depends on the time they consume a certain amount of electricity and/or on any potential concurrent consumption from different appliances (consuming a certain amount of electricity in a shorter time interval creates higher power demand).

4.5.1. Total energy consumption segmentation criterion

We use total energy consumption as our first segmentation criterion. It is expected that since the customers have different consumption habits and appliances, they will also show variety in their total energy consumption. This is confirmed by the variance of total energy consumption on the histogram (Fig. 20) and the boxplot (Fig. 21). We checked the between-groups differences among all adjacent bins of the histogram and found that they are significantly different at 99% confidence interval (pairwise t-test, $p < .01$). Since the number of clusters (k) is still uncertain, we will experiment with three possible values ($k \in [3,5]$).

The clusters resulting from applying k-means on the multi-residential building with possible values $k \in [3,5]$ are displayed in Fig. 22. This figure, together with Fig. 25, shows how the clustering of the households is done using Eq. (3). Each time (Figs. 22, 25) a different segmentation criterion is used to create the clusters. In addition, we show how changing the number of clusters (k) affects the outcome. In Fig. 22, we see that for $k = 3$ the households create two sufficiently populated clusters and one less populated one. This means that regarding total consumption, the households can be categorized in two sufficiently populated clusters and a less populated cluster.

By applying the TOU tariffs in Tables 9–11 to these clusters, we see average peak reduction and electricity cost savings shown in Table 12. We see that $k = 4$ and $k = 5$ yield the most beneficial results for the distribution grid (in terms of average peak reduction) and for the household customers (in terms of cost savings). However, looking at the clusters for different cases of k, we see that

[6] http://ec.europa.eu/eurostat/statistics-explained/index.php/Energy_price: statistics [Date Accessed: May 24, 2016].

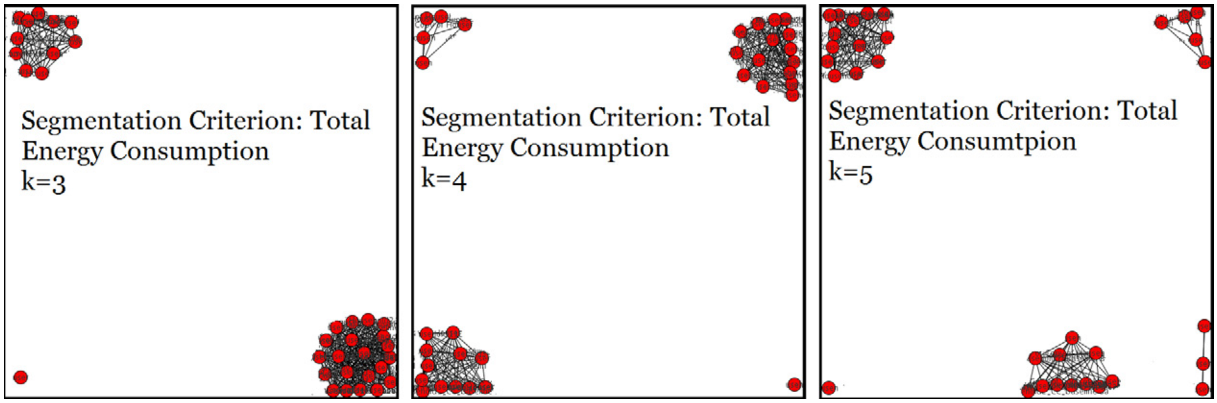

Fig. 22. Consumer groups for segmentation criterion: total energy consumption.

some clusters are heavily populated with customers, whereas others comprise only two or three customers. This results both from the commonalities between the two groups that are stronger but also from the relatively small consumer sample (33 households). These scarcely populated clusters might be the reason that peak demand reduction is relatively low in some cases. Behavior shifting in these clusters is not as big compared to that of the other more populated clusters, yielding a lower aggregate result. To get the results shown in Table 12, we repeated each 300-run simulation 10 times (sufficient number of runs to yield significant results) and performed statistical significance analysis. Specifically, we used the two-sample t-test to conduct pairwise comparisons of the electricity consumption per hour (before and after consumer segmentation). Table 12 presents the statistical significance of the result and the effect sizes in terms of Cohen's d coefficient[7] and effect size correlation (r) [12]. If Cohen's d coefficient belongs to $[0.2, 0.5)$, it indicates a small (but not trivial) effect size, if it belongs to $[0.5, 0.8)$, a moderate effect size and if it is $>.8$, a large effect size. A large effect size means that a large portion of the two samples does not overlap. The means and standard errors of each comparison are indicated as M and SE, respectively (M_1, SE_1 refers to the group of results after clustering and M_2, SE_2 to the baseline group of results without clustering). Table 12 indicates that Cohen's d is $>.8$ in all cases, meaning large effects wherever they are significant.

4.5.2. Maximum power segmentation criterion

We use maximum power of each household in the multi-residential building as our second segmentation criterion. This is expected to show differentiation among the consumers since it is heavily dependent on appliances, apartment occupancy, and general consumption habits. This is confirmed by the variance of maximum power demand on the histogram (Fig. 23) and boxplot (Fig. 24). We performed pairwise comparisons to check the between-groups differences among all adjacent bins of the histogram and found that they are significantly different at 99% confidence level (pairwise t-test, $p < .01$).

The clusters resulting from applying k-means on the multi-residential building with possible values $k \in [3, 5]$ are displayed in Fig. 25. After applying the TOU tariffs described at the beginning of the Section, we see average peak reduction and energy cost savings shown in Table 13. We observe that $k = 4$ and $k = 5$ create high benefits for the distribution grid and for the household customers. Furthermore, for $k = 4$ we have four clusters that are sufficiently populated and we also observe the highest electricity cost savings (Fig. 25), since the groups of customers are large and shifting their demand is effective. Also in Fig. 25, we observe that in the $k = 5$ case, two clusters are quite close to each other and could potentially be represented by one cluster. To get the results shown in Table 13, we applied the same process as described above. We observe that in almost all cases, Cohen's d is $>.8$, meaning large effects wherever they are significant. The effect size is medium only for $k = 3$, but in this case the results are not satisfactory for the grid or for the customers, hence it is not a case for creating policy recommendations and the medium effect size does not play an important role.

5. Robustness tests

To show that the proposed results are robust and generalizable independent from the data used, we apply the three TOU pricing schemes presented above, on two other datasets. The first dataset includes households from the Netherlands and the second includes households from Austin, Texas, USA. We argue that these two datasets have distinct differences because the Netherlands has a different climate than Austin, where temperatures are higher and air conditioning installations are frequently used. Furthermore, the data from the Netherlands and Austin differ in terms of behavior and appliances from the household data in Sweden, allowing us to derive more general results, not dependent on a particular dataset or region. Due to space limitations, we present indicative results of this analysis. The data from Austin and the Netherlands have 15 minute granularity, were collected during 2013 and 2009 respectively and represent mid-sized households, similar to those in Sweden (to allow for comparability). We present an example of a ten-day household consumption in the Netherlands and Austin in Fig. 26. Despite the geographical distance, we observe that both households show a similar consumption pattern. In the US household we observe a shift of the peaks of approximately 150 min which could be explained by differences in the daylight hours and in individual routines (i.e. people in Austin returning from work and starting their household activities later than people in the Netherlands). We also observe slightly higher peaks in the US household, which was expected due to its typically larger size and larger energy needs, compared to a northern European household. The maximum power consumption for this particular household in Austin is 7163 W and the maximum power consumption for this household in the Netherlands is 6188 W. With respect to volatility we use the metric $|max - min|$ and is

[7] $d = \frac{M_1 - M_2}{\sqrt{(SD_1^2 + SD_2^2)/2}}$, M_1— mean of the results after clustering and M_2— mean of the results without clustering, SD_1— standard deviation of the results after clustering and SD_2— standard deviation of the results without clustering.

Table 12
Average peak reduction and cost savings for $k \in [3,5]$ number of clusters with segmentation criterion: total energy consumption.

	$k = 3$	$k = 4$	$k = 5$
Average peak reduction	3.86%*	5.32%**	5.08%**
	$t(9) = -3.12$	$t(9) = -5.39$	$t(9) = -3.50$
	Cohen's d = 1.40, $r = 0.57$	Cohen's d = 2.41, $r = 0.77$	Cohen's d = 1.56, $r = 0.61$
	$M_1 = 10957.27, SE_1 = 136.25$	$M_1 = 10790.80, SE_1 = 106.89$	$M_1 = 10817.67, SE_1 = 161.82$
	$M_2 = 11396.73, SE_2 = 34.64$	$M_2 = 11396.73, SE_2 = 34.64$	$M_2 = 11396.73, SE_2 = 34.64$
Energy cost savings	1.08%	2.80%**	3.13%**
	$t(9) = -1.90$	$t(9) = -6.61$	$t(9) = -7.04$
	Cohen's d = 0.85, $r = 0.39$	Cohen's d = 2.96, $r = 0.83$	Cohen's d = 3.15, $r = 0.84$
	$M_1 = 40.14, SE_1 = 0.22$	$M_1 = 39.44, SE_1 = 0.16$	$M_1 = 39.30, SE_1 = 0.17$
	$M_2 = 40.58, SE_2 = 0.05$	$M_2 = 40.58, SE_2 = 0.05$	$M_2 = 40.58, SE_2 = 0.05$

* $p < .05$.
** $p < .01$.

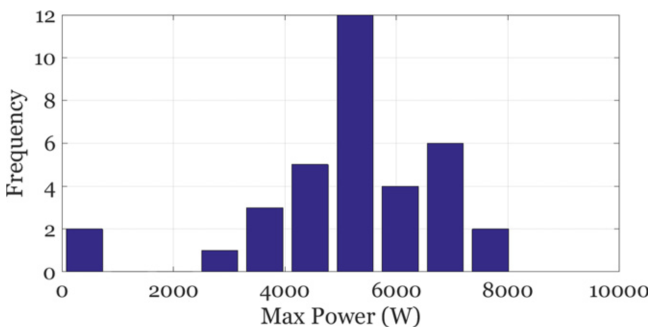

Fig. 23. Histogram for segmentation criterion: maximum power consumption.

higher for Austin (6915 W) compared to the Netherlands (6188 W). Overall, both households show the same consumption pattern and peaks of the same magnitude.

Tables 14 and 15 show how households in the Netherlands and in Austin react differently to pricing schemes. This mostly depends on the appliances they have and the activities they are willing to shift. We see that all tariffs have a beneficial effect both for households and the grid in the Netherlands. That is mostly attributed to the presence of shiftable appliances, unlike the households in Texas that might not be able to shift the functionality of appliances like air conditioning devices. In this case, Tariff 3 achieves both peak reduction and electricity cost savings.

We examine the electricity pricing policies and the regulatory constraints in applying the proposed tariffs in both countries. Although the electricity market is deregulated in Texas, a regulatory body oversees the market, ensuring fair use of this public good.[8] Therefore, if an electricity provider wanted to introduce new electricity tariffs for Austin, it would have to offer services at market prices so that it remains competitive. Currently, Austin has a multi-tier tariff,[9] offered by the main player (incumbent provider). In fact, it is a five-tier electricity tariff which varies in summer and winter. However, this tariff has multiple tiers that apply to different levels of energy consumption (e.g., \$0.033/kWh for [0, 500] kWh, \$0.08/kWh for [501, 1000] kWh, \$0.091/kWh for [1001, 1500] kWh, \$0.11/kWh for [1501, 2500] kWh, \$0.114/kWh for > 2500 kWh plus some regulatory charges of around \$0.045/kWh) instead of different times of the day, which is our proposed approach. On the one hand, we see that the multi-tier tariffs are already in place and therefore there is no need for extra regulation to allow for this tariff structure. On the other hand, we observe that overall electricity prices are lower compared to Europe. In Austin, the max rate is approximately \$0.19/kWh (electricity rate \$0.114/kWh + regulatory charges \$0.045/kWh), which is lower than the European average price of €0.21/kWh. Our price recommendations are tailored to European households and are therefore in a higher price range. Consequently, if we had to provide recommendations to household customers in Austin, Texas, we would keep the same tariff structures presented in the paper, adjusting however the tier levels to reflect a realistic price in this area. Specifically, the average electricity tariff in Austin (as given by the numbers above) is approximately \$0.13/kWh. Table 16 shows one potential formulation for recommended TOU tariffs for Austin.

In the Netherlands, the electricity market is also deregulated, with a regulatory body, which ensures fair competition and delivery of electricity to the end consumers [46]. The average electricity price is approximately €0.18/kWh,[10] and there are night tariffs in place (two-tiered tariffs). This means that multiple-tiered tariffs, as we recommend could also be implemented. If we had to tailor our recommendations to this area, we would have to adjust the prices so that the average corresponds to the average price there, so that our price suggestions are competitive in this market. Table 17 shows one potential formulation for recommended TOU tariffs for the Netherlands.

Tables 18 and 19 present the results after imposing the adjusted prices. We see that all three adjusted tariffs in Austin and in the Netherlands bring savings to the individuals, with the four-tier tariff yielding the highest savings. However, all of these tariffs create peak demand increase instead of reduction. This is because currently the prices in Austin are very low, and in the Netherlands they are lower than the European average, which leads to shifting electricity

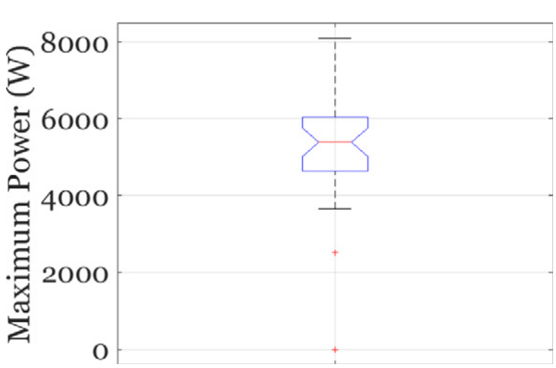

Fig. 24. Boxplot for segmentation criterion: maximum power consumption.

[8] https://austintexas.gov/department/regulatory-affairs [Date Accessed: May 24, 2016].
[9] http://austinenergy.com/wps/portal/ae/residential/rates/residential-electric-rates-and-line-items/ [Date Accessed: May 24, 2016].
[10] http://ec.europa.eu/eurostat/statistics-explained/index.php/Energy_price:statistics [Date Accessed: May 24, 2016].

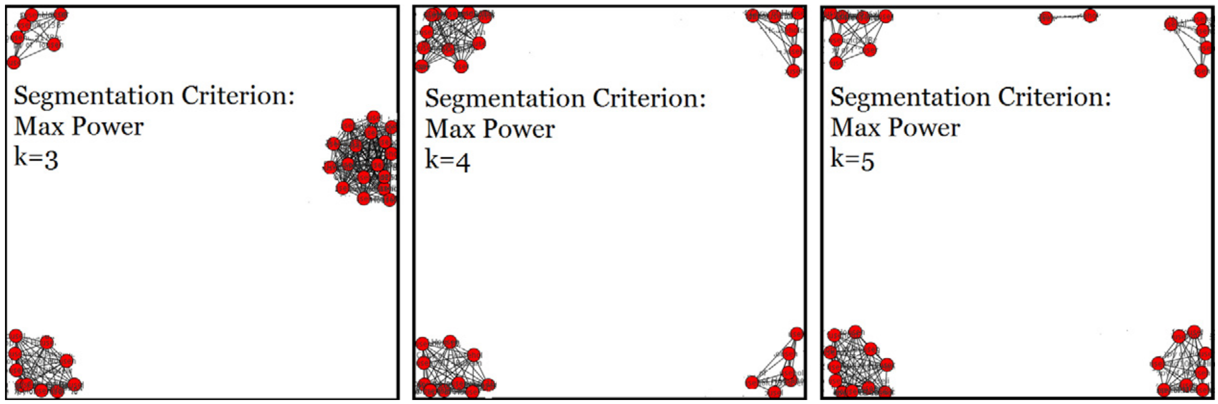

Fig. 25. Consumer groups for segmentation criterion: maximum power.

Table 13
Average peak reduction and cost savings for $k \in [3, 5]$ number of clusters with segmentation criterion: maximum power.

	$k = 3$	$k = 4$	$k = 5$
Average peak Reduction	1.98%	5.51%**	6.00%**
	$t(9) = -1.64$	$t(9) = -6.73$	$t(9) = -4.63$
	Cohen's d $= 0.74$, $r = 0.36$	Cohen's d $= 3.01$, $r = 0.83$	Cohen's d $= 2.07$, $r = 0.72$
	$M_1 = 11171.30, SE_1 = 132.27$	$M_1 = 10769.24, SE_1 = 86.49$	$M_1 = 10713.22, SE_1 = 143.35$
	$M_2 = 11396.73, SE_2 = 34.64$	$M_2 = 11396.73, SE_2 = 34.64$	$M_2 = 11396.73, SE_2 = 34.64$
Energy cost Savings	1.89%**	2.73%**	2.72%**
	$t(9) = -5.01$	$t(9) = -7.65$	$t(9) = -6.44$
	Cohen's d $= 2.24$, $r = 0.75$	Cohen's d $= 3.41$, $r = 0.86$	Cohen's d $= 2.88$, $r = 0.82$
	$M_1 = 39.81, SE_1 = 0.14$	$M_1 = 39.46, SE_1 = 0.13$	$M_1 = 39.47, SE_1 = 0.16$
	$M_2 = 40.58, SE_2 = 0.05$	$M_2 = 40.58, SE_2 = 0.05$	$M_2 = 40.58, SE_2 = 0.05$

* $p < .05$.
** $p < .01$.

use to low-price time intervals. Consequently, demand is accumulated in these time intervals, creating new peaks. This shifting to low-price intervals is indicated by the high cost savings compared to the tariffs before the adjustment. These results show that consumer portfolios require thorough investigation before introducing new tariffs. Currently, we assumed an average price sensitivity and awareness for all consumers in Austin and the Netherlands (due to lack of real data). These results also show that grid operators need to carefully analyze consumer responsiveness before introducing personalized tariffs. Therefore, if the grid operator in Austin and in the Netherlands wanted to introduce time-of-use tariffs, it should avoid setting large price differences during the day and should examine the customer portfolio carefully so that it identifies their responsiveness to prices. The Cassandra software platform can be useful in simulating such tariff design scenarios before applying them in practice, and preventing situations that might not be beneficial for both parties in the electricity market (grid and customers).

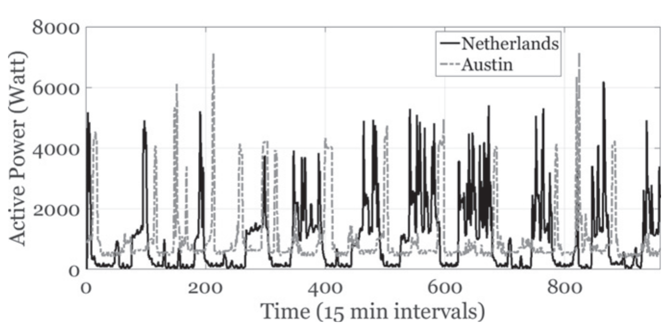

Fig. 26. Example consumption of a household in NL and in Austin over a 10-day time horizon (granularity 15 min).

Table 14
Cost reduction resulting from the adoption of each tariff.

	Tariff 1	Tariff 2	Tariff 3
Netherlands	10.00%	10.00%	7.70%
Austin	3.92%	4.14%	3.02%

6. Managerial insights

The presented analysis can be applied to any country, as long as the simulation experiments are calibrated to the particular datasets. Specifically, from the Robustness Tests Section, we know that consumer price responsiveness is an important component of a successful simulation on the software platform and subsequent implementation in the real-world. However, as long as the specific datasets are available, the software can produce accurate simulation scenarios, to examine the impact of specific pricing schemes. Furthermore, in order to generate realistic results, we need to take into account the electricity regulation in each part of the world. For example, some countries do not allow variable pricing schemes (e.g., due to lack of smart metering infrastructure) and other countries have monopolized electricity markets with certain electricity price caps. All these conditions need to be accounted for, before designing targeted pricing schemes for specific areas.

Table 15
Average peak reduction resulting from the adoption of each tariff.

	Tariff 1	Tariff 2	Tariff 3
Netherlands	30.82%	14.08%	19.13%
Austin	−3.56%	−9.88%	2.79%

Table 16
Adjusted TOU tariffs — Austin.

	Off-peak price ($/kWh)	Peak price ($/kWh)		
Tariff 1	[00:00–06:00] 0.03	[06:00–00:00] 0.17		
Tariff 2	[00:00–08:00] 0.03	[08:00–16:00] 0.14	[16:00–00:00] 0.24	
Tariff 3	[00:00–06:00] 0.03	[06:00–12:00] 0.20	[12:00–18:00] 0.18	[18:00–00:00] 0.23

Table 17
Adjusted TOU tariffs — Netherlands.

	Off-peak price (€/kWh)	Peak price (€/kWh)		
Tariff 1	[00:00–06:00] 0.06	[06:00–00:00] 0.22		
Tariff 2	[00:00–08:00] 0.06	[08:00–16:00] 0.18	[16:00–00:00] 0.30	
Tariff 3	[00:00–06:00] 0.06	[06:00–12:00] 0.14	[12:00–18:00] 0.22	[18:00–00:00] 0.30

In terms of economic impact, the Cassandra software platform can be used to simulate multiple economic scenarios and calculate the benefits for stakeholders. We presented a detailed analysis from the household customer's point of view and simulated the potential cost reduction after adopting one of the proposed electricity tariffs. Fig. 27 shows the economic impact of this adoption on the 33 households of the Swedish pilot. We see that overall, all pricing schemes result in lower electricity bills for customers. Specifically, we observe that a multi-tier electricity tariff is actually more beneficial for the customer and can lead to cost savings of up to 38%.

We also observed in the Robustness Tests Section that the presence of competition in the market has a positive effect on electricity customer savings. In other words, electricity providers have to adjust their prices to the market to remain competitive. In Fig. 28, we show the changes in cost reductions after introducing more competitive tariffs. We observe, that overall the presence of competition creates higher cost reductions for consumers compared to a situation in which prices are regulated exogenously.

7. Discussion and conclusions

Our analysis gives policymakers a better understanding of how individual consumers and groups of consumers react to DR schemes. We first discuss our recommendations for the distribution grid managers, whose main objective is to stabilize the grid. Second, we present recommendations for individual consumers, that want to minimize their electricity costs without compromising their individual comfort. And finally, we provide recommendations that lead to a win–win situation for both distribution grid and individual consumers.

7.1. Distribution grid and energy providers

Below we present findings related to the stability of distribution grid or a balanced consumer portfolio. We found that:

- If a portfolio has only consumers with high sensitivity, no extra benefits are needed to incentivize DR participation, but extra consumers need to be added to the portfolio to offset peaks created by the high sensitivity consumers. High sensitivity consumers benefit the most from prices, but become over-responsive to prices.
- If a portfolio has consumers with lower sensitivity and awareness, extra financial incentives might be needed, since these consumers do not benefit the most from price differences.
- Since consumers react differently to tariffs, clustering based on their sensitivity and awareness similarities creates more homogeneous behavior in terms of peak reduction.
- When clustering customers within a portfolio, the clusters need to be sufficiently populated. In our specific data set, creating four and five clusters achieved the highest alignment of benefits for consumers and distribution grid.

7.2. Household energy consumers

We saw that consumers' energy consumption, their household appliances and their price responsiveness need to be taken into account when making personalized recommendations. In general, we observed that:

- Consumers with the highest sensitivity and awareness benefit the most from DR in terms of electricity cost reduction.
- Consumers with medium sensitivity and awareness usually bring benefits for individuals and the grid.

7.3. Incentive alignment

Here we summarize the findings that achieve incentive alignment for the grid and its consumers.

- In the multi-residential building, four or five clusters showed the best alignment of benefits between consumers and the distribution grid.
- Consumers with medium sensitivity and awareness are more likely to bring a win–win situation with peak reduction and electricity bill savings.

In summary, we are combining insights from a real-world pilot with simulations to tackle one of the "wicked problems" in the smart grid domain, namely, to create effective DR schemes tailored to household electricity consumers. We demonstrate the effect of our personalized recommendations on individual households

Table 18
Cost reduction resulting from the adoption of each tariff: adjusted to location.

	Tariff 1	Tariff 2	Tariff 3
Netherlands	12.50%	14.29%	14.29%
Austin	6.67%	6.50%	6.90%

Table 19
Average peak reduction resulting from the adoption of each tariff: adjusted to location.

	Tariff 1	Tariff 2	Tariff 3
Netherlands	−1.07%	−8.91%	−5.30%
Austin	−7.93%	−5.66%	−8.15%

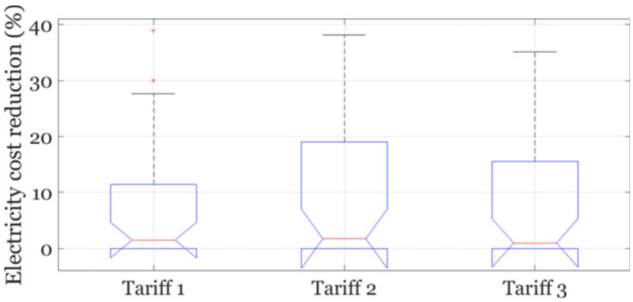

Fig. 27. Economic impact of adopting one of the proposed pricing schemes on the 33 households in Sweden.

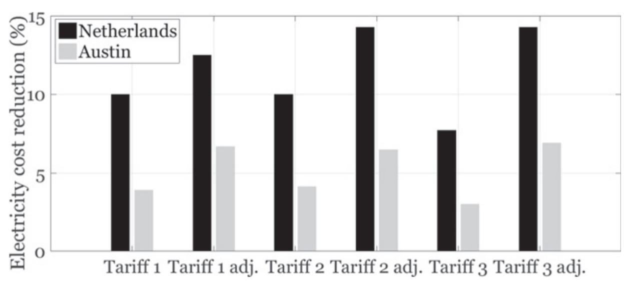

Fig. 28. Economic impact of adopting the proposed and adjusted pricing schemes in the Netherlands and Austin.

and benchmark our recommendations with existing methods in the literature. We show the importance of price responsiveness in creating successful DR schemes, since tariffs that are not tailored to specific populations tend to be less effective. We conduct robustness tests on two independent datasets and we show how the pricing recommendations can be adjusted to account for various regulatory constraints. Our results indicate the market deregulation and competition results in lower prices and higher cost savings for households. These are useful insights for policymakers. Finally, we measure the economic value of our DSS to household consumers. Our DSS can achieve up to 38% savings on the household electricity bill.

Since this is an exploratory study, the results might be dependent on the data. However, in the Robustness Tests Section, we present results applied on two other independent datasets. Another limitation is that the simulations conducted on the software platform depend on the disaggregation module, which might create some inaccuracies. We are currently training the disaggregation module with more data inputs, to increase its accuracy.

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