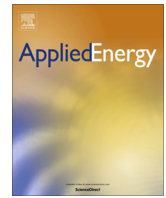


## Estimating the benefits of cooperation in a residential microgrid: A data-driven approach

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# Estimating the benefits of cooperation in a residential microgrid: A data-driven approach



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## HIGHLIGHTS

- Demand response puts pressure on energy providers to consider new pricing schemes.
- We introduce cooperative demand response. It can cut energy bills by 10%.
- A capacity-pricing component can encourage reductions in peak demand.
- Cooperative demand response can benefit consumers and energy providers alike.

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## ABSTRACT

Private households are increasingly taking cooperative action to change their energy consumption patterns in pursuit of green, social, and economic objectives. Cooperative demand response (DR) programs can contribute to these common goals in several ways. To quantify their potential, we use detailed energy consumption and production data collected from 201 households in Austin (Texas) over the year 2014 as well as historic real-time prices from the Austin wholesale market. To simulate cooperative DR, we adapt a load-scheduling algorithm to support both real-time retail prices and a capacity-pricing component (two-part pricing schemes). Our results suggest that cooperative DR results in higher cost savings for households than individual DR. Whereas cooperative DR that is based on real-time pricing alone leads to an increase in peak demand, we show that adding a capacity-pricing component is able to counteract this effect. The capacity-pricing component successfully reduces the cooperative's peak demand and also increases the cost savings potential. Effective peak shaving is furthermore only possible in a cooperative setting. We conclude that cooperative DR programs are not only beneficial to customers but also to energy providers. The use of appropriate tariffs allows consumers and suppliers to share these benefits fairly.

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## 1. Introduction

There is a strong imperative for us to alter the way that we use energy [1]: High levels of carbon emission, a growing opposition to nuclear power in response to the 2011 reactor melt-down in Fukushima, and technological advances have led to a shift towards renewable energy sources (RES) in many countries. However, the intermittency of RES creates considerable stability challenges for energy providers and grid operators. Grid management presents

additional challenges in that electricity networks themselves are increasingly being recognized as major sources of carbon emissions and need to be structured and operated in a more environmentally sustainable manner [2].

Centralized demand-driven energy systems that reactively balance supply against demand at all times are no longer able to cope with these challenges. Conversely, decentralization and the use of microgrid structures has been identified as a more viable alternative [3]. Microgrids serve as a platform for balancing demand and supply and they emphasize the idea of organizing and optimizing electricity networks locally [4]. Microgrids can be managed by commercial entities or even by retail consumers themselves via energy cooperatives [5]. These cooperatives offer a maximum level

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of flexibility in terms of ownership structure as they are able to handle conflicting interests of different stakeholders [4]. Although in Germany, for example, energy cooperatives are considered to be important building blocks in the transition towards more sustainable energy systems, there is surprisingly little in the literature on their practical potential [6]. Energy cooperatives can allow households to collectively optimize their energy systems and reduce their external dependencies, and can provide opportunities for effective *demand side management* (DSM). In general, DSM includes energy conservation efforts, energy efficiency measures, and *demand response* (DR) programs which encourage changes in electricity usage via price or grid management signals [7–11]. In this paper however, we only focus on demand response.

The idea of turning demand into an additional degree of freedom of the grid is not new. DR has been commonplace in the industry and commercial sector for more than 30 years [12]. However, developments in smart metering technology and the introduction of smart appliances have increased interest and research in residential DR. Consequently, recent years have seen considerable advances in both smart devices and operational concepts for residential DR. However, the role of choice and the human dimension of energy use have been downplayed in energy research [13]. Consumers do not change their consumption patterns unless they see benefits from such a change. A 2008 survey of 2900 households in five European countries (Austria, Germany, Italy, Slovenia, and UK) suggests that the general acceptance rate for smart devices is above 80%, but that consumers expect a perceptible economic benefit from contributing to load management in energy systems [14,15]. In other words, energy providers need to buy flexibility from their customers [16]. More recent studies on smart grid adoption suggest that acceptance levels are also increasingly driven by social norms and environmental concerns, but that financial benefits, i.e. lower electricity bills, still remain the most fundamental motivational factor [17–19].

Reservations to DR can still outweigh these factors, if DR programs are either too complex [20] or if cost savings fail to meet expectations [21]. In this context, Gottwalt et al. [22] calculate that, for individual consumers who do not engage in microgeneration, the savings from time-based tariffs and DR are rather low and are largely offset by the costs of acquiring smart devices. They therefore question whether the financial incentives are sufficient to encourage households to participate in DR. Feuerriegel et al. [23], however, argue that the real economic benefits of DR remain to be quantified, yet they only approach this evaluation from the limited perspective of an electricity retailer. One of their findings is that electricity retailers gain an immense advantage from DR while the average savings for the individual consumer are relatively small. Thus, the main objectives in this study are to quantify the economic benefits from the customer's perspective, to determine what additional economic potential energy cooperatives can provide, and to identify how a more widespread adoption of microgrid structures and residential DR can be encouraged.

To tap into the full economic potential of DR, previous studies have proposed a variety of control mechanisms that are most often tailored to single households. Rastegar et al. [24] e.g. present an one-household mixed integer linear programming (MILP) approach incorporating smart devices, photovoltaic (PV) generation, storage, electric vehicles, and a time-of-use pricing scheme. A similar MILP model formulation that additionally incorporates load peak limitations is presented by Erdinc [25]. These two mechanisms generate a single up-front schedule for the entire planning horizon, which makes them interesting for an evaluation study yet rather unsuitable for dynamic operational implementation. Conversely, Di Giorgio and Pimpinella [26] propose a MILP model for event-driven real-time scheduling. Their idea is to rerun the model, i.e. reschedule appliance execution times, whenever there

is a change in the environment, such as improved forecasts or user interaction. An extension of this work also focuses on prosumers by including distributed generation (DG), storage units, and electric vehicles (EV) [27]. Although all these mechanisms can offer considerable energy bill savings, none of the authors aim for a comprehensive evaluation of the actual economic potential.

While beneficial to consumers, individualistic DSM approaches are not ideal for the grid. By design single-household mechanisms attempt to cut individual electricity bills. This can cause a herding phenomenon, when all consumers shift their loads to periods when prices are low, generating new demand peaks [22]. However, introducing centrally coordinated peak control measures comes at a considerable electricity costs for individual consumers [26–28].

An alternative to single-household approaches are multiple-household DR schemes. These mechanisms generally follow either a decentralized or a centralized DR control paradigm [29]. Decentralized mechanisms do not have direct access to residential loads. Instead, they try to encourage households to behave in a mutually beneficial way. Ramchurn et al. [30] show that, in principle, globally optimal results are possible even without explicit coordination between households, as long as all households follow the same DR approach and do not readjust their load schedules too often. Veit et al. [31] on the other hand opt for explicit coordination via a dynamic pricing mechanism that presents consumers with personalized prices in order to incentivize beneficial load-shifting. These personalized prices effectively discourage suboptimal herding behavior. The authors set up an extensive case study to establish the economic potential of coordination but the mechanism often fails to provide feasible solutions.

Centralized DR approaches are more robust as they do not require iterative coordination. They transfer control from the individual household to a single overarching mechanism. Conceptually, these approaches best reflect the idea of an energy cooperative that centrally manages its own microgrid. Centralized approaches have been proposed for scenarios with and without microgeneration. Bradac et al. [32], for example, introduce a multi-household MILP model for consumers that do not own power generation systems. They indicate that their mechanism can generate considerable economic potential but do not support their results beyond exemplary appliance data. Zhang et al. [33] include shared RES and propose a MILP to minimize the energy cost of a microgrid that consists of a single smart apartment building. Based on illustrative appliance usage patterns they show that cooperative scheduling can reduce electricity costs by at least 11% compared to not using DR. However, they do not verify these findings for actual historic consumer behavior.

Multiple-microgrid management integrates several microgrids that might have differing objectives. Velik et al. [34] propose such a multi-objective strategy that enables the integration of microgrids with environmental and economic objectives. Although not explicitly considering DR, they find that cooperation between economically and environmentally oriented parties can be beneficial to both, regardless of their differing goals. Even without DR, cooperative behavior can thus be worthwhile for higher grid management levels as well.

Given the growing importance of residential DR, and especially the key role of financial stimuli, our work is intended to provide a realistic estimation of the cost savings that cooperative DR can offer today. As data from cooperative pilots is not yet available, previous research has suggested smart grid simulations to test cooperative DR in a risk-free environment [35,36]. We thus introduce a simulation framework for a residential microgrid and fit it with historic load and price data. The modelled microgrid connects several homes, each equipped with various household appliances and some homes additionally own EVs and/or photovoltaic panels. These homes employ a MILP mechanism to collectively optimize

their energy bills. Although the microgrid is operated independently, it is connected to a local energy provider which buys and sells energy at real-time prices.

For the residential load profiles, we use real-world data from the Pecan Street Inc. Dataport [37] which is the world's largest source of disaggregated (i.e. single appliance) data on residential customer energy usage. It provides detailed consumption and production data for more than 1200 households in the US, with 495 being located in Austin, Texas. For these Austin households, we extract individual load curves for each single appliance, EV, or photovoltaic system in this home at each 15-min interval in 2014. We subsequently fit these profiles into our framework and infer an individual level of flexibility for each appliance run. Next, we use wholesale market prices for the Austin area to derive appropriate real-time retail tariffs. We finally run 100 simulations, each covering a different cooperative of ten homes and a new random single week in 2014.

To the best of our knowledge, this is the first study to use such an extensive dataset of historic load data to investigate the potential of residential DR. In leveraging this data, our study has two specific objectives. First, we are interested in the actual economic advantage that cooperative DR offers over single household approaches. Since we assume energy prices and load curves to be known in advance, our results indicate an *upper bound* for these savings. Second, we want to investigate whether cooperatives can be financially incentivized to avoid the herding phenomenon and to create aggregated load profiles that will benefit the grid as a whole.

The remainder of this paper is organized as follows. Section 2 describes our evaluation framework. Specifically, we introduce our cooperative market setting and present the DR model applied in the subsequent evaluation. Section 3 describes our dataset and explains the modifications made to fit the data into the load-shifting mechanism. Section 4 summarizes and discusses the key results of our evaluations. Sections 5 and 6 provide concluding remarks, discuss limitations, and outline opportunities for further research.

## 2. Evaluation framework

By using a large set of real-world data we avoid simplifying usage characteristics and limitations regarding the number of utilized load patterns. Focusing on residential DR, we model energy cooperatives which only encompass domestic consumers and domestic prosumers. These cooperatives include neither mutually owned generation facilities nor commercial producers or storage facilities. However, our approach can easily accommodate other types of participants.

### 2.1. Approach

For our simulation, we make a set of assumptions regarding the cooperative environment. As illustrated in Fig. 1, the residential cooperative encompasses several different homes (consumers), each possessing various household appliances and occasionally electric vehicles. Homes that additionally own photovoltaic panels are denoted as prosumers. The cooperative pools all these consumer and prosumer loads in a big single virtual home. This virtual household is managed by an energy management system, termed the central controller (CC), that coordinates all load-shifting activities. Once users activate their devices and specify a discretionary level of flexibility, the CC takes full control over the shifting process. Importantly, the CC does not expose individual homes to real time price signals as these tend to overburden consumers [20]. To ensure this level of convenience, we effectively take the idea of

real-time, agent-assisted decision support [38] a step further and have the agent, i.e. the central control mechanism, make the decision on behalf of the user.

The cooperative can buy and sell energy to the local utility company. Residential microgrid research often assumes variable buying prices and flat selling (feed-in) tariffs for excess production [25,27,33,39]. However, we argue that this pricing scheme is not flexible enough to cope with future challenges to the energy grid and will not be a dominant model in the future. Therefore, we assume both buying and selling prices to be variable.

Retail electricity bills generally include charges for the local low- and medium-voltage distribution grid, and transmission fees for high-voltage lines connecting local grids. As cooperatives effectively operate their own distribution grid, they are billed only for transmission charges, which are added whenever energy is bought from the local utility company. Thus, the price for externally bought energy is higher than the price for externally sold energy, as it also includes the transmission charge. Energy transmitted within the cooperative only requires local distribution, and the resulting transmission savings can be shared between local consumers and producers.

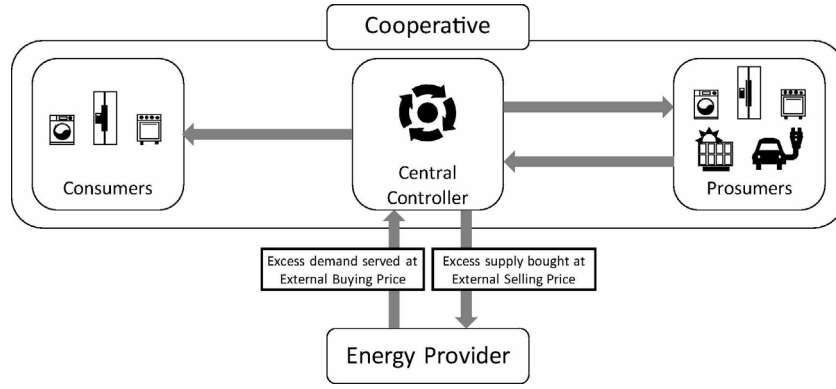
We will investigate the effects of collaboration among households by comparing the simulation results from a scenario without DR to two scenarios with DR: First, we consider each household as an individual customer, and, second, we consider all households to be part of an energy cooperative. This cooperative only exchanges excess demand and supply with the energy provider. For simplification we do not differentiate between different entities on the provider side (utilities, grid operator, etc.), and we use the term 'energy provider' for all external counterparts.

Furthermore, flat feed-in tariffs and consumption-based usage tariffs are generally designed for single residential customers. Cooperatives, however, have consumption and production levels closer to those of small or medium commercial customers. Commercial pricing schemes are often two-part, which means they consist of a capacity and a quantity fee. Combining this kind of pricing scheme with DR can result in reduced peak demand, which is beneficial for energy providers [23]. We argue that energy providers have to share their benefits from peak reduction with consumers in order to incentivize peak-shaving behavior. With the right proportion of quantity and capacity, two-part pricing schemes are then beneficial for both parties. Therefore, we will run our simulation with several tariffs and compare the effects on total energy bills and peak consumption.

### 2.2. Model

For the central control mechanism we adapt the scheduling mechanism proposed by Bradac et al. [32] which is designed to enable cost-optimal load shifting for domestic appliances. Their objective is to minimize the cost of electricity procurement for shiftable loads; microgeneration and fixed loads are not considered. Accordingly, loads are simply moved to periods when external buying prices are low.

The initial model uses the concept of energy phases to remodel discrete load curves for six types of household appliance (washing machine, dishwasher, tumble dryer, electronic water heater, electric oven, and home lighting subsystem) from historic energy profiles of such appliances. This results in one load curve for each type of appliance, which is then used to simulate this device in every household. Our data provides much more detailed consumption profiles that not only differ for every household but for every single time an appliance is used. Instead of modelling appliances uniformly, we adapt the model to support this large set of real-world data.



**Fig. 1.** Design of a high-level cooperative. The central controller acts as an aggregator/broker [40,41] for the cooperative that exchanges electricity with the external energy provider. The model is capable of including producers as well but the data used only includes consumers and prosumers.

Therefore, we modify the original MILP formulation [32] in two essential aspects:

- (i) We adapt the objective function from a pure real-time market (RTM) price optimal DR to also include revenues from production and peak charges. The overall cost is thus calculated as the sum of a capacity (peak) and a quantity (usage) component. We also introduce a set of new constraints to accommodate generation and to consider peak loads.
- (ii) We extend the model to support real-world input data. Therefore, we define  $i \in I$  as an appliance run, not as a specific appliance (For a table of notation, see Table 1). Thereby, every appliance run (e.g., every cooling cycle of a refrigerator or the single use of a washing machine) is defined by the unique properties {start-time, end-time, load} which we determine from historic data. To handle the increased complexity, we drop the differentiation between the different program phases. However, it is theoretically possible to model the different program phases as individual appliance runs.

$$\text{mintc} = \sum_t (EB_t \cdot z_{d_t} - ES_t \cdot z_{s_t}) + CC \cdot p, \quad (1)$$

$$x_{h,i,t} \leq AH_{h,i} \quad \forall h, i, t \quad (2)$$

$$\sum_{t=1}^T x_{h,i,t} = PT_i \quad \forall h, i \quad (3)$$

$$(x_{h,i,t-1} - x_{h,i,t}) - y_{h,i,t} \leq 0 \quad \forall h, i, t : t > 1 \quad (4)$$

$$x_{h,i,t} \leq UP_{i,t} \quad \forall h, i, t \quad (5)$$

$$x_{h,i,t} + y_{h,i,t} \leq 1 \quad \forall h, i, t \quad (6)$$

$$y_{h,i,t-1} - y_{h,i,t} \leq 0 \quad \forall h, i, t : t > 1 \quad (7)$$

$$\sum_{h,i} PC_i \cdot x_{h,i,t} - z_{d_t} + z_{s_t} = -(Gen_t + FL_t) \quad \forall t \quad (8)$$

$$z_{d_t} \cdot z_{s_t} = 0 \quad \forall t \quad (9)$$

$$z_{d_t} - p \leq 0 \quad \forall t \quad (10)$$

$$z_{s_t} - p \leq 0 \quad \forall t \quad (11)$$

$$z_{d_t} \geq 0, z_{s_t} \geq 0, x_{h,i,t} \in \{0, 1\}, y_{h,i,t} \in \{0, 1\} \quad \forall h, i, t \quad (12)$$

The objective of our mechanism is to reduce the overall electricity costs of the cooperative over the time horizon we are simulating. In Eq. (1)  $z_{d_t}$  signifies the amount of externally sourced electricity if there is overdemand (demand exceeds production), whereas  $z_{s_t}$  is the amount of feed-in electricity in times of oversupply (production exceeds demand). Excess demand and excess generation are weighted by the external buying price  $EB_t$  and the

**Table 1**  
Nomenclature.

Variable	Unit	Description
<i>Indices and model size parameters</i>		
$h$	None	Household index
$i$	None	Appliance run index. An appliance run represents, for example, a single use of a washing machine or one cooling cycle of a refrigerator
$t$	None	Time slot index
$H$	None	Total number of households
$I$	None	Total number of appliance runs
$T$	None	Total number of time slots in the simulation
<i>Variables</i>		
$p$	kW	Maximum peak over the entire simulation: maximum amount of electricity that is exchanged with the grid in a single period
$tc$	USD	Total cost for purchasing electricity
$x_{h,i,t}$	None	Appliance is active. Binary variable; one if appliance run $i$ in household $h$ is active in time slot $t$
$y_{h,i,t}$	None	Prevents repetition of an already finished appliance run. Binary variable; one if appliance run $i$ in household $h$ is already finished in time slot $t$
$z_{d_t}$	kW h	Difference between generation and usage if time slot $t$ is a period of <i>overdemand</i> ; to be weighted with the buying price of energy. Continuous variable (always non-negative)
$z_{s_t}$	kW h	Difference between generation and usage if time slot $t$ is a period of <i>oversupply</i> ; to be weighted with the selling price of energy. Continuous variable (always non-negative)
<i>Constants</i>		
$AH$	None	Appliance run to household matrix. Each appliance run can only belong to one household ( $H \times I$ )
$CC$	USD/kW	Capacity charge
$EB$	USD/kW h	External buying price ( $T \times 1$ )
$ES$	USD/kW h	External selling price ( $T \times 1$ )
$FL$	kW h	Fixed load. Residual, non-shiftable loads ( $T \times 1$ )
$PT$	None	Processing time of each appliance run ( $I \times 1$ )
$PC$	kW h	Power consumed by each appliance run ( $I \times 1$ )
$Gen$	kW h	Produced energy ( $T \times 1$ )
$UP$	None	User preference matrix that defines the possible execution window for appliances ( $I \times T$ ). A value of one states that appliance run $i$ can be scheduled in time slot $t$

external selling price  $ES_t$  respectively. In line with existing two-part pricing schemes (cf. Section 3.2), the capacity charge ( $CC$ ) is a monetary amount that is multiplied by the highest absolute peak demand or peak generation  $p$  over the optimization horizon. Put differently, we minimize the total costs ( $tc$ ) which consist of the costs for energy consumed plus peak costs minus generation revenues.



Eqs. (2)–(13) describe the set of constraints to our model. For these we introduce a set of binary decision variables  $x_{h,i,t}$  and  $y_{h,i,t}$ . The  $x$  variables are 1 if the particular appliance run  $i$  belongs to the particular household  $h$  and occurs at point  $t$ . The  $y$  variables are set to 1 after an appliance run is finished in order to prevent the same appliance run from being repeated.

The binary matrix  $AH$  defines which appliance run belongs to which household, and is 1 if the  $i$ -th appliance run belongs to the  $h$ -th household, and 0 otherwise. Eq. (2) consequently ensures that an appliance can only run in the particular household it belongs to. The vector  $PT$  defines the processing time for each appliance run. Constraint (3) hence requires that each appliance runs for precisely the time specified by  $PT$ . Constraint (4) ensures that an appliance run cannot be interrupted. The binary matrix  $UP$  specifies user preferences, i.e., the execution window for each appliance run. Its elements are 1 for each time point in the respective execution window, and 0 otherwise. Constraint (5) thus allows every appliance run to be performed only in its dedicated execution window. Constraint (6) and (7) ensure that a specific appliance run cannot be repeated after it has finished.

The vector  $PC$  describes the average load for each appliance run over its execution time. Constraint (8) allocates the amount of excess demand to  $z_{d,t}$  and the amount of excess supply to  $z_{s,t}$ . Constraint (9) is introduced so that there cannot be oversupply and overdemand at the same time. Constraint (10) and (11) are introduced so that  $p$  cannot be smaller than the highest absolute peak. As  $p$  is a major component of the total cost, the mechanism seeks to reduce  $p$ . Thus, its final value will equal the highest absolute peak. Lastly, constraint (12) stipulates that the  $z$  variables are non-negative to ensure that overdemand cannot be expressed by negative oversupply, and vice versa. Also, it ensures that the  $x$  and  $y$  variables are binary.

### 3. Dataset

For our evaluation, we utilize different data sources for the load data as well as for the price data. The Pecan Street Inc. Dataport [37] is the world's largest source of disaggregated customer energy data. It provides historic load profiles at the individual appliance-level as well as PV production data from 1200 volunteer households located in Texas, Colorado and California. The data is available for 15-min intervals for the years 2011–2015. Austin (Texas) is the city with the highest number of participating households ( $n = 495$ ). Since we aim to simulate local microgrids as realistically as possible, we only use load data from the Austin area for our simulation.

For the same area, electricity prices are provided by the Electric Reliability Council of Texas (ERCOT). Since no RTM prices are offered to retail customers in Austin, we use publicly available 15-min RTM settlement point prices (SPP) quoted for the Austin load zone, and we scale these to the retail level at a later stage.

#### 3.1. Load data

To use historic load profiles from the Pecan Street Inc. Dataport [37] for our model, we have to infer the flexibility that “smart” appliances would have. Because of the complexity involved we cannot handle all existing appliance types separately. Thus, the appliance-level data for smart devices is categorized according to their controllability. Similar approaches have already been used in recent literature [22,26,27]. Following the terminology of Gottwalt et al. [22], we distinguish between three different load types. *Fully automatically controllable loads* are consumed by appliances that are always turned on (*auto-shiftable devices*) and can be controlled within device-specific constraints. For example, a refrigerator

**Table 2**

Classification of available Pecan Street devices.

Controllable devices		Non-controllable devices
Fully automatic	Semi-automatic	Fixed
Air conditioning Freezer	Washing machine Dishwasher	Lighting Kitchen appliances (oven, garbage disposal, water heater, wine cooler, etc.)
Furnace Refrigerator	Dryer Electric vehicle	Plugs

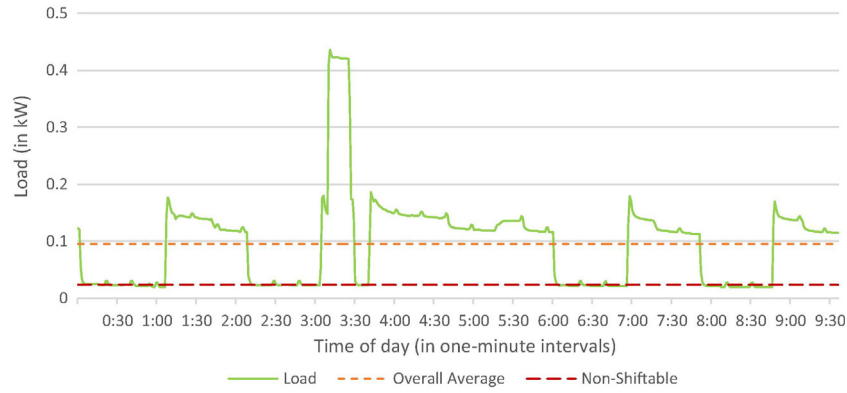
can shift its cooling cycles for a certain time period without affecting the temperature inside to any significant extent. *Semi automatically controllable loads* such as the cycles of a dishwasher (*semi-shiftable devices*), for example, require some user interaction in the beginning and can then be scheduled within certain user-dependent boundaries. *Fixed loads* depend completely on user interaction and have no potential for shifting. Table 2 shows how controllable devices are classified. All other loads such as stoves, lighting and instant water heaters are considered to be fixed.

Fixed loads do not require any modification to be used in our simulation, whereas controllable loads require some pre-processing before they can be plugged into our model. Both classes of controllable loads consume a certain base load which cannot be shifted. Although semi-shiftable devices are generally not running until users interact with them, some of them consume standby energy. All fully shiftable devices in Table 2 possess a natural thermal storage, and hence do not run continuously [22]. However, these appliances still consume energy even when not cooling or heating.

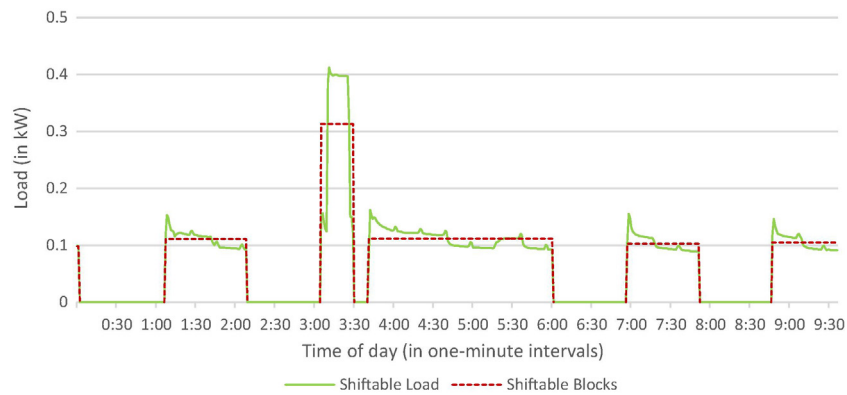
Therefore, both controllable load classes can be split into shiftable and non-shiftable parts of the load. Fig. 2 shows a typical load curve of a refrigerator from the Pecan Street dataset. The non-shiftable load is constant at a level below the average load, but we found that the shiftable parts are generally at a level above the average load. Therefore, the average load over the simulation period provides a viable indicator of whether a specific load is shiftable or non-shiftable. We use this to extract the non-shiftable part of an appliance's load: All data points below the average are considered non-shiftable while all data points above the average are considered to be part of a shiftable operation. Even during a shiftable operation, the non-shiftable part cannot be shifted. Therefore, the average of all loads smaller than the *overall average* is used to determine a constant load, which is then subtracted from the load curve and added to the fixed loads. This results in a new load curve of “pure” shiftable load (Fig. 3) with no non-shiftable part. All loads smaller than the average are now zero.

This shiftable load curve can now be cut into *shiftable blocks*. To fit our model, each of these blocks is described by its *start time*, *duration*, *latest finish* and *average load* and can be shifted within specific boundaries. Fig. 3 shows how the shiftable blocks deviate from the shiftable curve. On average, the shiftable blocks deviate by 7.7% from the actual loads, but are easier to work with for the purposes of our simulation. The total energy consumed when a shiftable load is converted to a shiftable block remains the same. Whenever a device starts to consume energy, we set the earliest start point. The distance between actual start and actual finish determines the duration of the appliance run. We determine the average load of a block by averaging all shiftable loads of the specific operation.

As mentioned before, for fully automatically controllable loads the boundaries for shifting are specific to each device class, while for semi-automatically controllable loads they depend on user preferences (cf. Fig. 4). Our idea on how to model these user preferences is inspired by a widespread belief of how smart appliances



**Fig. 2.** Cooling cycles of a refrigerator. Periods of high consumption alternate with periods of low consumption (only non-shiftable consumption).

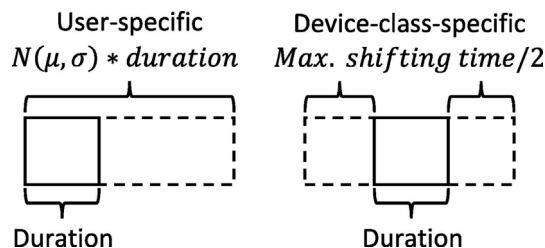


**Fig. 3.** Pre-processed shiftable loads of a refrigerator. On average, the shiftable blocks deviate by 7.7% from the actual loads, but are easier to work with for the purposes of our simulation.

will be operated in the future [14,18]. Instead of simply switching on a device, the user can define a deadline by which the appliance program needs to be completed. This idea has also been transferred to the charging of electric vehicles where the user provides information about the start of his or her next trip [42]. The actual execution time is then determined by the scheduling algorithm (cf. Section 2.2). To simulate varying user preferences, we determine user-defined finish times by multiplying the duration of an appliance run with a normally distributed random factor. A sensitivity analysis on the mean and standard deviation for this factor has shown no significant improvement beyond a mean greater than 3, and the standard deviation's impact on the results is negligible. Since we aim to estimate an upper bound for the benefits of DR but also to keep the setting realistic, we set this parameter for our simulations to  $N(3,1)$ . It is important to ensure that latest finish and

earliest start allow for the whole duration of the appliance run, i.e. the factor cannot be smaller than 1. In addition, a previous run has to be finished before a subsequent run is programmed. For example, if a user knows that he needs the dryer twice in one evening, he will set the latest end-point of the first run accordingly. In general, users might also decide to reclaim control over their devices as long as they have not started yet. For our simulation however, we assume that they only give up uncritical levels of flexibility and stick to their decision once they have set a shifting window.

Auto-shiftable devices generally operate in an intermittent mode. A refrigerator's heat pump, for example, only activates when the compartment temperature exceeds a certain limit. A furnace rarely reheats its water tank more than twice a day. Consumers also do not actively monitor these cycles. So, as long as there are no perceptible differences, as e.g. rotten vegetables in the refrigerator or the lack of warm water (for a shower), we assume that consumers can be convinced to grant control over their devices. The timeframes where changes are generally unnoticeable, i.e. the maximum allowable shifting times are derived from literature [14]. A list of these times is shown in Table 3. These shifting limits, however, only partially reflect the flexibility potential of auto-shiftable devices. Limited levels of user interaction not only make their load patterns intermittent but also highly predictable. This effectively means that they can be run preemptively as well. It matters little if a refrigerator starts cooling when its interior temperature hits 7 °C or only 15 min later when it hits 8 °C. We consequently refined the shifting window to allow for preemptive and delayed operability. A refrigerator's cooling cycle for example is



**Fig. 4.** Concept of controllable loads. On the left are semi-automatically controllable loads, on the right fully automatically controllable loads. The maximum shifting time for each device class is shown in Table 3.

**Table 3**  
Fully automatic shifting times.

Device class	Maximum shifting time (in min)
Air conditioning	60
Freezer	30
Furnace	60
Refrigerator	30

assumed to be shiftable for half an hour by Timpe [14]. To reflect the two-way shiftable, we split these 30 min and add 15 min of slack before the actual start time and after the finish time of the cooling cycle.

Using the methods described above, we pre-process the load curves of all schedulable appliances into shiftable blocks with the length of the load duration and height of the average consumption of each load that indicates an appliance run. Additionally, we calculate an execution window for each appliance run.

Fig. 5 shows the weekly load profile of a single household before and after converting the shiftable loads to shiftable blocks. Considering shiftable loads with their average consumption over their entire duration causes some smoothing, but both curves are highly correlated, with a Pearson correlation coefficient of 0.96.

### 3.2. Price Data

To determine the transmission spread between *selling prices* and *buying prices* (cf. Section 2.1) we utilize an existing regulatory charge. It covers ERCOT transmission service charges and credits as well as several administrative and regulatory fees. As of November 1st, 2013 the regulatory charge amounts to \$0.0794 per kW h [43]. This equals a spread between average buying and selling prices of about 22% from 2013 to 2015.

The objective function (1), introduced in Section 2.2, can handle two-part pricing schemes that are split into a capacity part and a quantity part. To conduct a sensitivity analysis of our results regarding the chosen energy tariff, we derive a set of six hypothetical tariffs from two existing electricity rate schedules offered by Austin Energy to small commercial customers [43]. The first schedule is based solely on energy consumption and is offered to customers with a capacity of less than 10 kW. The second schedule is split into a capacity and a quantity part and is offered to customers with a capacity of between 10 and 50 kW. For both schedules we calculate a retail adjustment factor (RAF) which is

**Table 4**  
Consumption-based scheme.

	October–May	June–September	Weighted average
Capacity charge (per kW)	n/a		
Retail price (per kW h)	\$0.08	\$0.10	–
Retail adjustment factor	2.10	2.79	2.34

**Table 5**  
Two-part pricing scheme.

	Oct–May	June–September	Weighted average
Capacity charge (per kW)	\$9.15	\$10.15	\$9.50
Retail price (per kW h)	\$0.06	\$0.07	–
Retail adjustment factor	1.54	1.85	1.65

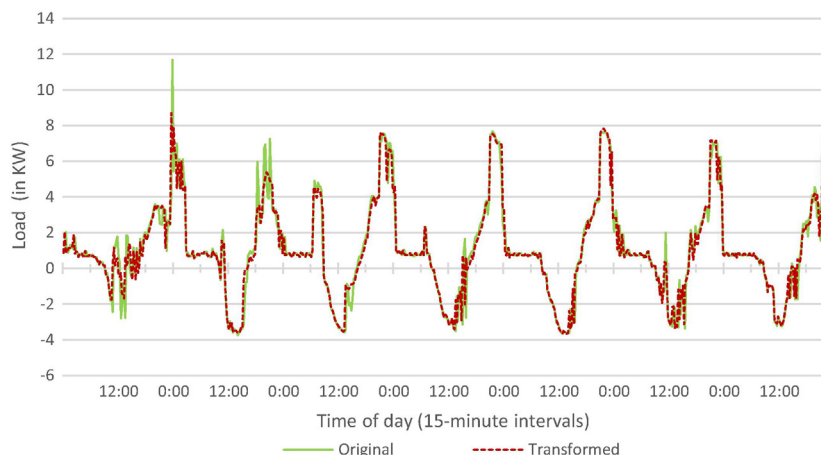
**Table 6**  
Interpolated tariffs for the simulation.

	Retail adjustment factor	Capacity charge
Tariff 1 (Consumption-based)	2.34	\$0.00
Tariff 2	2.20	\$1.90
Tariff 3	2.06	\$3.80
Tariff 4	1.93	\$5.70
Tariff 5	1.79	\$7.60
Tariff 6 (Two-part)	1.65	\$9.50

the quotient of the flat retail price and the average wholesale price for the corresponding year. As shown in Tables 4 and 5, Austin Energy charges higher energy prices during the summer months from June to September. We decided to utilize weighted average values for the RAFs and the capacity charge for simplification.

The capacity charge is multiplied by the metered kilowatts during the 15-min interval of greatest monthly use (monthly peak). For simulation runs of less than one month, the charge is adjusted to the particular duration and is applied to the highest peak of the simulation period.

Tariffs 1 and 6 are derived directly from the two pricing schemes; the other tariffs are determined by linear interpolation (see Table 6).



**Fig. 5.** Total net load of a household before and after conversion. The conversion causes smoothing, but both load curves are highly correlated.



#### 4. Evaluation results

All subsequent results are based on 2014 data for households in Austin. To ensure data quality, we only included households for which single-appliance-level data is available for all 15-min intervals throughout 2014. This effectively reduces the number from 495 households registered with Pecan Street to a set of 201 households. From this pool, we built 100 cooperatives by randomly picking 10 individual households each. A cooperative size of 10 households results in an aggregated peak load of between 20 and 30 kW, which fits the two-part tariffs described in Section 3.2.

Due to the computational complexity, we chose a simulation timeframe of a single week. Therefore, loads can only be scheduled within a particular weekly block, and there is no overlap between blocks. This loss in scheduling flexibility is also known as the end-of-horizon effect [44]. Comparing monthly simulations to weekly blocks for smaller cooperatives, however, showed the end-of-horizon effect to be negligible. Additionally, we cannot apply a monthly capacity charge to a weekly load profile. We thus scaled down the monthly charge by 7/30 to arrive at a weekly charge. To cover the entire year 2014, we randomly selected a new week for each of the 100 cooperatives. Finally, we averaged the results over 100 weekly simulations, effectively eliminating the effects of seasonal variations.

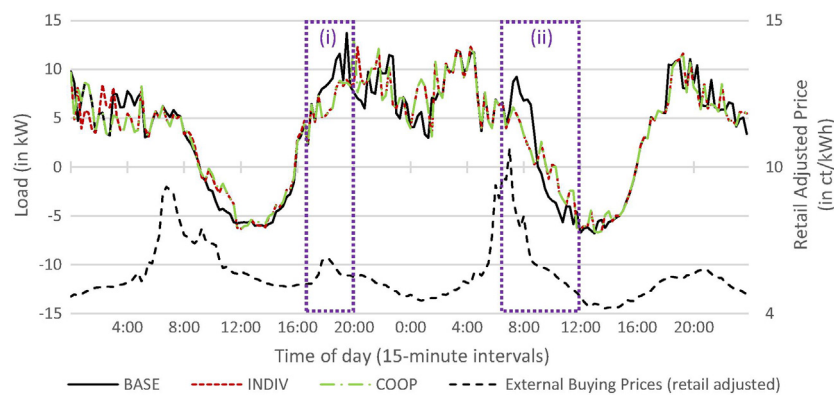
For each simulation, we calculate three scenarios (BASE/NO-DR, INDIV, and COOP). Scenario BASE serves as a benchmark scenario, in which consumers do not shift loads although real-time prices are used to calculate their energy bills. Scenario BASE only exists for tariff 1 (consumption-based); for all two-part tariffs (tariffs 2–6) the scenario without DR is called NO-DR. Scenario INDIV does not permit cooperation between households. Rather, every household applies the DR mechanism introduced in Section 2.2 to its own loads independently. Scenario COOP reflects an actual cooperative with both internal trading and a single common DR mechanism – i.e., all loads are pooled and load shifting is centrally coordinated. Scenario Coop generally took the longest to solve, averaging 57 min on a 16 GB RAM (100 GB virtual memory) computer with an INTEL® Xeon® CPU with two cores @ 2.53 GHz, running Gurobi® 6.0.4.

Fig. 6 depicts the resulting aggregated load levels of all households (left y-axis) on two subsequent sample days. To emphasize the connection between load and price, the retail adjusted price is also plotted (right y-axis). Collectively, the household groups we examined are net consumers most of the time. This observation holds not only for the two sample days but also for most of the sampled weeks. PV production depends not only on weather conditions but also on the angle of incidence. This results in only a few hours every day during which PV production can be exploited to its full potential. As PV is the only source of microgeneration we consider and as the households are located very close to each other, generation patterns are very similar for all prosumers.

Scenarios INDIV and COOP generally focus on two interdependent objectives: (i) Loads are moved from periods of high prices to periods of cheaper electricity. This can be observed e.g. between 5 pm and 8 pm on day 1. As far as possible, loads are shifted to avoid the 6 pm price peak. (ii) The results can be improved further by shifting from periods of overdemand to periods of oversupply, thereby increasing the level of self-consumption. This adjustment generally has the greatest potential as it does not only take advantage of a change in price but also of the spread between buying and selling prices. In Fig. 6 this objective is visible on the second morning between 6 am and 12 pm. Loads are shifted to avoid having to buy energy expensively during a period of overdemand and high prices and having to sell the same amount of energy cheaply during a period of oversupply and low prices.

Clearly, objective (ii) has more potential for cost savings per unit of energy. However, utilizing only microgeneration from PV panels provides few opportunities to maximize self-consumption as many execution windows of shiftable operations do not coincide with periods of PV production. Therefore, taking additional RES such as wind into account is likely to improve the effectiveness of DR measures.

For the pure consumption-based tariff (tariff 1), the simulation results indicate that in scenario INDIV non-cooperative behavior yields average cost savings of 5.5% (compared to BASE), and in scenario COOP the savings for cooperative behavior are 6.8% (cf. Table 7). On an annual basis, this equates to average electricity bill savings of 59 USD per household in scenario INDIV. For



**Fig. 6.** Different simulation scenarios without capacity pricing (tariff 1). In (i) loads are shifted to periods of cheaper electricity. In (ii) loads are shifted from periods of overdemand to periods of oversupply.

**Table 7**

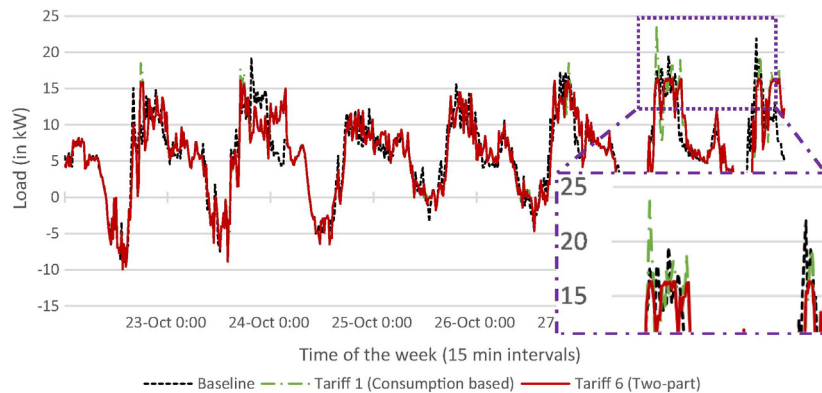
Averaged results for tariff 1 (consumption-based).

Tariff	Scenario	Electricity cost (in \$)	Electricity cost reduction (change in % compared to BASE)	Peak load (in kW)	Peak load reduction (in % of BASE)	Load kurtosis	Load kurtosis reduction (change in % compared to BASE)
1 (RAF = 2.34 CC = 0.00)	BASE	209.7	0.0	28.1	0.0	3.2	0.0
	INDIV	198.3	5.5	29.3	−4.1	3.3	−2.1
	COOP	195.6	6.8	29.3	−4.1	3.3	−1.2

**Table 8**

Averaged results for tariff 6 (two-part pricing scheme).

Tariff	Scenario	Electricity cost (in \$)	Electricity cost reduction (change in % compared to BASE)	Peak load (in kW)	Peak load reduction (in % of BASE)	Load kurtosis	Load kurtosis reduction (change in % compared to BASE)
6 (RAF = 1.65 CC = 9.50)	NO-DR	272.5	−29.9	28.1	0.0	3.2	0.0
	INDIV	251.4	−19.9	27.8	1.9	3.2	1.2
	COOP	188.7	10.0	24.0	14.5	3.0	8.1

**Fig. 7.** Load curves of two different pricing schemes under cooperative behavior. The pure quantity-based tariff 1 creates new peaks while tariff 6 (two-part pricing scheme) reduces the overall peak of the cooperative.

comparison, in their optimal scenario Gottwalt et al. [22] achieve cost savings from load shifting of 24.4 EUR (33.4 USD in October 2011) per household per year. The potential for greater cost savings in scenario INDIV can be explained by incorporating additional appliance types (furnaces and electric vehicles) as well as PV production. Also, both electricity prices and consumption behavior in Europe differ from those in Texas.

Scenario COOP results in annual savings of 74 USD. Evidently, consumer cooperation has an economic advantage. From a grid stability perspective however, pure price-driven DR seems to be counterproductive. The peak load jumps from 28.1 kW (BASE) to over 29.3 kW (INDIV and COOP), an increase of 4.1%. The increase in kurtosis of 2.1% (INDIV) and 1.2% (COOP) also indicates that there is not only a more pronounced maximum peak but that the entire load profile is more extreme. For energy providers, residential DR activities therefore not only lead to lower revenue but also mean that they have to manage more extreme load profiles. Thus, we suggest that energy providers should consider different pricing schemes for consumers who follow price-driven DR programs.

Table 8 illustrates the aggregated results for the two-part pricing scheme (tariff 6). Without DR (scenario NO-DR), this tariff substantially increases electricity cost by 29.9% compared to BASE. Also, Table 8 indicates that scenario INDIV leads to neither cost savings nor peak reduction. In terms of the electricity cost, this is because the underlying tariff is designed for customers with a peak load of between 10 kW and 50 kW. Each individual consumer alone has a far lower peak, however. The sum of all the individual peaks on the other hand is much higher than the aggregated peak load of the cooperative. Therefore, energy providers would need to offer tariffs with a different mix of capacity charges and retail adjustment factors to individual customers. The lack of peak reduction stems from the way that independent households optimize their profiles. Individual households only know their own loads, and reduce their own peak, which generally occurs at a different time for each household. Thus, the overall peak is usually not the sum of all individual peaks but rather occurs at a time when all households are consuming above average simultaneously. This consequently means that the overall peak is not affected by the

optimization efforts of individual households. Energy providers should therefore actively encourage centrally coordinated energy cooperatives. Based on these first insights, we expect scenario COOP to deliver the most promising results and focus on this scenario in the rest of this paper.

Comparing scenario COOP in Tables 7 and 8 show that the potential savings from cooperative DR increase from 6.8% under tariff 1–10.0% under the two-part tariff 6. This equates to annual savings per household of 109 USD. By making the customer worse off in the general case (NO-DR) but offering higher savings under DR (COOP), the tariff thus offers a strong peak-shaving incentive for cooperatives. Also, the peak load decreases by 14.5%, and kurtosis is reduced by 8.1%, indicating that the aggregated load profile is considerably less extreme.

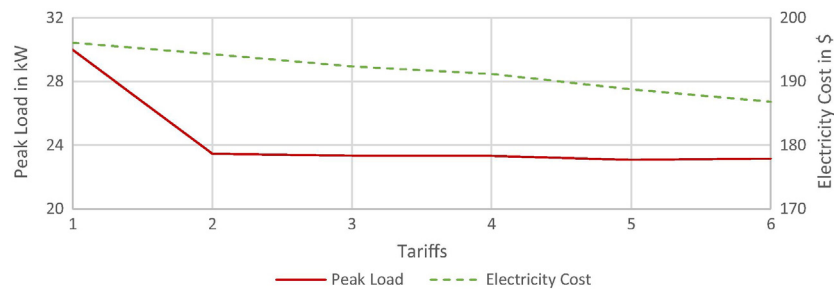
The positive characteristics of the cooperative case are also visible in Fig. 7, which compares the aggregated load curves resulting from cooperative DR under tariffs 1 and 6 for a sample week in October. The green<sup>1</sup> (dash-dotted) line depicts the results for tariff 1 without a peak pricing component and the red (solid) line the results for tariff 6. Whereas the first tariff produces a new peak at the end of day 5 (purple dotted box) the second tariff not only prevents this new peak but also reduces the peak load below the baseline scenario's peak at all times. The pronounced peak reduction and the less extreme load profile are clearly beneficial to energy providers. As this is combined with the higher potential savings for customers, we argue that a tariff which includes both dynamic prices and a peak pricing component benefits consumers and energy providers alike.

Table 9 compares the results for all the tariffs. Notably, the peak reduction effect already occurs under the tariff with the smallest capacity-pricing component (tariff 2) and does not increase significantly with a rising share of capacity pricing. However, the costs for the scenarios without DR (BASE and NO-DR) increase progressively from tariff 1 (consumption-based) to tariff 6 (two-part) but decrease for scenario COOP.

<sup>1</sup> For interpretation of color in Fig. 7, the reader is referred to the web version of this article.

**Table 9**  
Simulation results for different tariffs.

Tariff	Scenario	Electricity cost (in \$)	Electricity cost reduction (change in % compared to BASE)	Peak load (in kW)	Peak load reduction (in % of BASE)	Load kurtosis	Load kurtosis reduction (change in % compared to BASE)
1 (RAF = 2.34 CC = 0.00)	BASE	209.7	0.0	28.1	0.0	3.2	0.0
	COOP	195.6	6.8	29.3	−4.1	3.3	−1.2
2 (RAF = 2.20 CC = 1.90)	NO-DR	222.1	−5.9	28.1	0.0	3.2	0.0
	COOP	193.7	7.6	24.2	13.9	3.0	7.8
3 (RAF = 2.06 CC = 3.80)	NO-DR	234.5	−11.8	28.1	0.0	3.2	0.0
	COOP	192.6	8.2	24.1	14.2	3.0	7.8
4 (RAF = 1.93 CC = 5.70)	NO-DR	247.8	−18.1	28.1	0.0	3.2	0.0
	COOP	191.9	8.5	24.1	14.2	3.0	8.0
5 (RAF = 1.79 CC = 7.60)	NO-DR	260.1	−24.0	28.1	0.0	3.2	0.0
	COOP	190.1	9.4	23.9	14.9	3.0	8.2
6 (RAF = 1.65 CC = 9.50)	NO-DR	272.5	−29.9	28.1	0.0	3.2	0.0
	COOP	188.7	10.0	24.0	14.5	3.0	8.1



**Fig. 8.** Peak reduction vs electricity cost. It is striking that the peak reduction already occurs under tariff 2 and that the peak load level remains constant for the other two-part tariffs while the electricity costs drop further.

Fig. 8 depicts the resulting trade-off between peak reduction and potential cost savings. The higher the capacity-pricing component grows, the more the financial incentive for cooperative peak shaving increases. However, energy providers are tempted to offer tariffs with a very small element of capacity pricing but a high peak reduction to cost ratio.

To design new effective energy tariffs, three central findings of our work have to be considered:

- Effective peak shaving only works in a centrally coordinated setting. The more households pool their loads, the better this will be in terms of peak shaving.
- Two-part tariffs have to be tailored to the size of the cooperative with regard to the monthly peak load.
- The extent of the capacity charge in two-part tariffs influences the potential savings that can be achieved by cooperative DR.

In a nutshell, energy providers need to create tariffs that incentivize not only peak-shaving behavior but also the formation of large cooperatives to increase the effects. Our results indicate that, in terms of peak shaving, the bigger the cooperative grows, the better the results are for the energy provider. However, our research ignores any geographical or capacity constraints. Thus, more work is still needed to examine the effects of cooperative size and to determine what types of tariffs might provide win-win situations for both households and energy providers. Especially peak charges should be tailored to reflect weak spots in residential grids. These bottlenecks are often distribution transformers that connect individual neighborhoods to the wider distribution grid [45]. We assume that capacity pricing might thus be suited best for moderately sized residential microgrids which only cover a single neighborhood.

## 5. Conclusion

The purpose of this work is to provide a realistic estimation of the economic benefits that cooperative demand response can offer to households and energy providers. We therefore created an evaluation framework which included a cooperative market environment and a load-scheduling model. We applied this framework to a very detailed dataset covering 201 households in Austin, Texas. As a first step we show that, with a real-time market pricing scheme, demand response measures lead to cost savings of 5.5%. Cooperative behavior adds further savings of 1.3%.

However, with a real-time market pricing scheme shifting decisions result in more extreme load profiles. We therefore propose to introduce two-part pricing schemes that incorporate a capacity-pricing component. Such schemes can reduce peaks by an average of 14.5%, and increase the savings potential for cooperatives to 10.0%. Thus, two-part tariffs can create win-win situations for energy providers and customers alike.

Furthermore, we find that effective peak reduction is only possible in a cooperative setting. The results improve when more participants pool their loads. Thus the optimal amount of capacity pricing should be determined not only by the need to incentivize peak shaving but also by what will stimulate the creation of larger cooperatives.

## 6. Limitations and potential for future research

There are two major operational challenges to cooperative demand response which we did not account for in our calculations. Firstly, we did not consider how to fairly share the benefits among the members of the cooperative. This reallocation is important however, to encourage households to constantly contribute

flexibility. Secondly, we assume that our scheduling mechanism has access to all relevant load and price information. In real life, neither load curves nor prices are known in advance, and mechanisms need to rely on often inaccurate forecasts. Especially load forecasting at the individual household level can be challenging as users tend to behave unpredictably. With broader adoption of residential DSM, price forecasting will also become more complex as each cooperative's shifting decision can influence prices.

Against the backdrop of these challenges, our estimations likely overestimate the actual operational benefits of cooperative demand response. Recent research is up to the forecasting challenge however and new methods can yield good predictions even for individual homes [46]. Similarly, price forecasting models also increasingly offer good accuracy and computational efficiency [47]. We consequently believe that, with constantly improving predictions for both prices and loads, energy cooperatives can facilitate considerable operational savings.

The results might vary for different markets however. Even though the US market is undoubtedly one of the most important in the world, we would like to see our results verified using European data, i.e. electricity prices as well as usage data. Air conditioning units for example are much less common in many European countries. Nevertheless, due to the low electricity prices in the US we expect that our results will not deviate significantly in a European setting.

Ultimately, we believe that there are two additional levers that could make cooperative demand response even more beneficial. The first option is to include other forms of renewable energy. Specifically, we suggest investigating the effects of wind turbines, as owned by many cooperatives in Germany, Denmark and the Netherlands [48]. We also believe that storage plays a key role in increasing the benefits of cooperative demand response, and we plan to extend our model in the near future.

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