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Abstract

Local electricity markets (LEMs) are a promising approach to integrate flexible appliances into electricity systems and manage system constraints on the distribution level. In this article, we suggest an approach to derive bidding functions for time-interdependent electricity-based services and use our framework to analyze the welfare implications of an LEM. Previous work has left such bidding functions undefined which are, however, an important bridge between customer preferences and technology in a smart grid. Furthermore, while welfare analyses exist for the transmission level, we are not aware of equivalent studies for residential distribution systems. We specify a bidding function for Heating, Ventilation, and Air Conditioning (HVAC) systems – a major load in residential distribution systems – and pursue a case study of 437 houses. We find that, over a year, the introduction of an LEM can realize welfare gains of more than 17,000 USD. These benefits are largely driven by savings in energy procurement costs during a few weeks. Moreover, all houses contribute to this gain and houses which contribute more benefit over-proportionally. Furthermore, LEMs can contribute to the management of constrained systems. We derive the marginal value of investment and show that optimal grid expansion is less than under a fixed retail tariff. Our results demonstrate that LEMs can provide system benefits, however, important design questions remain open, for instance who should incorporate the role of an LEM operator.

Keywords: Local electricity markets, flexible loads, smart home systems, automated bidding, congestion management

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1 Introduction

With the ongoing deployment of variable renewable energy resources such as solar or wind energy and new flexible loads such as heat pumps, electric vehicles, or residential battery storage, today's electricity systems are becoming increasingly decentralized and volatile. Given this development, it is discussed if the current hierarchical and centralized structure of power markets is still suitable [e.g. Parag and Sovacool, 2016, Gramlich and Hogan, 2019]. As an alternative, local electricity markets (LEMs) have been proposed. Following Weinhardt et al. [2019], we 'define LEMs as market platforms for trading locally generated (renewable) energy among residential agents within a geographic and social community. Supply security is ensured through connections to a superimposed electricity system (e. g. superimposed grid or adjacent LEMs).' While the direct integration of consumers or even appliances in wholesale markets would be very complex, LEMs cover a smaller part of the power system and could be able to locally coordinate customers, prosumers, and generators at reduced transaction costs and leverage their flexibility according to the spatial and temporal scarcities present [e.g. Rosen and Madlener, 2016, Gramlich and Hogan, 2019, Kiesling et al., 2019]. In practice, LEMs could be operated by (local) integrated utilities or cooperatives, community choice aggregators, distribution system operators, or a third party provider.

Like other approaches for demand-side management, LEMs can provide a variety of benefits [Strbac, 2008]. First, by propagating real-time costs of energy supply to participating appliances, LEMs can help to incentivize efficient dispatch and increase customer welfare [Borenstein and Holland, 2005, Borenstein, 2007]. Second, unlike pure real-time prices, LEMs can help to manage congestion by reflecting the local value of electricity supply [Hammerstrom, 2007, Widergren et al., 2014]. Local congestion is becoming more relevant as generation and new flexible loads are increasingly deployed on the distribution level [Strbac, 2008]. Third, recent research has demonstrated that customers experience additional value from local and/or renewable energy [Tabi et al., 2014, Ecker et al., 2018, Mengelkamp et al., 2018c, Ableitner et al., 2020]. LEMs provide customers with the possibility to access these qualities, express preferences through bidding, and directly engage in the energy transition. Fourth, LEMs can help to operate local electricity systems even when they are disconnected from the public grid, e.g. as a result of natural disaster. In that case, LEMs increase the resiliency of the system and avoid lost load [e.g. Khodaei, 2014, Moslehi and Kumar, 2019]. Furthermore, the efficient short-term dispatch of resources enables long-term efficiency of the power system, e.g. through investment in appropriate generation capacity [e.g. Borenstein, 2007] or flexibilization of residential load [e.g. Comello and Reichelstein, 2019].

Despite these benefits, real-world LEMs have hardly exceeded the piloting stage [e.g. Weinhardt et al., 2019]. The reasons are manifold and include the unclear implications on residential customers [Widergren et al., 2017], the distribuion of benefits between them [Burger et al., 2019], unresolved operational challenges [Parag and Sovacool, 2016], or the need for a comprehensive market design framework [Parag and Sovacool, 2016], among others. Furthermore, it is unclear how customers should participate in such markets. Automation has been recognized as key to accessing demand flexibility [Faruqui and Sergici, 2010], however, it is unclear how customer preferences could automatically be represented in such a market. A major challenge is that customers usually have a preference towards the service provided by the appliance but not the electricity consumption itself.

In this article, we contribute to these open questions by, first, suggesting an approach to derive bidding functions for time-interdependent electricity-based services and, second, analyze the implications of LEM operations for the system, customers, as well as the utility. Specifically, we use an intertemporal optimization approach to derive a bidding function and specify it for HVAC systems, a major load in residential systems. Previous work has used bids which did not reflect the opportunity cost of intertemporal dispatch [e.g. Ableitner et al., 2020], reduced optimal dispatch to a scheduling problem [Lin et al., 2015, Vrettos and Andersson, 2016], or approached it in a simplistic way [Hammerstrom, 2007, Widergren et al., 2014], without explicitly addressing the trade-off between comfort and cost. Second, we use our framework to perform an extensive case study and analyze the impacts of the introduction of an LEM in a residential system. We find that substantial welfare gains can be realized through energy procurement cost savings. However, they are driven by a few weeks during the year and are not equally distributed among customers. Customers with high utility bills under a fixed retail rate benefit the most. These customers can largely be characterized by large houses and their savings are over-proportional as compared to the actual welfare gains they provide to the system. Furthermore, LEMs can help to manage system constraints and, therefore, provide value beyond the mere introduction of real-time prices. We find that the marginal value of grid investment is non-monotonously decreasing and less than under a fixed retail rate which indicates that optimal grid investment can be reduced by the deployment of an LEM. While tools exist to evaluate the cost and benefits of investments on the transmission or wholesale level [e.g. CAISO, 2017, ENTSO-E, 2018], to the best of our knowledge, no such framework for the analysis of welfare effects exists for residential systems. However, with the growing relevance of distribution systems and the increasing prevalence of smart home devices, such tools will be needed to efficiently address local operations and planning problems.

Our work has promising implications for policy makers and management. First, LEMs enable the integration of flexible appliances into electricity markets. Dispatching flexible loads through an LEM increases customer welfare and enables the management of a capacity constraint. These benefits, however, are largely driven by a few days or weeks within a year. Second, while savings can be substantial, they depend on the local system characteristics. For instance, welfare changes can be small if wholesale market prices are largely constant. Therefore, benefits need to be accessed and compared to applicable costs such as the deployment of a suitable information and communication system. Third, the institutional framework for LEMs has to be clarified and the rules of LEMs need to be detailed. Importantly, it needs to be clarified which stakeholder would be able to operate an LEM to avoid adverse incentives. Other open questions are how balancing is organized and how unresponsive loads are integrated in the system. Finally, LEMs and automated dispatch can provide opportunities for innovative business models. Suitable bidding functions provide a mapping between customer preferences and electricity prices and are key to the automated dispatch of devices. Furthermore, LEMs can be open to new stakeholders, for instance load aggregators, which act on behalf of customers to insure against time-varying costs or deploy forecast-based bidding.

We proceed as follows: Section 2 describes the relevant literature on LEMs. In Section 3, we formalize the setup of an LEM, characterize our customer model, and specify bidding functions for HVAC systems. Subsequently, in Section 4, we introduce our case study of 437 residential customers in Austin, Texas. We provide our results for customers and the utility in Section 5. Section 6 concludes this paper by a discussion of our contributions, managerial and policy implications, as well as a research outlook.

2 Literature Review

In the following section, we present an overview of the literature relevant to our work and contributions. First, we summarize the literature on customer utility and bidding functions (Section 2.1). Then, we provide the relevant literature on the evaluation of LEMs (Section 2.2).

2.1 Customer Utility and Bidding Functions

The operation of LEMs requires active bidding of customers, i.e. a submission of a willingness to pay for the consumption of a unit of energy. One strain of the relevant literature consists of theoretical and simulation studies which have largely focused on testing and demonstrating various characteristics of LEMs such as efficiency or the control of a capacity constraint. For this purpose, the literature has mainly based their analysis on an abstract utility description of non-specified electricity services. These include bids which are based on randomly drawn willingness to pay [e.g. Ilic et al., 2012], linear demand function with random price elasticity [e.g. Olivella-Rosell et al., 2016, Mieth and Dvorkin, 2020], or quasi-linear utility functions over sets of possible consumption [e.g. Morstyn et al., 2019]. Bompard and Han [2013] suggest a demand function which allows for a trade-off between comfort and price by introducing an abstract comfort parameter. Furthermore, the listed approaches do not consider temporal interdependencies which are common in energy services such as internal temperature regulation, water heating, or electric vehicle charging. As a consequence, these bidding functions and utility frameworks can hardly be used to evaluate real-world distribution systems.

Theoretical studies which consider the intertemporal optimization in LEMs with active bidding for storage operations include Mengelkamp et al. [2018b] and Lüth et al. [2018]. Mengelkamp et al. [2018b] use a Reinforcement Learning approach to derive bids and minimize electricity costs. Lüth et al. [2018] use the dual variables of an intertemporal optimization as a basis for bids for revenue-maximizing electric storage deployment. As such, their setting resembles an optimal scheduling problem. While many studies assume that electric storage will play an important role in future distribution systems, it does not necessarily face the same complexity of other potentially flexible electricity-based services for which an additional trade-off between customer-specific comfort/quality/reliability and cost exists. To the best of our knowledge, the trade-off of such services – for instance internal temperature regulation by HVAC system operations, water heating, or electric vehicle charging – has so far been insufficiently addressed. Existing studies mostly focus on the cost-minimizing dispatch of such devices for a given comfort level, such as Lin et al. [2015] or Vrettos and Andersson [2016] for HVAC systems. We extend this work by proposing a general inter-temporal valuation framework for flexible energy services which we specify for HVAC systems, a major load in residential distribution systems.

In extension of the theoretical studies mentioned, an increasing number of LEM demonstration projects investigates the bidding behavior of actual customers [Weinhardt et al., 2019]. Many allow for the manual user input of bidding prices [e.g. Mengelkamp et al., 2018a, Wörner et al., 2019, Ableitner et al., 2020]. These projects focus on customers' general willingness to pay for local and renewable energy and do not expose customers to varying wholesale market-based prices [Mengelkamp et al., 2018a, Wörner et al., 2019, Ableitner et al., 2020]. Previous work has, however, argued that the response to real-time prices enables efficiency in the electricity system [Borenstein, 2005]. Furthermore, research has shown that automation is more effective in increasing load response than manual user input [Faruqui and Sergici, 2010]. Other demonstration projects have therefore worked with automated near real-time bidding strategies, including the Olympic Peninsula project [Hammerstrom, 2007] and the Columbus project [Widergren et al., 2014] in the US. These two projects included local generation, HVAC systems, and water heaters. Real-time bids were derived based on heuristics, e.g. that prices increase if the internal temperature diverges from the comfort temperature. Because of the missing utility framework, it has, however, not been demonstrated that such strategies increase customer welfare. In contrast to the contributions mentioned, we motivate our suggestion for a bidding function based on an inter-temporal utility function and tailor it to a specific energy service – temperature control in a house. Therefore, we are able to provide an economically well-founded derivation of the bidding strategy which also makes it useful for the direct evaluation of customer surplus.

2.2 LEM Evaluation

The existing literature has provided multiple measures to evaluate the benefits of LEMs. Criteria deployed have been self-sufficiency of households or the distribution system [e.g. Ableitner et al., 2020, Wörner et al., 2019] or the ability to manage grid constraints [e.g. Hammerstrom, 2007, Widergren et al., 2014]. The benefits of investments and policy measures on the transmission or wholesale level, however, are usually evaluated by the impact on social welfare. The literature on wholesale energy markets and transmission has developed a consistent theory on the valuation of load flexibility [Bohn et al., 1984, Borenstein, 2005, 2007], market design [Bohn et al., 1984, Stoft, 1997], and transmission constraints [Hogan, 1992, Joskow and Tirole, 2005]. Those approaches are widely used in practice [CAISO, 2017, ENTSO-E, 2018, CAISO, 2020, PJM Capacity Market & Demand Response Operations, 2020]. These approaches are, however, not directly applicable to the distribution system as they largely operate based on aggregated demand elasticities and can leverage available locational price information. Hammerstrom et al. [2016] have proposed a comprehensive valuation framework for distribution systems but have abstained from specifying the (subjective) utility change for customers from flexible operations. Furthermore, bids collected in demonstration projects cannot directly be used to evaluate consumer welfare because they reflect the opportunity costs of electricity consumption in time rather than the actual marginal value of the electricity-based service. Likewise, other LEM projects known to us have abstained from analyzing consumer surplus given the lack of an economically grounded bidding function and a consistent valuation framework, as discussed in Section 2.1. In our work, however, we propose a theoretical framework which captures the trade-off between customer utility and costs. The framework can be parametrized based on the dispatch behavior of customers under a fixed retail rate. Furthermore, in contrast to theoretical studies using social welfare as a criterion [e.g. Block et al., 2008, Bompard and Han, 2013, Olivella-Rosell et al., 2016], we are able to estimate benefits in a realistic case study, providing detailed insights into the distribution of welfare changes throughout a typical year and between customers.

3 Model of a Local Electricity Market Framework

We consider an LEM according to the definition provided by Weinhardt et al. [2019]. In the following section, we describe the setup of an LEM in Section 3.1, characterize the demand model for flexible electricity-based services in Section 3.2, and specify the demand model for HVAC systems in Section 3.3.

Symbol	Description	Symbol	Description
Market variables and parameters		***Customer variables and parameters***	
t	Time index	$u(x_t)$	Utility provided by energy service
i	Buyer index	x_t	Quality of energy service
I	Set of buyers	U_T	Disposal utility
$b_t^{d,i}$	Buy price bid in t	λ	Lagrange multipliers
$q_t^{d,i}$	Demand bid in t	T	Optimization horizon
j	Supplier index	$f(x_t)$	Quality transition function
J	Set of suppliers	$g(q_t)$	Impact of electricity supply on quality of energy service
$b_t^{s,j}$	Supply price bid in t	$\mathbb{C}^{load}$	Energy service constraints
c_t^j	Marginal supply costs	θ	Internal temperature
$q_t^{s,j}$	Supply bid in t	θ^{com}	Comfort temperature
$q_m^{s,j}ax$	Maximum supply capacity	α	Comfort preference
p_t	LEM price	d_t	Dispatch of the HVAC system in t
$\mathbb{C}^{grid}$	Grid constraint set	m	HVAC mode (heating/cooling)
p_t^{WS}	Wholesale market price in t	P	HVAC rated power
a_t	Additional import costs	θ^{out}	Outside temperature
		β	Thermal characteristics
		γ	HVAC efficiency

Table 1: Variables and parameters

3.1 General LEM Model

In this section, we describe the supply and demand side of an LEM, present the deployed auction mechanism, and characterize the LEM equilibrium. All variables and parameters are described in Table 1.

Supply. On the supply side, LEMs usually coordinate two types of resources: supply procured at the wholesale market and local (distributed) generation. Based on typical assumptions usually made for the analysis of wholesale markets [e.g. Al-Gwaiz et al., 2017, Sunar and Birge, 2019, Sunar and Swaminathan, 2020], we propose the following specifications of the supply functions.

First, the marginal costs c_t^{WS} of wholesale market supply correspond to the applicable real-time price p_t^{WS} and additional potential import costs or fees a_t, i.e. $c_t^{WS} = p_t^{WS} + a_t$. The real-time price can, for instance, correspond to the locational marginal price and the import costs to applicable grid losses. Furthermore, we assume that the imported wholesale market supply $q^{s,WS}$ can be continuously adjusted in order to balance local supply and demand, i.e. it is residual. This is in line with typical contract arrangements, e.g. for cooperatives. Therefore, the wholesale market supply function is described as follows,

$$q^{s,WS}(p) = \begin{cases} 0, & \text{for} \quad p_t < c_t^{WS}; \\ \sum_i q_t^{d,i}(p_t) - \sum_{j \neq WS} q_t^{s,j}(p_t), & \text{for} \quad p_t \geq c_t^{WS}. \end{cases} \tag{1}$$

Second, local *distributed generation* is typically represented by photovoltaics (PV) or conventional back-up generators. A local generator j exhibits constant marginal supply costs of c_t^j. Accordingly. the continuous supply function can be described as follows,

$$q^{s,j}(p) = \begin{cases} 0, & \text{for} \quad p_t < c_t^j; \\ \sum_i q_t^{d,i}(p_t) - \sum_{j' \neq j} q_t^{s,j'}(p_t), & \text{for} \quad p_t = c_t^j; \\ q_{max}^{s,j}, & \text{for} \quad p_t > c_t^j. \end{cases} \tag{2}$$

A local supply resource j supplies no electricity if the local LEM price p_t is lower than the marginal supply cost c_t^j. *Vice versa*, it supplies at maximum capacity $q_{max}^{s,j}$, if the price increases above c_t^j. If it is the marginal supply resource, it is only partially dispatched such that demand and supply are balanced, if possible. If this is technically not possible, we assume that the additional supply gets absorbed by a behind-the-meter storage or by a decrease in the wholesale market contribution to the local supply.

Demand. The demand side of the LEM is characterized by unresponsive load and flexible appliances. The unresponsive load $q_t^{d,unresp}$ is not price-dependent. We assume that loads are unresponsive because they can either not be operated in a flexible way (e.g., important medical devices) or because they lack the ICT infrastructure to participate in the market clearing. In both cases, the retailer submits a constant demand function on their behalf,

$$q_t^{d,unresp}(p) = \begin{cases} q_t^{d,unresp}, & \text{for} \quad \forall p_t. \end{cases} \tag{3}$$

In contrast, customers with flexible appliances submit a demand function on their own. As most appliances work with an ON/OFF control, electricity demand for appliance i is characterized by a piece-wise constant function with a jump at the valuation or price bid $b_t^{d,i}$. This willingness to pay to switch on appliance is derived as described in Section 3.2. The demand function is described by the following expression,

$$q^{d,i}(p) = \begin{cases} P^i, & \text{for} \quad p_t \leq b_t^{d,i}; \\ 0, & \text{for} \quad p_t > b_t^{d,i}. \end{cases} \tag{4}$$

This requirement corresponds to typical appliance behavior. For instance, an HVAC system can only be fully dispatched at P^i (dispatch $d_t^i = 1$) or not at all ($d_t^i = 0$).

Auction mechanism. Bids are cleared in a centralized double auction with discrete trading times $t, t+1, ...$ This is an established concept for the design of LEMs [Weinhardt et al., 2019] and furthermore corresponds to wholesale market designs. At the beginning of each market interval Δt, the LEM operator collects the bids of appliances $i \in I$ and generators $j \in J$ submitted by the market participants. I also includes unresponsive load and J wholesale market supply, for instance submitted by the local retailer. The LEM operator collects the bids and maximizes social welfare by the choice of the LEM price p_t,

$$\begin{aligned} &\max_{p_t}\{\sum_i (b_t^{d,i} - p_t) q_t^{d,i}(p_t) - \sum_j (p_t - b_t^{s,j}) q_t^{s,j}(p_t)\} \\ &\text{s.t.} \sum_i q_t^{d,i}(p_t) = \sum_j q_t^{s,j}(p_t), \\ &\quad \mathbf{C}^{grid}. \end{aligned} \tag{5}$$

Social welfare is the sum of consumer surplus (first part of the sum) and producer rent (second part of the sum). The optimization is subject to the balance of aggregate demand and supply as well as a set of grid constraints $\mathbf{C}^{grid}$. The latter can, for instance, consist of a maximum import capacity from the wholesale market.

Equilibrium. Given the constant marginal cost of supply and willingness to pay, respectively, the aggregate demand and supply function are staircase functions. As a result, in some cases, multiple prices $p_t \in [p_t^{min}, p_t^{max}]$ can solve Eq. (5). For our further analysis and case study, we assume that $p_t = p_t^{min}$. However, the price could be differently chosen to affect the distribution of the surplus between consumers, (local) suppliers, and the market operator. For instance, the price could be $p_t = p_t^{max}$ or even differ for the demand and supply side.

3.2 Model of Flexible Demand

Customers deploy flexible appliances to receive utility or comfort from the operations of an electricity-based service, for instance temperature support by an HVAC system or topping up the mileage of an electric vehicle. The dispatch of these appliances is motivated by an inter-temporal utility maximization problem as described in Eq. (6),

$$\begin{aligned}
&\max_{\mathbf{b}} \mathbb{E}\{\sum_{t=0}^{T-1}[u(x_t) - p_t P d_t(b_t)\Delta t] + U_T(x_T)\} \\
&\text{s.t. } x_{t+1} = f(x_t) + g(d_t(b_t)), \forall t \in \{0, ..., T-1\} \\
&\quad x_t \in \mathbf{C}^{load}, \forall t \in \{0, ..., T-1\}.
\end{aligned} \tag{6}$$

At each stage t of the optimization horizon T, the customer experiences a utility $u(x_t)$ which is a function of the quality x_t of a service provided by an electric appliance. For instance, x_t can reflect the internal temperature of a house (for the service of an HVAC system) or the range charged by the battery of an electric vehicle (for driving). The quality of service x_t is usually coupled in time and can be influenced by the discrete dispatch of the respective appliance, $d_t \in \{0, 1\}$. This relationship is generally described by the transition function $x_{t+1} = f(x_t) + g(d_t)$. The dispatch of the appliance is subject to electricity costs. $P d_t \Delta t$

describes the energy consumed during the market interval Δt. p_t is the price per energy unit. Furthermore, the service provided by the electric appliance is subject to a set of constraints $\mathbf{C}^{load}$. For instance, this constraint set can describe the maximum or minimum internal temperature or the minimum mileage of the battery of an electric vehicle at the estimated time of departure. $U_T(x_T)$ describes the disposal utility after the end of the optimization horizon. Furthermore, we assume that customer utility is linear in money.

We can describe the value of optimal dispatch for a given expected price vector using the Bellman equation and finding the value function $V_0(x_0)$,

$$V_0(x_0) = \max_{\mathbf{b}} \mathbb{E}\{\sum_{t=0}^{T-1}[u(x_t) - p_t P d_t(b_t)\Delta t] + U_T(x_T)\} \tag{7}$$

$$\text{s.t. } x_{t+1} = f(x_t) + g(d_t(b_t)), \forall t \in \{0, ..., T-1\}$$

$$x_t \in \mathbf{C}^{load}, \forall t \in \{0, ..., T-1\}.$$

For a given vector of prices, the customer is indifferent between dispatching ($d_0 = 1$) and not dispatching ($d_0 = 0$) if the value of dispatching equals the value of not dispatching,

$$u(x_0) - p_0 P\Delta t + V_1(x_1|d_0 = 1) = u(x_0) + V_1(x_1|d_0 = 0) \tag{8}$$

Therefore, given future prices, p_0 characterizes the maximum price at which the customer is willing to dispatch in the current time period. This price corresponds to the bid b_0^d which the customer would submit to express his maximum willingness to pay,

$$b_0^d = \frac{V_1(x_1|d_0 = 1) - V_1(x_1|d_0 = 0)}{P\Delta t}. \tag{9}$$

3.3 Model of HVAC Demand

In the following section, we will specify the demand model for an HVAC system. We describe the decision problem of the customer (Section 3.3.1) and solve it by deriving the willingness to pay if the customer is a price taker ((Section 3.3.2)).

3.3.1 Decision Problem of Customers

We start by specifying Eq. (6) for the customer's intertemporal utility maximization problem for HVAC operation,

$$\max_{\mathbf{b}} \mathbb{E} \sum_{t=0}^{T-1} (u(\theta_t) - p_t P d_t(b_t) \Delta t) + U(\theta_T). \tag{10}$$

The customer experiences comfort $u(\theta_t)$ from a convenient temperature. He can control the temperature θ_t through the operation d_t of his electric HVAC system, with $d_t \in \{0, 1\}$. The HVAC system will be dispatched if $p_t \leq b_t$ and is off otherwise. The operation of the HVAC system causes total electricity cost $p_t P d_t \Delta t$ where p_t the LEM price in time t, P denotes the power required by the HVAC system, and Δt the duration of dispatch. In the LEM, Δt corresponds to the length of a market interval. $U(\theta_T)$ is the disposal utility at the end of the optimization period. Furthermore, the customer is only one LEM participant among many. Therefore, the customer is a price taker, i.e. the LEM price p_t is not a function of the bidding behavior of the customer. The comfort from HVAC operations, measured in monetary terms, is described by Eq. (11),

$$u(\theta) = \overline{u} - \alpha(\theta - \theta^{com})^2. \tag{11}$$

The provision of temperature control provides a baseline utility $\overline{u}$ to the customer. The comfort is a function of the current temperature θ_t and the optimal comfort temperature θ^{com}. We furthermore assume that the customer evaluates positive and negative deviations of the temperature θ_t from the comfort temperature θ^{com} as equally discomforting. The comfort of the customer decreases with an increasing difference between the internal temperature and the comfort temperature, i.e. $\frac{du(\theta)}{d|\theta-\theta^{com}|} < 0$, and that comfort deteriorates more intensively at larger temperature differences, i.e. $\frac{d^2u(\theta)}{d|\theta-\theta^{com}|^2} < 0$. Comfort is furthermore scaled by a comfort preference α which can differ among customers. We describe the dynamics of the internal temperature θ_t by the following equation, using a modified version of the transition function proposed by Mathieu et al. [2013],

$$\theta_{t+1} = \beta\theta_t + (1-\beta)\theta^{out} + m\gamma P d_t \Delta t. \tag{12}$$

β describes the thermal properties of the house. Higher β are associated with larger thermal inertia of the house, e.g. because of better insulation, and slow down the speed of convergence between the outdoor temperature θ^{out} and the indoor temperature θ_t. The internal temperature θ_t can be controlled through the operation of the HVAC system. For $m = -1$, the HVAC system is in cooling mode and decreases the internal temperature; for $m = 1$, it is in heating mode and increases the internal temperature. γ indicates the efficiency of the HVAC system.

3.3.2 Optimal Bidding Behavior

To solve for the intertemporal optimality condition, we formulate the Lagrange function, as a function of optimal dispatch d_t. This is possible because customers are assumed to be price takers,

$$\begin{aligned}\mathcal{L}(d_t, \lambda_t, \lambda_t^{min}, \lambda_t^{max}) = &\sum_{t=0}^{T-1}[u(\theta_t) - p_t P d_t \Delta t] + U(\theta_T) \\ &+ \sum_{t=0}^{T-1} \lambda_t[\beta\theta_t + (1-\beta)\theta^{out} + m\gamma P d_t \Delta t - \theta_{t+1}] \\ &+ \sum_{t=0}^{T-1} \lambda_t^{max}(1-d_t) + \sum_{t=0}^{T-1} \lambda_t^{min}(d_t - 0).\end{aligned} \tag{13}$$

We assume that the smart home system does not have any detailed information about the future development of supply costs and outside temperatures. Therefore, it optimizes dispatch based on the assumption that these values stay constant over the short time horizon which is relevant for HVAC operations: on average, the temperature difference between the outside and inside temperature more than halves within one hour for typical parametrizations and HVAC systems therefore usually dispatch several times within one hour.

Given the expectation of external parameters staying constant, the smart home system aims to keep the internal temperature constant at the respective utility-maximizing level. As this is not entirely possible due to the discrete dispatch behavior of the HVAC system and resulting temperature oscillations, we instead look at the average dispatch and the average temperature. We redefine average dispatch as follows,

$$d := \frac{1}{T} \sum_{t=0}^{T-1} d_t \tag{14}$$

As $d_t \in \{0, 1\}$, consequently, d is continuously defined, i.e. $d \in [0, 1]$. d can be interpreted as the share of periods within which the HVAC system is active ('duty cycle') or the probability of dispatch in a certain period. Given stochastic dispatch, we can re-write the transition function Eq. (12) for expected temperatures as follows,

$$\mathbb{E}\,\theta_{t+1} = \beta\,\mathbb{E}\,\theta_t + (1-\beta)\theta^{out} + m\gamma P d \Delta t \tag{15}$$

The average dispatch d is associated with an average temperature θ which is defined equivalently to Eq. (14). Consequently, we can re-write Eq. (15) using $\mathbb{E}\,\theta_t = \mathbb{E}\,\theta_{t+1} = \theta$ to describe the relationship between the average temperature θ and the average dispatch d,

$$d = \frac{1-\beta}{m\gamma P \Delta t}(\theta - \theta^{out}) \tag{16}$$

We now re-write the inter-temporal optimization problem of Eq. (13) to a problem which maximizes the average utility from HVAC operations,

$$\mathcal{V}(d) = u(\theta(d)) - pPd\Delta t. \tag{17}$$

Inserting Eq. (16), we can write average utility as a function of temperature, take the first derivative with respect to θ, and solve for the optimum temperature θ^* as a function of price,

$$\theta^* = \theta^{com} - \frac{1-\beta}{2\alpha m\gamma}p. \tag{18}$$

Inserting Eq. (16), the optimal dispatch is described by the following theorem.

Theorem 3.1 (Optimal Average Dispatch.)

$$d^* = \frac{1-\beta}{m\gamma P}(\theta^{com} - \theta^{out}) - \frac{(1-\beta)^2}{2\alpha\gamma^2 P}p \tag{19}$$

We now turn to the derivation of the optimal bidding behavior. Importantly, a bid cannot be an average bid but must be period-specific. Otherwise, for instance, provided that external parameters stay indeed constant, the HVAC system would always be on or off and would not reach the optimal average dispatch or duty cycle. To achieve the close tracking of a certain desired temperature θ^*, instead, it is optimal if the HVAC system switches on for one market interval, reaching a change from θ_t to θ_{t+1}, and remains off until time t' when $\theta_{t'} = \theta_t$. Such a behavior will result in an average empirical temperature of $\overline{\theta}$. Given that, we can derive the willingness to pay at a time t given the current internal temperature θ_t.

Theorem 3.2 (Willingness to Pay.) *The customer's willingness to pay under stationary conditions is described by,*

$$b_t^d = \frac{2\alpha\gamma m}{1-\beta}(\theta^{com} - \overline{\theta}). \tag{20}$$

Proof 1 *The theorem follows directly from Eq.* (18)*.*

We find that the bid price b_t^d increases linearly in the difference between the empirical average temperature $\overline{\theta}$ and the comfort temperature θ^{com}. In the case of heating ($\theta_t < \theta^{com}$), the HVAC system is dispatched whenever $p_t \leq b_t^d$. Let us now assume that the electricity price moves from a low to a medium level. In that case, the HVAC system first follows a relatively high temperature close to the comfort temperature. The willingness to pay is relatively low but given low prices, bids often exceed the price level and the HVAC system dispatches. When the price increases, the bids do not get cleared anymore and the temperature in the house decreases to a cooler level. With the lower temperature, the difference between the empirical and the comfort temperature increases and the bid increases until it gets cleared again. Through this mechanism, the customer can constantly adjust to new equilibria if the price fluctuates throughout the day.

Theorem 3.3 furthermore describes the demand function.

Theorem 3.3 (Demand Function.) *The price-dependent demand function is described by,*

$$q^d(p_t) = \begin{cases} 0, & \textit{for} \quad p_t > \frac{2\alpha\gamma m}{1-\beta}(\theta^{com} - \overline{\theta}); \\ P, & \textit{for} \quad p_t \leq \frac{2\alpha\gamma m}{1-\beta}(\theta^{com} - \overline{\theta}). \end{cases} \tag{21}$$

4 Case Study

In this section, we present the setup of our case study. We describe how we compile our simulation model (Section 4.1), describe the benchmark scenario of a fixed retail rate (Section 4.2), and explain the chosen market design (Section 4.3).

4.1 Simulation Model and Data

We consider a local electricity system in Austin, Texas, which consists of 437 residential households on a distribution feeder with one connection to the aggregated system level. We characterize the building stock based on US Energy Information Administration [2015] and US Environmental Protection Agency [2001] which provide data on the geography-specific floor area, house weatherization, HVAC system characteristics, etc. The base load of houses (non-flexible load) is derived from household data provided by Inc. Pecan Street [2019] for the year 2016. The electric distribution system is represented by the IEEE 123 feeder [IEEE Power Engineering Society, 2014]. The size of the system represents a geographic and social community and therefore complies with the LEM definition provided by Weinhardt et al. [2019]. We use the distribution system software GridLAB-D [SLAC, 2020] to simulate the internal temperature of houses, the operation of HVAC systems, and the distribution system. Further details on the population of the feeder and the technical characterization of houses are described in Section 8. We furthermore use real-time price data from ERCOT, the system operator of Texas, provided for the Southern Load Zone for the year 2016 [Ercot, 2019, 2020].

4.2 Benchmark Scenario

We now describe the base case, i.e. the system when it is operated at a fixed retail rate. We simulate one year of operations in five minute intervals, with HVAC systems dispatching according to their internal control.

System. Fig. 1 shows the resulting average system load for each hour of the day in each month of the year, as measured at the point of connection to the aggregate system level. Summer months are depicted in dark colours, winter months in light colours. We use dashed lines to represent the months of the first half of the year and solid lines for the months of the second half. We can see that, in the summer months, system load is generally higher

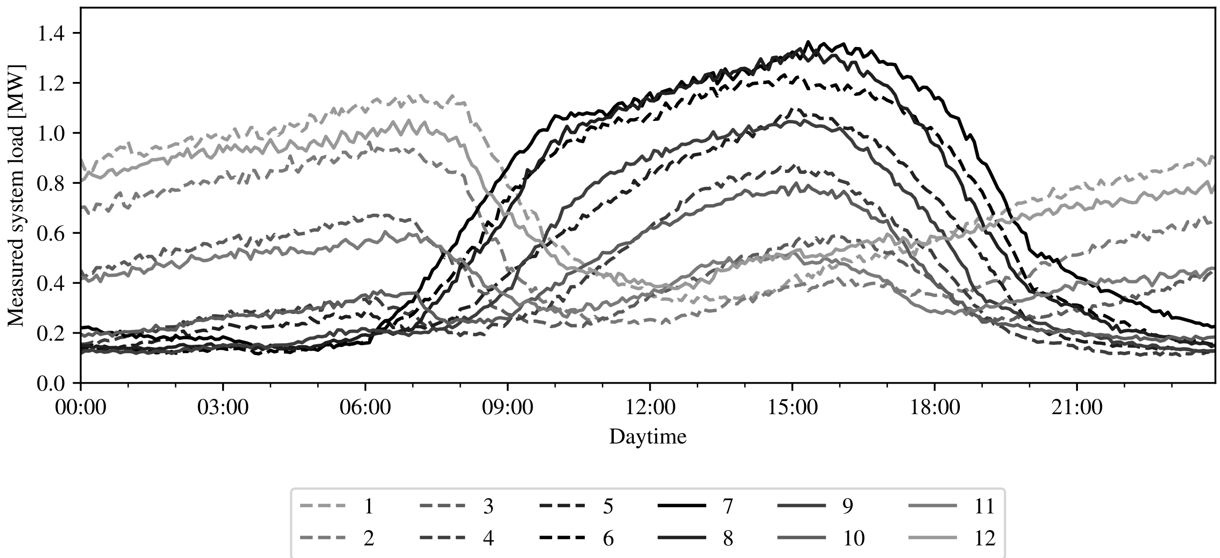


Figure 1: Average hourly aggregate system load for each month, from January ('1') to December ('12')

during the day. It reaches its maximum around 3 to 5pm and decreases afterwards. In contrast, in the winter months, average system load reaches its maximum between 7 and 9 am. Aggregate load is generally higher for the middle of the summer and the middle of the winter. This is driven by electricity consumption of HVAC systems during hot and cold temperatures. HVAC systems are the dominant consumers of electricity and account for 75.5% of total residential electricity consumption.

We further analyze the cost structure of energy procurement. The average cost of a MWh imported to the distribution system is 27.01 USD/MWh and varies significantly throughout the year. Average procurement costs are minimal (13 to 15 USD/MWh) during the month of February and reach a maximum in the first week of August, with 68.91 USD/MWh. Maximum real-time prices can even reach a level of 1,772.80 USD/MWh, as on March 31, 2016. Furthermore, weeks experience very different levels of price variations, ranging from an unweighted standard deviation of 4.4 USD/MWh to 136.6 USD/MWh. A detailed description can be found in Table 6 in the appendix.

Fig. 2 shows the load duration curve of the system for the whole year, i.e. for what

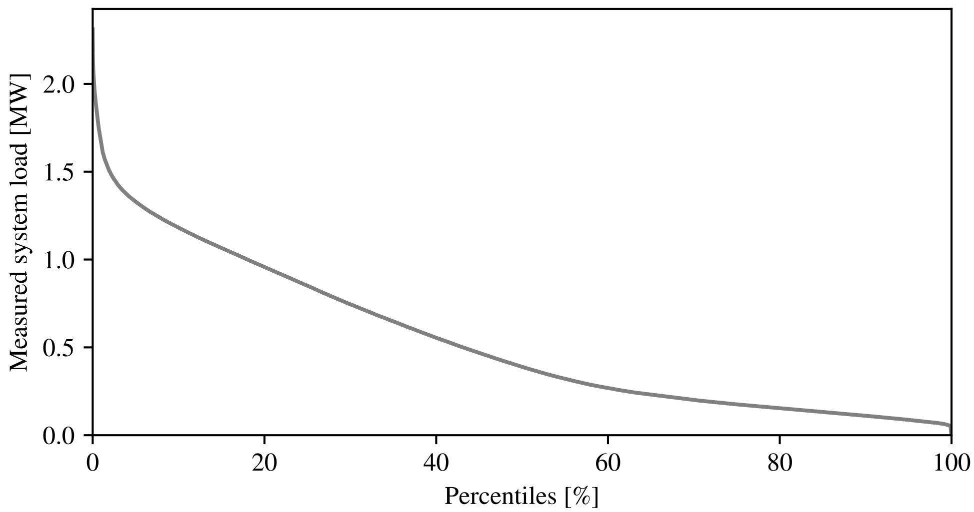


Figure 2: Load duration curve over a year

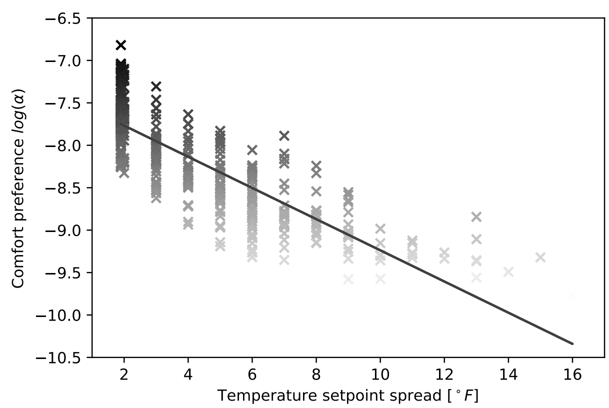
share of the time a certain load level or higher is reached. The maximum of the system load is 2.311 MW. Furthermore, in 1% of the time, the load is equal or higher than 2.124 MW (91.9% of peak load) and, in 5% of the time, 1.723 MW (74.6%), respectively. This indicates that the system peak load and required capacity is only driven by a few days within a year. The maximum peak for each week as well as more details can further be found in Table 6 in the appendix.

Customers. In the benchmark scenario with fixed retail rates, customers dispatch their HVAC systems according to their internal control. The internal control aims to keep the internal temperature θ_t around a heating setpoint θ^{heat} (when $\theta^{out} < \theta^{heat}$) or a cooling setpoint θ^{cool} (when $\theta^{out} > \theta^{cool}$). Due to the ON/OFF control of the HVAC system, the temperature θ_t usually fluctuates around the applicable setpoint by $\pm 1°F$.

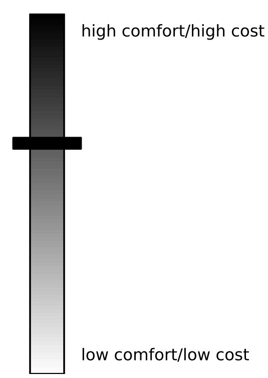
Analyzing the drivers for HVAC bills under a fixed retail rate, we find that 90% of the variance in bills for HVAC operations is explained by the floor area, the thermal characteristics of the house β, the type of heating system (gas or other), and the comfort preference parameter α. The bill increases with an increasing floor area (0.072 USD/sqf), decreases with improving thermal characteristics (-2,886.62 USD), and increases with increasing comfort preference (4.919e+05 $^\circ F^2$). Furthermore, electricity bills are on average 44.09 USD less for houses which run on gas for heating. The summary of the regression results can be found in Table 7 in the appendix.

Based on HVAC system behavior in the benchmark scenario, we further parametrize the transition and utility functions of the HVAC systems as established in Section 3.3. We leverage the temperature time series to estimate house-specific parameters β and γ of Eq. (12). As, in the context our case study, HVAC parameters as well as comfort parameters can change due to unobserved characteristics such as humidity or radiation, we estimate HVAC parameters separately for each week, using linear regression. We further determine the comfort parameters α by calibrating the utility function of each customer to reproduce the given temperature setpoints for the week-specific cost-recovering average procurement costs (including losses).

Figure 3: Mapping of comfort preference α to temperature setpoints in fixed retail rate scenario (August 1 - 7, 2016)



(a) Translation of temperature setpoints into comfort preference



(b) Slider for comfort setting

Fig. 3a shows the resulting mapping between the allowable temperature range, i.e. the difference between the cooling and the heating setpoints, as provided by the customer in the fixed retail rate setting and the estimated comfort preference parameter α. Customers who provided a narrow temperature band in the fixed retail rate scenario are optimally participating in the LEM based on a higher comfort preference α. As customers are unlikely to have a specific understanding of their comfort preference in numerical terms, the customer could enter the comfort preference α by a slider as displayed in Fig. 3b. Such a slider would represent the trade-off between comfort and costs and can be intuitively set by the customer. Importantly, the participation in an LEM does not require more information on the side of the customer than under a fixed retail rate. Instead of two temperature setpoints, the customer would be required to provide his comfort temperature and the comfort preference.

4.3 LEM Design

On the supply side, the load serving entity or retailer imports electricity at the wholesale market price of the local transmission node. It passes on those costs to the LEM, including a mark up which accounts for grid losses. This constant mark up is calculated based on the benchmark scenario. The average relative grid loss in our study is 3.7%, with losses defined as the difference between the electricity imported and the consumption of the households as measured at their meters, divided by the total energy imported.

We run the LEM every five minutes. This is a reasonable time interval during which HVAC systems can work efficiently. For comparison, the minimum run time of an HVAC system as measured in the benchmark case for the month of August is three minutes and the average duration of consecutive dispatch is 5.6min.

5 Results

Using the case study introduced in Section 4, we quantify the general welfare effect of introducing an LEM in Section 5.1. Then, we analyze the implications on customers and the utility in Section 5.2 and Section 5.3, respectively.

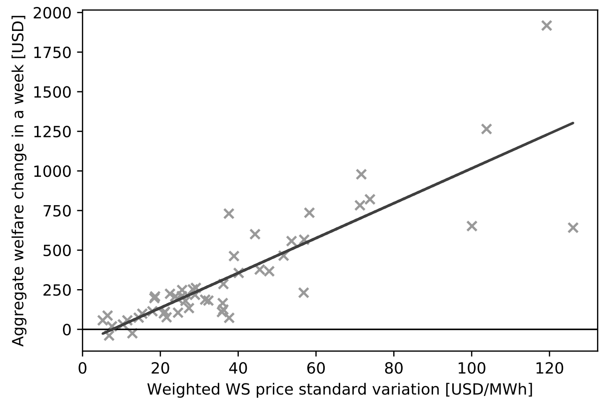
5.1 General Welfare Effects

We calculate welfare changes as the sum of comfort changes for customers, energy procurement cost savings, and avoided congestion costs. This perspective does not require any assumptions about the distribution of welfare gains between customers and the utility.

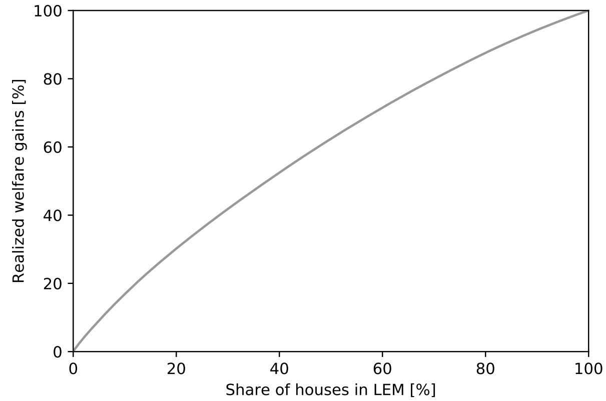
Unconstrained system. First, we consider the case of an unconstrained system, i.e. transactions are not constrained by limitations of the grid. In that case, no congestion costs apply. We find that, over the course of the year 2016, welfare changes of operating an HVAC system under an LEM add up to 17,043 USD. Fig. 4a shows realized welfare gains for the 51 full weeks of the year 2016 and the dependence on the standard deviation of the wholesale market price, weighted by the system load. This figure allows for two important insights. First, we find that, in most weeks, the system experiences significant positive welfare changes, reaching up to 1,918 USD within a week. There are two weeks for which the welfare change is slightly negative, adding up to a loss of 64 USD. We contribute this observation to an imperfect description of the thermal dynamics of the system by the linear model. Second, the welfare change is increasingly positive with a higher standard deviation of the wholesale market price within a week, weighted by system load. With the weighted standard deviation increasing by 1 USD/MWh, the welfare gain from switching from a fixed retail tariff to an LEM increases by 11.00 USD. The correlation between the welfare gains and the weighted standard deviation of the price is 0.85.

Fig. 4b furthermore illustrates the cumulative distribution function of welfare gains over households, sorted from the house contributing the most to the one contributing the least to the overall welfare gain. We find that houses do not contribute equally to the welfare gain but that the 50% most valuable households, for instance, realize 62.3% of maximum welfare gains. The most valuable household contributes 92.86 USD while the least nearly 18.53 USD.

Figure 4: Distribution of welfare changes under an LEM



(a) Distribution of weekly welfare changes under an LEM

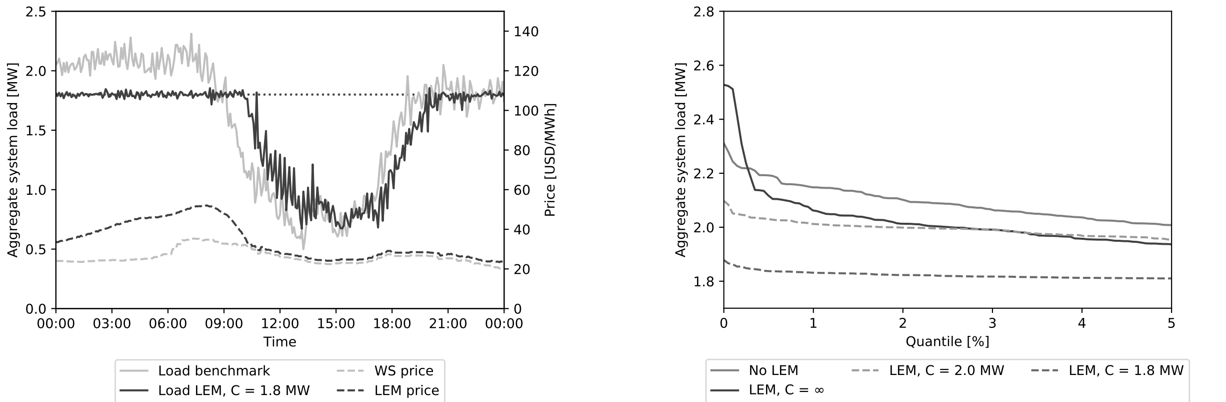


(b) Cumulative welfare gain distribution over households

Constrained system. We further analyze the welfare effects of an LEM in a constrained system. Fig. 5a exemplarily demonstrates the ability of an LEM to integrate a capacity constraint for the peak day of the year, December 19. In the benchmark scenario, the aggregated system load (solid light grey line) reaches the system peak of 2.311 MW in the early morning hours of the peak day. For demonstration purposes, Fig. 5a showcases system behavior for a capacity limit of 1.8 MW (dotted line). The dark grey solid line plots the resulting aggregate system load which can successfully be controlled around the constraint. This is achieved through an increase in the LEM price. If there is no congestion, the LEM price is 1.69 USD/MWh above the wholesale market price, representing payments for losses to the retailer. However, if the import constraint binds, the LEM price (dashed dark grey line) deviates from the real-time price of the wholesale market (dashed light grey line) by up to 20.76 USD/MWh. Local demand is reduced at the higher local equilibrium price and equals the available supply, especially during the morning hours until approximately 11am.

Fig. 5b further demonstrates how the load duration curve changes under an LEM with different capacity constraints. Without an LEM, the maximum load equals the year-long maximum of 2.3 MW. If an LEM is deployed without a capacity constraint, however, the peak system load increases to 2.5 MW. The reason is that low prices and especially sudden

Figure 5: Implication of a constraint limit (December 19 - 25, 2016)

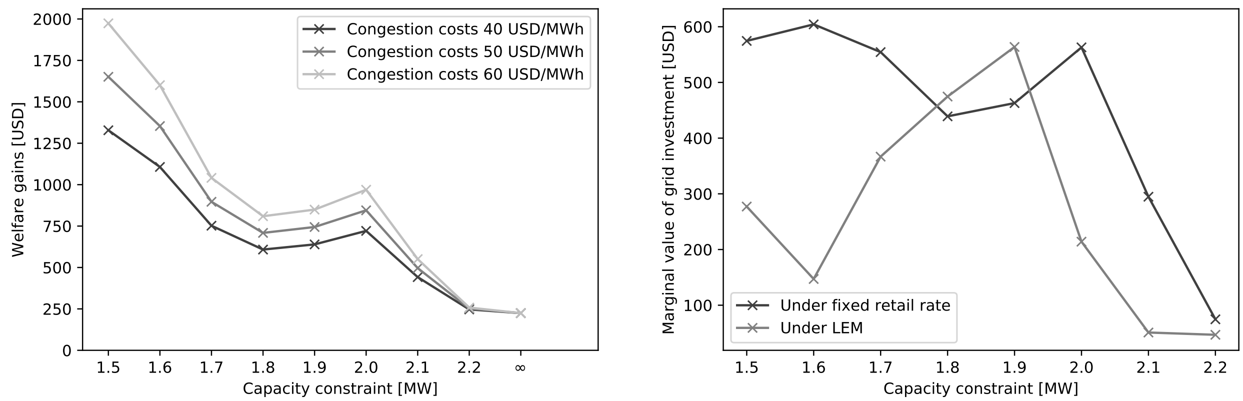


(a) Aggregated load on peak day 12/19/2016 with and without system constraint

(b) Load curves under different scenarios for 5% quantile

price drops can lead to a simultaneous dispatch of many HVAC systems. While this is individually rational and decreases the cost of energy procurement, sudden load increases can be problematic from a system operations perspective [Parag and Sovacool, 2016]. If a binding capacity constraint is imposed, aggregate load can generally be effectively controlled and decreased (here displayed for system constraints of 2.0 MW and 1.8 MW). It is notable that the aggregate system load can be nearly but not entirely reduced below the capacity constraint. There are multiple reasons for that. First, the system operator makes forecasting errors with regard to the unresponsive load. If the unresponsive load is under-estimated, too much capacity will be allocated to the flexible load in the LEM and the resulting aggregate system load will exceed the capacity constraint. The maximum forecasting error is 140 kW. Second, the bids do not correspond to the actual generation or consumption of LEM participants. For instance, the power drawn by appliances can deviate from their rated power, depending on the grid conditions and other characteristics of the environment such as the outdoor temperature or the voltage quality in the system. The maximum deviation caused by HVAC systems not complying with their bids is 27kW. The error introduced by these two channels are detailed in the appendix, see Fig. 10a and Fig. 10b. Third, system load will be too high if flexible demand is exhausted and unresponsive load in itself exceeds the capacity constraint.

Figure 6: Welfare effects of introducing an LEM in a constrained system (December 19 - 25, 2016)



(a) For a given constraint (b) Compared to a constraint of 1.5 MW

Exceeding such a capacity limit can come at considerable cost, e.g. through the degradation of grid components or because of the dispatch of expensive reserve capacity (e.g. diesel generators). We calculate congestion costs by multiplying the energy consumed by excess load (i.e., exceeding the respective capacity constraint) by an estimate for congestion costs. In our analysis, we apply default cost of 50 USD/MWh which, for instance, corresponds to the cost of operating a diesel generator. Then, for the peak load week of December 19 - 25, 2016, congestion costs can add up to 3,568 USD if the system is constrained to 1.5 MW which is the tightest system constraint included in this analysis. Fig. 6a illustrates how the introduction of an LEM can then help to decrease congestion costs and, for a given capacity, increase system welfare. In addition to energy procurement cost savings and welfare gains, these include savings in congestion costs. We find that, for a given capacity constraint, an LEM can realize significant savings of up to 1,651 USD over a fixed retail rate through its capability to manage load, under congestion costs of 50 USD/MWh. The advantage of an LEM over a fixed retail rate is generally higher for more constrained systems and higher congestion costs. For the unconstrained system, the system does not experience congestion costs, therefore, the value of introducing an LEM covers the changes in comfort and procurement costs, as discussed in the previous paragraph.

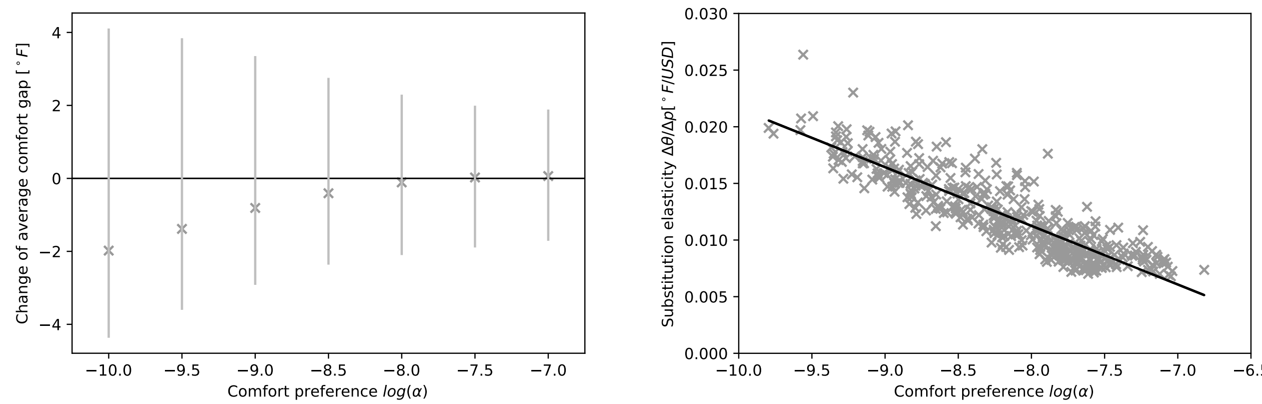
According to Joskow and Tirole [2005], efficient investment in the grid infrastructure is the result of a trade off of short-term cost of congestion and long-term cost of grid investment. Fig. 6b provides an insight on the marginal value of investment for the peak load week of December 19 - 25, 2016. The marginal value of investment is calculated as the difference between the welfare under the given constraint and the welfare under a constraint relaxed by 0.1 MW. We observe the following facts: first, the marginal value of investment is not monotonously decreasing. This indicates that relaxing some levels of grid constraints can be particularly valuable. Importantly, the fact that the marginal value of investment is not monotonously decreasing also adds another layer of complexity in the optimal grid investment problem described by Joskow and Tirole [2005]. Second, the marginal value of investment under an LEM reaches it maximum at a lower capacity than under a fixed retail rate. Except for the maximum, the marginal value lies below or is equal to the curve for the fixed retail rate. That indicates that, under an LEM, grid investment is possibly less valuable and less grid investment will be optimal than under a fixed retail rate, decreasing investment costs in the long-run. We do not provide an estimate for the associated savings as the cost of grid investment are non-trivial and depend on the topology of the grid, geographical conditions, etc. Investment costs can, however, be substantial.

5.2 Implications for Customers

The introduction of LEMs impacts customers in two ways: through changes in operations of their HVAC systems and the resulting comfort as well as their monthly bills. We will first discuss each of these components separately and then consolidate our findings in a combined analysis of customer surplus.

Comfort. Our evaluation framework allows to quantify the welfare changes associated with these temperature changes. We find that the mean comfort change across households and throughout the year 2016 is -2.62 USD, with the maximum comfort increase of 17.88 USD and a maximum decrease of 26.75 USD. Furthermore, customers with low comfort preference tend to experience comfort increases while those with high comfort preferences experience comfort losses. Fig. 11a and Fig. 11b provide more detailed evidence in the appendix.

Figure 7: Temperature as a function of comfort preference α (August 1 - 7, 2016)



(a) Average comfort gap and temperature spread

(b) Substitution effect between temperature and cost

We furthermore provide a detailed analysis of the internal temperature as the driver for comfort changes. As operating modes (i.e. heating/cooling) change between seasons, we focus on the first week of August (week 31) which requires constant operations of HVAC systems because of high outside temperatures and exhibits the highest potential welfare gains under an LEM. We find that, under a fixed retail rate, customers' average internal temperature differs from their comfort temperature by $1.7°F$ ('average comfort gap'). The average comfort gap is larger than zero as the cost of electricity is positive (see Eq. (18)). Under LEM participation, this gap reduces to $1.4°F$ on average which corresponds to a decrease in the average comfort gap of 18.0%.

Fig. 7a shows the dependence of the comfort gap change on the comfort preference of customers, aggregated for customer classes $log(\widehat{\alpha})$ of size 0.5 (e.g., $log(\widehat{\alpha}) = -8.0$ covers $log(\alpha) \in [-8.25, -7.75[$). We find that the customers of the lowest comfort preference experience the largest reduction in the average comfort gap (-2.0$°F$) while customers with the highest comfort preference hardly experience changes in their comfort gap ($0.1°F$). The reason is that customers with low comfort preferences react particularly sensitive to price changes and accordingly adjust their comfort when LEM prices drop below the fixed retail rate which only represents the average price. This indicates that many periods with low prices allow for a more comfortable dispatch of the HVAC system than in the benchmark case where the relatively high constant retail rate is driven by few high-price periods. However, customers with low comfort preference also react particularly sensitive to high prices. As a consequence, customers with a low preference parameter α experience higher temperature variations. The bars of Fig. 7a represent the temperature spread which is defined as the difference of the 95% and the 5% quantile of the temperature distribution under LEM participation. We find that, for customers with the lowest comfort preference, the temperature can oscillate up to $6.1°F$ above and $2.4°F$ below the comfort temperature. For customers with high comfort preference, this spread reduces to $1.8°F$ above and $1.8°F$ below. In general, we find that the temperature range under an LEM is higher than under a fixed retail tariff and increases from $3.0°F$ to $4.8°F$, averaged over all customers.

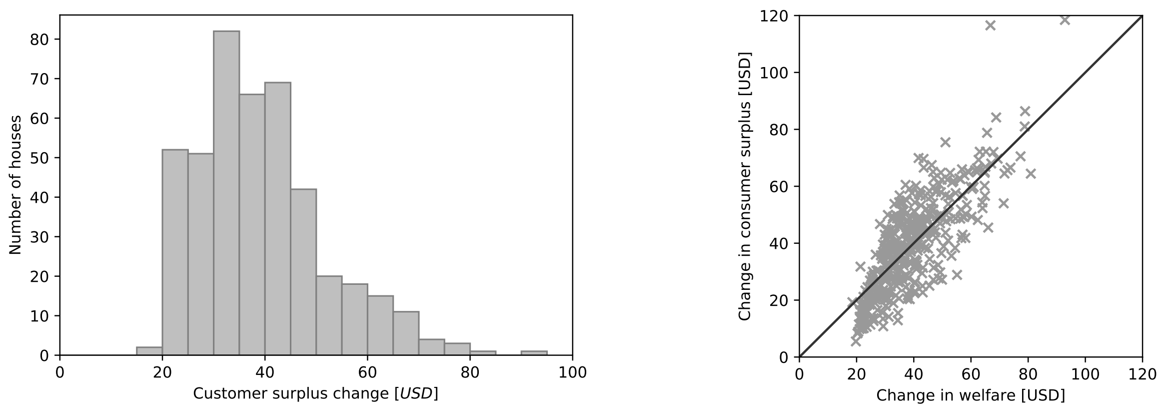
Bill changes. The exact bill changes of customers generally depend on how savings from energy procurement and grid infrastructure expansion will get re-distributed to customers. For the further analysis, we will assume that 1) all savings get re-distributed to customers (i.e. savings are not partially retained by the retailer/utility by increasing other fees), 2) LEM participants pay a fee to cover grid losses, and 3) that the fixed retail rate for unresponsive load is re-calculated based on its energy procurement cost. We find that customers benefit from substantial bill savings. In total, customers save 18,188 USD which corresponds to 41.62 USD per customer (14.5%). These bill changes are driven by more cost-effective operations of HVAC systems which contribute 15,660 USD in savings. Savings for the unresponsive load account for an additional 2,528 USD via reduced retail rates. The maximum bill saving per household is 140.36 USD, the minimum bill saving 7.15 USD. The maximum relative bill saving per household is 21.4%, the minimum relative bill saving 8.6%. Fig. 7b visualizes the empirical substitution effect between cost and comfort. Customers with a low comfort preference are willing to accept a temperature increase by up to 0.02 $°F$ if the electricity price increases by 1 USD/MWh. Customers with a high comfort preference only accept one fourth of a temperature increase, on average.

We furthermore provide an analysis of which customers profit the most. We find that absolute bill savings can largely be explained by utility bills in the first place (79% of variance), as described in Section 4. Second, savings increase with the share of unresponsive load as of total load, as a result of the decrease in the fixed retail rate for remaining loads. Furthermore, savings are less for customers with a higher correlation of HVAC operations under a fixed retail rate and the wholesale market price, as well as those with gas heating. More details can be found in Table 8. Similar results can be derived for relative bill savings which are higher for customers with higher bills under the fixed retail rate scenario.

Total welfare. Final consumer surplus is a combination between the changes in thermal comfort and the bill. Fig. 8a shows the distribution of consumer surplus changes by house for the whole year. We find that the average change is 39.00 USD and consistently positive across customers. The household with the maximum consumer surplus change gains 118.46 USD, the one with the lowest 5.50 USD. The distribution of consumer surplus among customers and weeks can be found in the appendix, see Fig. 12.

Finally, we investigate to which extent consumer surplus gains of houses coincide with their welfare contribution to the system. Fig. 8b plots how these values line up. We find that customers which contribute more to system welfare also experience higher consumer surplus gains. This observation ensures that the most valuable customers also have a strong private incentive to join the LEM. However, we also observe that the most valuable customers experience an over-proportional gain in consumer surplus while less valuable customers receive under-proportional gains. This adds to the concerns with regard to the equity between cus-

Figure 8: Distribution of consumer surplus changes of houses



(a) Throughout the year

(b) Coincidence of consumer surplus gains versus system welfare contribution

tomers which we observed earlier, with customers with large houses (and potentially higher incomes) profiting the most from the introduction of an LEM.

5.3 Implications for Utility

In the following, we analyze how the situation of the retailer changes if an LEM is deployed. Table 2 summarizes the most important facts. We find that the amount of electricity imported by the retailer increases slightly (by 2.4%). However, thanks to the fact that 75.4% of the consumption can be flexibilized through the LEM, energy procurement cost can be decreased by 14.6%. The flexible load requires only an under-proportional share of procurement costs of 70.7%. The substantial decrease in procurement costs is reflected in a substantial reduction of the fixed retail tariff for unresponsive loads by 75.5%, from 2.71 ct/kWh to 0.65 ct/kWh. Eventually, we find that the peak load increases by 26.7%, caused by the synchronization of HVAC systems by the price.

We finally investigate the market income, i.e. the income from importing at the wholesale market and re-selling at the LEM price. For that purpose, we analyze the market income for the week of the year experiencing the load peak (December 19 - 25, 2016) under different constraints, as documented by Table 3. If no constraint applies, the market income from

	No LEM	LEM
Energy procured [MWh]	4,607.646	4,716.519
Share of flexible load [%]	0.00	75.44
Procurement cost [USD]	125,063.16	106,850.66
Share of flexible procurement cost [%]	0.00	70.66
Average procurement price [USD/MWh]	27.14	22.66
Fixed retail rate [USD/kWh]	0.027	0.007
Total peak load [MW]	2.311	2.928

Table 2: Changes in key measures of retail business

Capacity constraint [MW]	Market income [USD]
∞	0.00
2.2	3.03
2.1	4.35
2.0	8.92
1.9	96.20
1.8	362.29
1.7	848.95
1.6	1439.96
1.5	2084.60

Table 3: Market income under different capacity constraints for December 19 - 25, 2016

congestion is 0 USD. However, with the constraint of the grid being increasingly tight, the market income increases to more than 2,000 USD. As explained for Fig. 6b, this market income should ideally be invested in grid expansion. However, if the role of the market operator is incorporated by the same entity which is responsible for grid enhancements, this might create an incentive to delay or under-size investment in the grid.

6 Conclusion and Discussion

In this paper, we evaluate the economic impact of LEMs on customers and the utility. In the following, we reflect on our contributions and how they are supported by our findings (Section 6.1). Furthermore, we discuss the implications of our findings for management and policy (Section 6.2) and provide a research outlook (Section 6.3).

6.1 Discussion of Contributions

6.1.1 Bidding Functions

In this article, we suggest an approach to derive bidding functions for time-interdependent electricity-based services. Previous work has used bids which did not reflect the opportunity cost of intertemporal dispatch [e.g. Ableitner et al., 2020], reduced optimal dispatch to a scheduling problem [Lin et al., 2015, Vrettos and Andersson, 2016], or approached it in a simplistic way [Hammerstrom, 2007, Widergren et al., 2014], without explicitly addressing the trade-off between comfort and cost. Instead, we define a net utility framework which combines the utility from consuming an electricity-based and time-interdependent service and the cost of electricity. We specify the framework for the service of temperature control, i.e. HVAC operations, and derive the willingness to pay based on the assumption of myopicity of consumers with regard to time-dependent but uncertain parameters. While this assumption might be simplifying, our case study demonstrates that substantial savings can still be realized. The resulting bidding function is a function of the temperature sensitivity, the comfort temperature of the customer, as well as the physical characteristics of the house and the HVAC system.

6.1.2 Welfare Effects

We furthermore use our framework in an extensive case study of 437 houses in a residential system to evaluate the welfare impacts of introducing an LEM. While such studies are common to evaluate the cost and benefits of investments on the transmission or wholesale level [e.g. CAISO, 2017, ENTSO-E, 2018], to the best of our knowledge, no such framework for the analysis of welfare effects exists for residential systems.

We first study the short-term effects of introducing an LEM. In general, for the unconstrained system, we find substantial welfare gains of 17,043 USD over the year studied which can mostly be explained by energy procurement cost savings. However, we also observe that they are largely driven by a few weeks with high price variance on the wholesale market. This indicates that systems which are exposed to higher wholesale market price variance profit more than systems which are not. As increased price variance is becoming more prevalent with higher shares of renewable energies, it is likely that LEMs may become more beneficial in the future. With regard to customers, we find that all households studied contribute to the welfare increase of the system although contributions are moderately unequally distributed. The most valuable 50% of customers realize 62.3% of welfare gains. Our case study furthermore quantifies the finding of the theoretical model with regard to the price-dependence of the internal temperature. We find that customers with a high comfort preference hardly experience a change in their mean temperature and only small temperature variations. In contrast, for customers with a low comfort preference, the internal temperature is on average $1.5°F$ closer to their comfort temperature. However, their temperature range can more than double if price variation in the LEM is high. Finally, customers save on average 14.6% of their utility bills when switching to an LEM. These savings can be explained by a more efficient dispatch of HVAC systems and a decrease in fixed retail rates for other, unresponsive loads. Customers which have high utility bills in the benchmark scenario profit the most in absolute terms. As bills can largely be explained by the floor size of the house, LEMs are potentially most beneficial for high income customers. This concern is reinforced by the finding that consumer surplus increase for such customers is over-proportional as compared to the actual welfare gain they provide to the system.

LEMs also have an impact on the long-term welfare of a system, in particular with regard to DER investment and grid enforcement. First, customers benefit from the introduction of an LEM by up to 120 USD per year. This provides an individual incentive to invest into the necessary infrastructure to flexibilize HVAC operations and connect it to the LEM. Second, LEMs enable active constraint management and, therefore, decrease congestion costs and necessary grid investments. This functionality cannot be provided by the introduction of real-time prices alone. In fact, real-time prices can aggravate capacity violations through effects of price-coordinated simultaneous dispatch. If no capacity constraint applies, real-time prices propagated through the LEM increase peak load by more than 10%. However, we also find that capacity constraint management is not perfect and depends on the quality of unresponsive load forecast and bids. Third, our results show that the marginal value of grid investment is consistently positive but not monotonously decreasing. This indicates that the marginal value of grid investment is highest in moderately constrained systems and declines substantially for only slightly constrained systems. Finally, we find that the marginal value of investment is often lower in an LEM than if a fixed retail rate applies. This suggests that optimal grid investment may be reduced if an LEM is deployed.

6.2 Managerial and Policy Implications

Our work has important implications for utilities and policy makers. First, LEMs enable the integration of flexible appliances into electricity markets and realize important value streams like energy procurement cost savings and managing capacity constraints. Furthermore, LEMs provide a large amount of controllability of local system load. This controllability can be leveraged to also provide other ancillary services of additional value, including avoiding coincident aggregate system peaks, providing resiliency services, or implement carbon pricing on a local level. Policy makers should study the cost and benefits of LEMs and the required infrastructure more closely and consider them in the relevant legislation. This concerns, for instance, the consideration of LEMs for generation and grid capacity planning or the determination of regulated tariffs.

Second, policy makers and utilities should study where the deployment of LEMs makes sense and which consumers and appliances should be included. Our analysis has shown that LEMs are particularly valuable in systems with a high wholesale market price variance and slightly constrained systems. Additional value might be realized through ancillary services, resiliency, and customer preference for a local market. Aggregate benefits must outweigh the cost associated with an LEM, most importantly the setup of the relevant information and communication technology as well as operations. With regard to customers and appliances, we have seen that some customers are more valuable than others and that targeting HVAC systems already flexibilizes 75% of energy consumption in our system. An effective LEM might therefore optimally only incorporate the most valuable customers with their most flexible and largest loads. However, the impacts on customers with less ability to flexibilize – e.g. because they do not own their house or apartment, have financial constraints, or whose dispatch is inelastic because of medical reasons – should be closely studied. While our case study has demonstrated that the flexibilization of HVAC load decreased the fixed retail rate for unresponsive load as well, an increase would also be possible.

Third, the deployment of LEMs requires a change in the responsibilities of current stakeholders and the detailing of market rules. One important question is who should incorporate the role of the market operator. Our analysis has shown that the income from market operations due to capacity constraints might incentivize under-investment in the grid. Also, artificial shortening of grid capacity in the market can reduce consumer surplus. To avoid this kind of behavior, the roles of the utility, the grid operator, and the retailer/load serving entity have to be well defined and it needs to be clarified how an abusive shortening of available grid capacity can be identified. Moreover, our analysis has shown that, by deploying an LEM, the procurement cost risk of the load serving entity will be reduced to the remaining 24.4% of unresponsive consumption. The flexible loads bear the wholesale market price risk directly and, depending on who incorporates the role of the market operator, only require the utility as a trader and/or grid provider. If the application of LEMs extend to an increasing share of the consumption, this can significantly change the role of utilities and retailers. Other important questions include the requirement of balancing, billing, or the recollection of fixed cost components like grid investment or maintenance.

Finally, automated bidding functions and LEMs can provide opportunities for innovative business models and new energy services. Our bidding functions can, for instance, be deployed as a basis for demand response decisions of load aggregators. An open LEM trading platform can further enable the participation of other agents such as aggregators which can act on the LEM on the customers' behalf. By doing so, they can provide additional value, first, to customers by providing insurance against volatile prices and, second, to the system by including more sophisticated bidding strategies with professional forecasting information. An LEM also incentives the flexibilization of load which could extend to smart appliances like electric vehicles, washing machines, dish washers, etc. Those appliances could be able to connect to the LEM and adjust their schedule optimally to the LEM price. Competitive advantages of suppliers could then be a particularly smart bidding algorithm of devices and technical adjustments which allow for more flexible operations of appliances (e.g. by interrupting and resuming operations in between).

6.3 Research Outlook

Our research provides multiple opportunities for future research. First of all, the analysis should be extended to other appliances, including batteries, electric vehicles, and water heaters, as well as local generation. This can enable the analysis of residential systems where heating and cooling loads are not the major end-uses of electricity. Second, other distribution systems should be explored. We expect the benefits of LEMs to differ depending on the wholesale market price variance, the correlation of price with residential load, and the available load portfolio. These characteristics can also have an important impact on the distribution of welfare effects among customers. Finally, while this work has assumed a time-discrete centralized double auction, other market designs are possible. Potential design aspects include uniform versus nodal pricing, central versus peer-to-peer trading, and a discrete versus a continuous orderbook. It should be explored which market design choice is most suitable and if additional services such as ramping or reserve capacity provision should be considered.

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7 Data

House data. To parametrize the houses, we randomly generate the floor area as well as temperature setpoints based on mean and standard deviation values as reported by US Energy Information Administration [2015]. Furthermore, to specify the thermal characteristics of the building stock, we rely on parameters as reported by the US Environmental Protection Agency [2001]. Those include, in particular, the rate at which air is exchanged with the exterior.

Residential load. In order to characterize residential base load, we took advantage of the smart meter data published by the Pecan Street data project [Inc. Pecan Street, 2019]. We chose a dataset from Austin as of 2016 for the reason that, during that time, the most year-long profiles of town homes and single-family homes were available.

Price data. We use Ercot price data. Austin is part of the Southern Hub [Ercot, 2018] and we use the historical price data for 2016 which is available for the Southern Hub in one hour intervals for Day-Ahead and 15 min intervals for the Real-Time market [Ercot, 2019].

Weather data. We use tmy3 data (722540TYA) for Austin [NREL, 2015].

Feeder. To represent the physical network, we choose the IEEE 123 feeder. It operates at a nominal voltage of 4.16 kV and represents a typical residential distribution grid. The feeder is connected to the overlaying voltage level by a single transformer where congestion potentially happens. The maximum hosting capacity is 3.6 MW. The feeder itself branches out, representing multiple streets with electrical loads connected to it in regular spaces. The feeder is represented in Fig. 9.

We further established a routine to populate the feeder to build an electrically balanced distribution system which is described by Section 8.

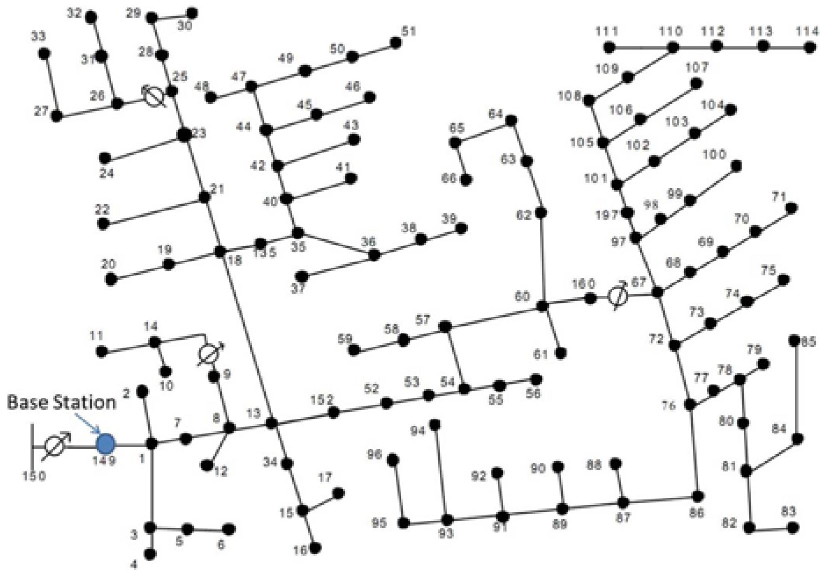


Figure 9: IEEE 123 feeder [IEEE Power Engineering Society, 2014]

8 Assembly of the Feeder

We accommodate 2,000 detached single-family houses for an initial hosting capacity analysis. For the technical characterization, we randomly classify houses as having one or two stories and, using a normal distribution, assign the floor area according to the survey results provided by the US Energy Information Administration [2015]. For the heating and cooling systems, we consider the most important technologies resistive heating, heat pump, and natural gas (for heating) as well as electric cooling with or without a heat pump (for cooling). For each feasible combination, we estimate the probabilities for a house operating a certain type of HVAC system as well as heating and cooling setpoints based on the data for the West South Central CENSUS region provided by the US Energy Information Administration [2015]. For the other technical characteristics, we use the recommendations for default parameters as provided by GridLAB-D [SLAC, 2020]. Table 4 and Table 5 summarize the parameters. Furthermore, we calculate natural air changes by hour for one and two story buildings in Zone 2 under normal conditions, using the ACH_{50} value specific to climate zone 2A and the LBL factor provided by US Environmental Protection Agency [2001].

We simulate electric load for the month of July, using GridLAB-D [SLAC, 2020]. We

Parameter	Average Value	Standard Deviation	Share
Floor size $[ft^2]$			
- 1 story	1976.96	47.05	72.09
- 2 stories	3202.38	226.41	27.91
Heating [%]			
- resistive			49.60
- heat pump			8.80
- natural gas			41.60
Cooling [%]			
- heat pump			83.04
- electric, no heat pump			16.07
Setpoints $[^\circ F]$			
- heating	70.77	2.93	
- cooling	73.70	3.33	

Table 4: Parametrization of detached single-family houses (West South Central)

HVAC System	1 story	2 stories
Electric cooling / NG heating	24.90%	9.64%
Electric cooling / resistive heating	29.69%	11.49%
Heat pump	17.50%	6.77%

Table 5: HVAC system statistics for housing types

determine the average power per house at the time of maximum load, the After Diversity Maximum Demand (ADMD) factor, which is 4.59 kW.

In a second step, we use this factor to randomly assign houses to nodes of the IEEE123 feeder while respecting the maximum hosting capacity of each node. The maximum hosting capacity of each node is provided by the specifications of the IEEE123 model [IEEE Power Engineering Society, 2014]. We determine the design capacity by multiplying this value with a safety factor of 0.66 and iteratively assign houses to nodes until none of the nodes is able to accommodate more load of the size described by the ADMD anymore. We find that 437 houses in total can be accommodated.

9 Detailed Results for Base Case

Table 6 presents key figures for each week of the simulation year 2016. The first three columns provide information on the energy procurement cost. The average procurement cost describe the average price which the utility pays for energy imported from the wholesale market, weighted by the energy consumed in each period. The maximum price is the maximum real-time price on the wholesale market during this week. The standard deviation of the wholesale market price reflects the price variability during the week. The last column provides the maximum feeder load, measured at the connection to the aggregate system level. The feeder load is important for the sizing of the transformer at the connection to the aggregate system level and a relevant cost driver.

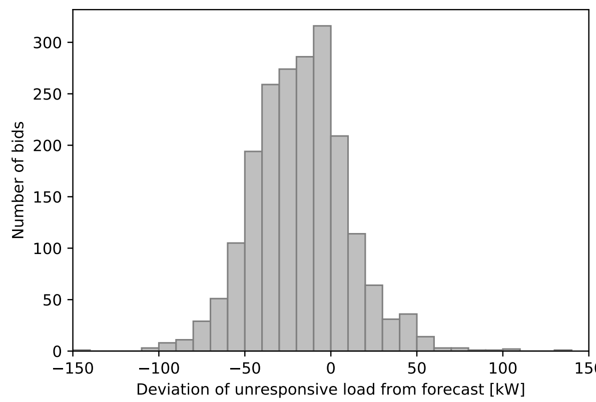
Week	**Av. procurement cost** $[USD/MWh]$	**Max. price** $[USD/MWh]$	**Standard deviation price** $[USD/MWh]$	**Max. load** $[MW]$
01/04 - 01/10	20.76	639.13	26.023	2.116
01/11 - 01/17	17.03	355.41	24.656	1.539
01/18 - 01/24	17.73	340.31	14.373	2.260
01/25 - 01/31	21.87	306.75	42.504	1.802
02/01 - 02/07	13.45	61.67	4.387	1.818
02/08 - 02/14	14.71	108.95	6.675	1.453
02/15 - 02/21	14.53	363.37	26.223	1.441
02/22 - 02/28	14.65	972.00	45.911	1.462
02/29 - 03/06	14.70	360.59	28.310	1.316
03/07 - 03/13	23.25	538.92	50.576	1.731
03/14 - 03/20	33.40	277.84	38.529	1.281
03/21 - 03/27	20.43	799.56	44.566	0.995
03/28 - 04/03	26.73	1772.80	136.637	1.430
04/04 - 04/10	17.47	350.21	20.482	1.241
04/11 - 04/17	19.48	211.40	16.814	1.484
04/18 - 04/24	32.33	235.26	28.651	1.369
04/25 - 05/01	32.79	1507.76	72.479	1.348
05/02 - 05/08	18.95	500.21	28.521	1.244
05/09 - 05/15	29.81	638.87	34.401	1.346
05/16 - 05/22	30.88	860.73	61.269	1.615
05/23 - 05/29	27.30	415.24	29.861	1.471
05/30 - 06/05	21.23	165.89	9.796	1.454
06/06 - 06/12	26.83	338.21	20.587	1.714
06/13 - 06/19	27.97	214.30	13.541	1.599

Week	**Av. procurement cost** $[USD/MWh]$	**Max. price** $[USD/MWh]$	**Standard deviation price** $[USD/MWh]$	**Max. load** $[MW]$
06/20 - 06/26	25.14	163.41	8.543	1.622
06/27 - 07/03	33.72	548.80	28.132	1.523
07/04 - 07/10	26.97	183.80	12.440	1.684
07/11 - 07/17	28.81	397.44	21.364	1.652
07/18 - 07/24	46.52	665.79	50.329	2.079
07/25 - 07/31	34.72	693.30	38.253	1.659
08/01 - 08/07	68.91	899.52	86.736	1.674
08/08 - 08/14	34.30	221.10	15.130	1.621
08/15 - 08/21	25.08	313.94	18.239	1.751
08/22 - 08/28	34.16	377.76	30.518	1.698
08/29 - 09/04	26.34	64.64	5.753	1.536
09/05 - 09/11	29.20	297.98	20.420	1.514
09/12 - 09/18	55.08	871.30	71.342	1.383
09/19 - 09/25	35.22	417.36	26.327	1.231
09/26 - 10/02	31.32	319.19	21.474	1.421
10/03 - 10/09	48.31	734.63	46.305	1.448
10/10 - 10/16	27.75	329.99	14.999	1.316
10/17 - 10/23	24.96	749.98	35.899	0.985
10/24 - 10/30	28.77	443.80	24.266	1.123
10/31 - 11/06	23.81	379.71	17.515	1.257
11/07 - 11/13	17.50	271.73	11.926	1.246
11/14 - 11/20	18.87	450.85	22.181	0.958
11/21 - 11/27	20.70	340.64	24.628	1.176
11/28 - 12/04	28.19	812.22	72.477	1.654
12/05 - 12/11	24.75	504.45	30.528	1.501
12/12 - 12/18	20.78	505.19	23.617	2.194
12/19 - 12/25	21.22	398.08	24.170	2.311

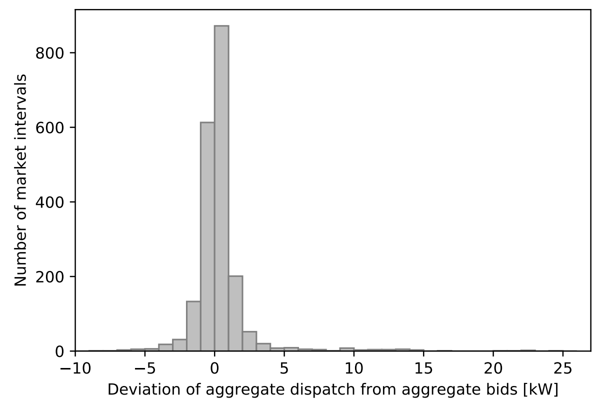
Table 6: Load and price summary for each week of the year

10 Further Analyses for Case Study

Figure 10: System deviations from market results (December 19-25, 2016)



(a) Distribution of forecast errors of unresponsive load



(b) Distribution of system imbalances caused by bid deviations

Fig. 10a illustrates forecasting errors with regard to the unresponsive load (by the retailer). The unresponsive load covers the unresponsive load share of customers as well as grid losses. Fig. 10a shows that the actual unresponsive load tends to be over-estimated. The maximum absolute deviation is up to 140 kW. Furthermore, system imbalances can occur if the actual dispatch of flexible appliances deviate from the bid placed in the LEM. Fig. 10b shows the distribution of such deviations, aggregated over all customers. While deviations exist, they are distributed close to zero, with a maximum net deviation of 22 kW. This is much less than the error introduced by the unresponsive load forecast and suggests that potential deviations are not or only slightly correlated across devices.

Table 7: OLS regression results: Determinants of utility bills under a fixed retail rate

	Dependent variable:
	(1)
const	2762.033***
	(148.145)
floor_area	0.072***
	(0.002)
α	491943.471***
	(22039.625)
β	-2886.618***
	(157.644)
GAS	-44.094***
	(3.372)
Observations	437
R^2	0.903
Adjusted R^2	0.902
Residual Std. Error	25.647(df = 432)
F Statistic	1002.101*** (df = 4.0; 432.0)
Note:	*p<0.1; **p<0.05; ***p<0.01

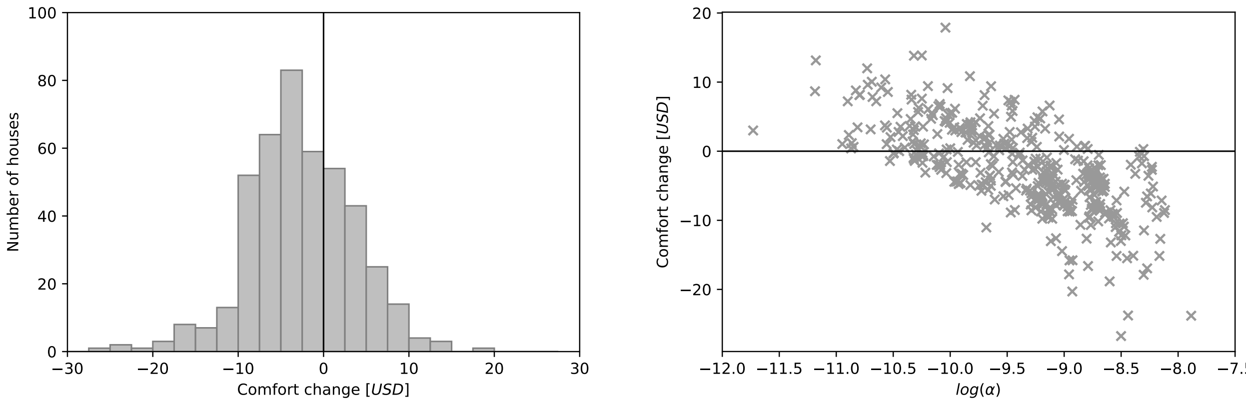
The table illustrates to which extent house-specific parameters explain the utility bills for electricity under a fixed retail rate. We find that bills are driven by the floor area, temperature sensitivity, thermal characteristics, and gas versus electricity-based heating.

Table 8: OLS regression results: Determinants of absolute bill savings with LEM deployment

	Dependent variable:	
	(1)	(2)
const	1.573	12.018***
	(1.043)	(2.151)
fixed_cost_HVAC	0.184***	0.173***
	(0.004)	(0.003)
share_unresp		0.277***
		(0.012)
corr_HVAC_WS		-168.208***
		(25.300)
GAS		-5.867***
		(0.858)
Observations	437	437
R^2	0.794	0.923
Adjusted R^2	0.794	0.923
Residual Std. Error	7.683(df = 435)	4.707(df = 432)
F Statistic	1681.540*** (df = 1.0; 435.0)	1301.690*** (df = 4.0; 432.0)
Note:		*p<0.1; **p<0.05; ***p<0.01

The table illustrates to which extent house-specific parameters explain the utility bill savings when houses participate in an LEM. We find that utility bills under a fixed retail rate explain 79% of the variance in savings, i.e. households with large bills are likely to save more. Additional significant factors are the share of unresponsive load, the correlation of HVAC dispatch and WS prices under a fixed retail rate, and the existence of a heating system.

Figure 11: Welfare changes attributed to comfort change



(a) Histogram of comfort changes by household

(b) House-wise comfort changes by comfort parameter

Fig. 11a displays the distribution of welfare changes attributed to internal temperature changes. This is detailed by Fig. 11b which additionally shows the comfort change as a function of the comfort parameter α. While households with a low comfort preference largely experience positive comfort changes, we observe a deterioration in comfort in particular for households with high comfort preferences despite only small temperature changes indicated by Fig. 7a.

Figure 12: Distribution of welfare changes of houses

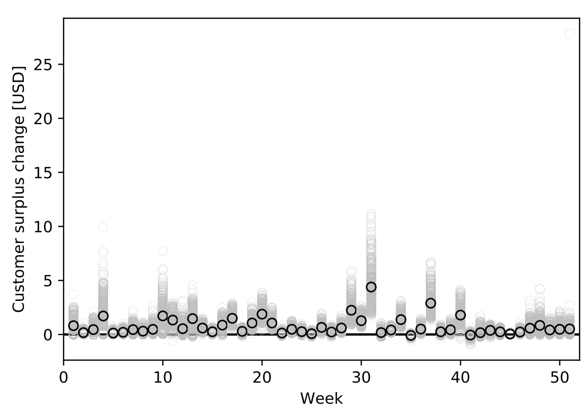


Fig. 12 further disentangles the consumer surplus changes for each week. Each grey circle represents an individual house during a specific week, the black circle represents the mean consumer surplus change. We find that changes differ throughout the year but can be high for some weeks and some customers both of which drive overall welfare gain.