



Research paper

A hybrid electricity pricing mechanism for joint system optimization and social acceptance within energy communities

Victor M.J.J. Reijnders^{*}, Marco E.T. Gerards, Johann L. Hurink

Faculty of EEMCS, University of Twente, Drienerolaan 5, Enschede, The Netherlands

ARTICLE INFO

Article history:

Received 8 July 2022

Received in revised form 21 September 2022

Accepted 2 October 2022

Available online xxxx

Dataset link: <https://doi.org/10.4121/14447257.v1>

Keywords:

Electricity pricing mechanism

Load-dependent pricing

Piecewise linear cost

Social acceptance

Peak shaving

ABSTRACT

This article presents a framework for local electricity pricing mechanisms for households designed for social acceptance. The optimization goal of the mechanisms is to flatten the neighborhood electricity profile. The motivation and need for such mechanisms result from the expectation that the energy transition leads to high peaks in the distribution grid, both in electricity consumption and renewable generation, posing a significant challenge to these grids.

Following the literature, quadratic cost functions have the potential to achieve the envisioned system optimization. However, their drawback is that consumers find the resulting pricing mechanisms too complicated and are generally not willing to participate in systems offering such prices. In contrast, the simpler pricing mechanisms currently used in practice are socially accepted. However, these mechanisms lack sufficient incentive to reduce electricity peaks in the distribution grids.

Our approach is to combine these concepts in a hybrid pricing mechanism for local energy communities, using a piecewise linear cost function, that approximates a quadratic function. The resulting pricing mechanism is evaluated in a field test, and, based on the feedback of participating consumers and other criteria defined in literature, we can conclude that the proposed mechanism is socially accepted.

In the implementation of this hybrid pricing mechanism, its performance can be improved such that it obtains results comparable to those of quadratic cost functions. Based on these findings, a detailed numerical evaluation, and the results from the field test, we conclude that the presented pricing mechanism has the potential for being used in practice.

© 2022 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Traditionally, the electricity system was built to distribute electricity from centralized power generation to households. However, nowadays, more and more renewable energy is injected into this system at a decentralized level. This renewable generation has a highly intermittent character and creates enormous peaks in the supply of electricity. Furthermore, electricity loads will also increase drastically and place an additional burden on the distribution grids due to the current electrification. In particular, the charging of electric vehicles (EVs) may lead to immense peaks in the local part of the electricity system due to their synchronous occurrence. However, the distribution network is not well prepared for such increased peak demands and intermittent generation. Therefore, we need to either invest heavily in upgrading the network, or reduce the expected peaks by spreading the loads responsible for these peaks more evenly, for example,

by demand-side management or demand response (Siano, 2014). One demand response method for reducing peaks in electricity consumption is to use dynamic electricity prices, e.g., a time-based pricing mechanism with flexible prices. The resulting price variations may encourage (residential) consumers to modify (the timing of) their electricity usage, thereby unburdening the grid. In addition, smart appliances may automatically react to such prices without reducing the comfort of the consumer (see, e.g., Gerards et al., 2015).

At a single household level, the available smart appliances generally do not provide sufficient flexibility for completely flattening the consumption profile of that household. Therefore, we focus on flattening the profile of a group of households in a specific part of the grid: a neighborhood or local energy community. The advantage is that now the system can support the households in flattening their *combined* peaks.

A further reason to focus on the neighborhood level is that people are in general more eager to participate in initiatives when there is a local incentive together with social cohesion (Naus

^{*} Corresponding author.

E-mail addresses: v.m.j.j.reijnders@utwente.nl (V.M.J.J. Reijnders), m.e.t.gerards@utwente.nl (M.E.T. Gerards), j.l.hurink@utwente.nl (J.L. Hurink).

Nomenclature

\mathcal{H}	Set of households h
\mathcal{T}	Set of time intervals t
e_t^h	Electricity consumption in kWh of household h in time interval t
E_t	Vector of electricity consumption e_t^h for all households h in time interval t
$p_t^h(x)$	Function that gives the price in € per kWh for household h in time interval t
S_t	Total electricity consumption e_t^h of all households h in time interval t
$c_t^h(x)$	Function that gives the cost in € of household h in time interval t
$C_t(x)$	Function that gives the total costs in € of all households h in time interval t
m	Number of pieces used in the piecewise function
a_i	Price of additional used or produced electricity in € per kWh of piece i
b_i	Breakpoints of the piecewise function in kWh of piece i

et al., 2015). In addition, to achieve the required amount of flexibility, the consumers have to be convinced to enable this flexibility to be used for the overall neighborhood goals (Goulden et al., 2014). Thus, to ensure consumer participation in a pricing mechanism, social acceptance needs to be considered as well. However, this important aspect is often ignored in research (Sovacool, 2014).

Literature in this direction distinguishes two branches of research. Firstly, some studies focus on simple mechanisms for single households where the consumer is only a price taker (see, e.g., Herter, 2007; Celebi and Fuller, 2007; Wesseh and Lin, 2022). These mechanisms do not always solve the problems in the local grid, or could even worsen them (see, e.g., Mohsenian-Rad and Leon-Garcia, 2010). Secondly, there are studies that focus on more complex mechanisms incorporating multiple households, where consumers are both price takers and makers. However, these mechanisms make it complicated for consumers to determine the prices and to determine how to adapt their behavior (see, e.g., Woo, 1990; Wang et al., 2022, or Aljohani et al., 2021). Taking into account that the participation of the consumers is a crucial element in implementing the envisioned mechanisms, the approach we propose takes the viewpoints of consumers on such mechanisms as a starting point. Based on the aspects mentioned above, our aim is to present a hybrid pricing mechanism for a neighborhood behind one medium-to-low-voltage (MV/LV) transformer, combining unburdening the grid by lowering the electricity peaks, and social acceptance. For this, the goal is to ensure that the consumers understand and accept the underlying concept of the pricing mechanism. In this paper, we present a framework consisting of multiple similar neighborhood pricing mechanisms all supporting this two-fold aim, where the electricity price for each household depends on the total load at the transformer. This implies that all neighborhood inhabitants pay the same price per unit of electricity while these prices can differ throughout the day.

Summarizing, the main contributions of this article are:

- An analysis of current pricing mechanisms (from literature and used in practice) for both system optimization and social acceptance, discussing their advantages and disadvantages.

- A framework for creating hybrid pricing mechanisms for a neighborhood or energy community that perform well on both system optimization and social acceptance, based on a piecewise linear approximation of a quadratic cost function.
- A technique to speed up the convergence of the proposed mechanisms when used in optimization algorithms.
- An extensive numerical evaluation of the proposed hybrid pricing mechanism compared to other pricing mechanisms, based on simulations and a field test within an energy community.

This paper is organized as follows. First, in Sections 2 and 3, we discuss existing concepts of system-based pricing mechanisms and socially acceptable pricing mechanisms, respectively. This is followed by the introduction of our hybrid pricing mechanism in Section 4 and the implementation of the pricing mechanism in an optimization algorithm in Section 5. Then, in Section 6, we evaluate and compare the performance of the hybrid pricing mechanism. This paper is concluded in Section 7, where also recommendations for further research are given. These results are an extension of the work presented in Reijnders et al. (2020a).

2. System-based pricing mechanisms

In this section, we describe the formal setting and the considered pricing mechanisms. Given are a set $\mathcal{H} = \{1, \dots, H\}$ of households in a neighborhood (a group of households connected to the same part of the grid) and a time horizon divided into a set $\mathcal{T} = \{1, \dots, T\}$ of consecutive time intervals. Let $E_t = (e_t^1, \dots, e_t^H)$ denote the electricity demand of the households in time interval t , where e_t^h is the electricity consumption of household h in time interval t in kWh.

The general model for the costs is given by a price function $p_t^h(E_t)$ that specifies the price per kWh depending on the consumption vector E_t for each time interval $t \in \mathcal{T}$ and each household $h \in \mathcal{H}$. This allows for the modeling of a variety of different price functions, such as, e.g., a constant price, a time-dependent price, but also a price that depends on the load e_t^h of household h , or on the sum $S_t = \sum_h e_t^h$ of the loads of all households in interval t . Based on this price function, the cost function for a household results from multiplying the consumption of a household with the price function:

$$c_t^h(E_t) = p_t^h(E_t)e_t^h.$$

The total costs of all households in time interval t then can be expressed as $C_t(E_t) = \sum_h c_t^h(E_t) = \sum_h p_t^h(E_t)e_t^h$. As these costs heavily depend on the price function $p_t^h(E_t)$, we discuss some possible design choices for this function in more detail.

Under static time-of-use (ToU) pricing, all prices are set beforehand, so $p_t^h(E_t) = p_t$. This type of pricing gives consumers certainty about the price they have to pay, but this does not incentivize them to avoid higher peaks caused by synchronized loads (Mohsenian-Rad and Leon-Garcia, 2010). An alternative is to have dynamic prices, where these prices are not set up front but depend on the electricity load. There are multiple choices for such dynamic pricing strategies. For example, they may depend on the load of the individual household ($p_t^h(E_t) = p_t^h(e_t^h)$), or on the load of the neighborhood ($p_t^h(E_t) = p_t(S_t)$). An important reason to use dynamic prices is that they may provide incentives to alleviate congestion on the grid (Joskow and Wolfram, 2012).

These dynamic prices $p_t^h(E_t)$ may be set beforehand (a certain amount of hours ahead of time), making the resulting cost more predictable and, therefore, more socially accepted by the consumers. Alternatively, the price could be set in real-time, taking into account more actual information, e.g., on the congestion. However, this makes it more difficult for consumers to determine the price they need to pay in advance.

If pricing mechanisms aim to support a system-based perspective, the goal of the system has to be defined first. In this article, we already mentioned that we want to flatten the electricity profile, so the system goal is peak minimization. Minimizing the peaks improves the power quality, and minimizes the electricity transport losses (Siano, 2014). As the losses cause depreciation of the assets in the grid (e.g., the cables and the transformer), lowering these losses can result in a prolonged lifetime of these assets (Groen, 2018). Similarly, with lower peaks, investments needed to upgrade the assets can be deferred (Siano, 2014). Furthermore, peak demands are covered mainly by more polluting energy sources, such as natural gas and oil (European Commission, 2008; Stoll et al., 2014). Therefore, by avoiding high peaks, we reduce the CO₂ output.

With the total neighborhood load S_t , this goal can be expressed, similar as done in Gerards et al. (2015), by

$$\begin{aligned} \min_{e_t^h} \quad & \sum_t (S_t)^2, & (1) \\ \text{s.t.} \quad & S_t = \sum_{h \in \mathcal{H}} e_t^h, & \forall t \in \mathcal{T} \\ & e_t^{h,\min} \leq e_t^h \leq e_t^{h,\max}, & \forall t \in \mathcal{T}, \forall h \in \mathcal{H} \end{aligned}$$

where $e_t^{h,\min}$ and $e_t^{h,\max}$ are the permitted range for the energy consumption that each household h can attain, given their flexible loads. As the focus of this paper is not to create a mathematical model of the flexibility in a household, the values of $e_t^{h,\min}$ and $e_t^{h,\max}$ are considered to be known.

Note that by squaring loads, the highest peaks get penalized the most. Optimizing over this goal results in the flattest electricity profile. To reach the objective (1), a natural choice is to have the costs related to the square of the load, i.e., to have $C_t(E_t) \approx (S_t)^2$. Besides corresponding to the objective, this choice is also motivated by the marginal costs of electricity in peak hours scaling quadratically with respect to the load (Tushar and Assi, 2017). If we furthermore assume that the price functions are independent of the households, meaning that each household is given the same price of electricity, we get $c_t^h(E_t) = p_t(E_t)e_t^h$. This results in a total cost of:

$$\begin{aligned} C_t(E_t) &= \sum_h c_t^h(E_t) \\ &= \sum_h p_t(E_t)e_t^h \\ &= p_t(E_t)S_t. \end{aligned}$$

Since we aim for $C_t(E_t) \approx (S_t)^2$, the price function has to fulfill $p_t(E_t) \approx S_t$. This leads to costs for an individual household that are quadratic with respect to their consumption:

$$c_t^h(E_t) = p_t(E_t)e_t^h \approx S_t e_t^h = (e_t^h)^2 + e_t^h \left(\sum_{i \in \mathcal{H} \setminus \{h\}} e_t^i \right).$$

Note that this may lead to costs for delivering electricity back to the grid. However, from a network perspective, this makes sense, especially when the pricing mechanism aims to lower the peaks, also those arising from energy production.

Quadratic costs have already shown their effectiveness in the literature:

- In Kim et al. (2013) a linear wholesale price is used, which gives a quadratic cost for the consumers, that they can use to optimize over.
- In Rajasekhar et al. (2019) quadratic costs are assigned to the “transformer”-aggregator, which transfers the costs to the consumers.

- In Morstyn and McCulloch (2018) losses are minimized as the central objective, which is quadratic in the consumption. The consumers then have approximately linear costs, and the resulting problem is solved using ADMM.
- In Morstyn et al. (2018) quadratic costs are assumed for an aggregator, and these costs are minimized while charging EVs.
- In Xia et al. (2022) a quadratic cost function is used to maximize the welfare of customers in a peer-to-peer trading model.

Next to the above, other pricing mechanisms supporting different system objectives have been used in literature:

- In Sharma and Abhyankar (2017) the Shapley value is used to attribute the losses.
- In Reijnders et al. (2019) prices are created based on the Shapley value to minimize losses based on households getting an average location in the grid.
- In Li et al. (2011) real-time pricing is used such that individual best responses coincide with the system objective.
- In Ibars et al. (2010) a congestion game is presented to come to dynamic prices for the grid.
- In Fang et al. (2022) different locational marginal prices based on carbon-related costs are used to lower the carbon emissions.

Pricing mechanisms, such as those mentioned above, aim to steer an electricity profile of a household or neighborhood to a best possible solution for a given goal in an iterative way. The reason that this best solution is achieved in an iterative fashion and cannot be achieved in one step is that the individual households do not know beforehand what the values of the neighborhood loads E_t or the total neighborhood load S_t are, as it is unknown to the individual households how the other households respond to the prices. Based on an initial prediction of the electricity profile S_t of the neighborhood, individual households get price information and utilize their flexibility accordingly. However, this may lead to an overshoot or undershoot in some time intervals. Therefore, updated prices based on the planned electricity profiles are sent to the households. This is iteratively done until no, or only minor, changes in the profiles are made (see Fig. 1 for a schematic overview), meaning that the process has converged. This convergence process typically takes seconds, or at most a few minutes. Only then, the definitive prices for the coming time interval(s) are set. Depending on the chosen method and the pricing mechanisms, the electricity profile may come close to or precisely be the optimal profile.

Although the introduced linear prices, and thus the quadratic costs, have advantages from a system-based perspective, there are issues with these prices on a social level. For example, it is difficult to convince people to participate in these pricing mechanisms due to their unpredictable and complex nature. When only focusing on technocratic aspects of mechanisms (i.e., technological experts deciding on bureaucracy), consumers likely will not accept a change towards such new pricing mechanisms, especially when these changes are mandatory. Examples of rejections of forced technological solutions can be found, e.g., in the roll-out of Smart Meters in the Netherlands, which only considered technical and commercial aspects. As a result, a lot of resistance still exists (Hoenkamp et al., 2011). Another example can be found in the forced Smart Metering and Time-of-Use prices in Australia, where people heavily resisted this change (Global Smart Grid Federation, 2012).

A further aspect that makes people hesitant to use linear prices, is that the prices continually change over time, and even minor differences in the load may lead to substantial differences

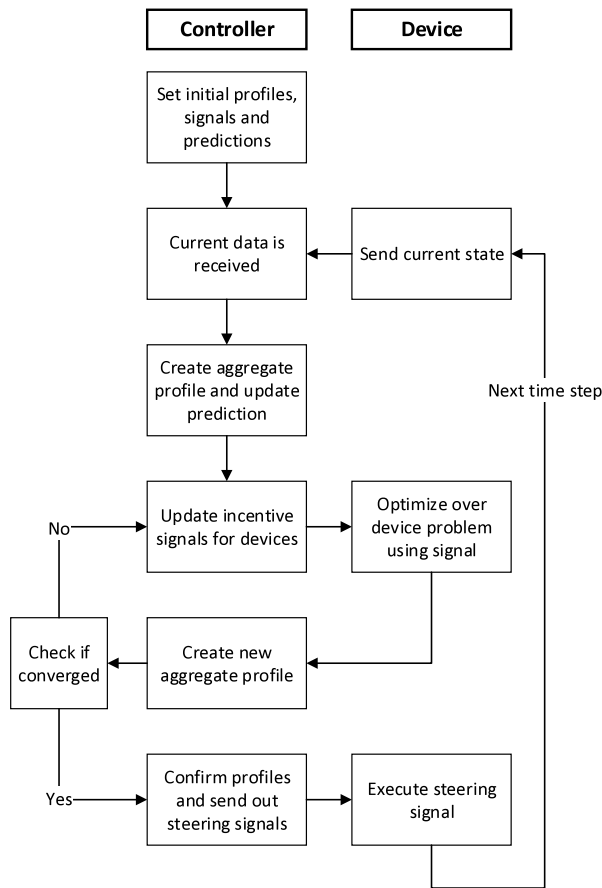


Fig. 1. Flow of iterative energy management algorithms.

in the costs. In Neuteleers et al. (2017), the unpredictability of the prices for consumers was seen as a significant point for people judging these prices as unfair. However, the fairness of prices as perceived by the consumers is seen as an essential criterion for regulators (Jones and Mann, 2001). Therefore, there is a need for pricing mechanisms that take fairness into account as well as acceptance by consumers.

3. Socially-acceptable pricing mechanisms

As concluded in the previous section, it is crucial to consider how consumers perceive pricing mechanisms. When the mechanism is too complicated, or it is unclear to the consumers how much they have to pay, it will be difficult to convince them to use these mechanisms (Neuteleers et al., 2017; Dütschke and Paetz, 2013). Examples can be seen in the difficulties for energy research projects to get participants. Within the e-Balance project, it was noted that the difficulty in understanding both the energy system and usage of smart appliances led to reduced cooperation of users (Piotrowski et al., 2018). Furthermore, the final document of JEM 2.0 (JEM 2.0 consortium, 2018) reports that it was challenging to have consumers participating in the project when the financial aspects were not directly apparent (in their case, the prices were dynamically updated via the Dutch spot market prices).

Looking at current practice, the implemented models used for electricity pricing are often simple. The price of electricity is offered as a constant price (or perhaps as a static Time-Of-Use price). For the Netherlands, even the network costs are constant (Autoriteit Consument en Markt, 2016). Consumers rate

these constant prices fairer than a price that is more complex (Neuteleers et al., 2017). However, these ‘simple’ prices do not reflect the actual costs occurring in the system. Additionally, the resulting network costs will increase drastically with the expected increase in loads, showing that the current pricing mechanisms are not future-proof.

Nevertheless, there are already examples of socially acceptable pricing mechanisms that provide some incentive to unburden the grid, e.g., time-dependent constant prices (Time-Of-Use prices). Furthermore, an often-used example is peak pricing, where a grid operator can raise the price of electricity a few times a month or year when the grid is extremely congested. Practice shows that these schemes can reduce peaks (Stromback et al., 2011). However, these mechanisms also have their disadvantages, as they may even increase the synchronization of loads, e.g., for charging electric vehicles, thereby creating large peaks in the grid (McKenna and Keane, 2014; Mohsenian-Rad and Leon-Garcia, 2010).

Introducing thresholds that require either no action from the consumer, or require a lot of flexibility, such as those resulting from peak pricing, can lead to undesirable behavior for the network. This behavior was observed in a previously proposed price model from the Distribution System Operators (DSOs) in the Netherlands and Belgium. Here, the consumer can choose a specific contractual capacity (lower than the maximum physical capacity) in advance. If the consumer exceeds this contractual limit, they pay a fee proportional to the energy (in kWh) exceeding the limit (Halkin, 2019). Even though this model encourages consumers to stay within their contractual capacity, it does not support the previously-mentioned goal of unburdening the grid, as it may still be possible that all consumers are just below their maximum contracted capacity but jointly congest the network. Moreover, the scheme does not support neighbors who “cancel out” their joint peaks, e.g., when one of the neighbors has a large PV installation and the other has a large load during the daytime. A solution for this is to consider a neighborhood as a whole.

A further disadvantage of the model mentioned above is that a consumer with an electricity profile, where the load exceeds the contractual limit by an amount \bar{e} in two intervals, is penalized by the same amount as a consumer who exceeds the limit during one interval by $2\bar{e}$. This is because the fee is proportional to the energy and not to the maximum power. However, the latter consumer has a higher probability of causing a larger peak, implying that the model does not discourage having one large peak instead of multiple smaller peaks.

Based on the considerations in this section, we present a hybrid pricing mechanism in the next section that addresses the stated issues.

4. Hybrid pricing mechanism

4.1. Definition

The hybrid pricing mechanism we propose in this work combines the system-oriented and the socially-acceptable regimes. It is based on prices that grow linearly with the neighborhood load S_t , implying quadratic costs. More concrete, the price for each additionally consumed or produced kWh is chosen as a staircase function (see the blue solid line in Fig. 2), which represents a piecewise linear cost function.

Mathematically, this is expressed as

$$p_t(S_t) = \begin{cases} a_1, & \text{for } S_t \leq b_1, \\ a_2, & \text{for } b_1 < S_t \leq b_2, \\ \vdots & \vdots \\ a_{m-1}, & \text{for } b_{m-2} < S_t \leq b_{m-1}, \\ a_m, & \text{for } b_{m-1} < S_t, \end{cases} \quad (2)$$

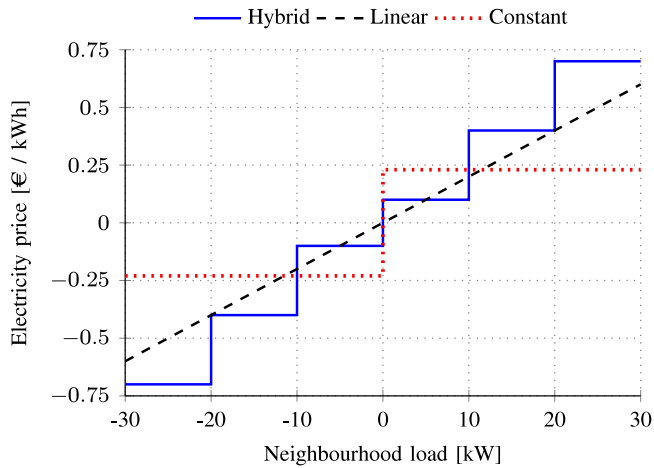


Fig. 2. An example of the proposed hybrid price function p_t compared to a linear and a constant price function.

where m is the number of pieces of the price function, b_1, \dots, b_{m-1} represent the breakpoints at which the electricity price changes, and a_1, \dots, a_m are the corresponding prices per kWh for the additional consumed or produced electricity in that piece. Here, we assume that $a_1 \leq \dots \leq a_m$ to ensure the cost function is convex. W.l.o.g., we assume that one of the breakpoints b_1, \dots, b_{m-1} is 0 and we let b_j be this breakpoint, i.e., $b_j = 0$. Then, for a positive load \bar{S}_t , given that $b_{j-1} < \bar{S}_t \leq b_j$, the cost is calculated as

$$c_t(\bar{S}_t) = \sum_{k=i+1}^{j-1} a_k(b_k - b_{k-1}) + a_j(\bar{S}_t - b_{j-1}). \quad (3)$$

For a negative load, a corresponding formulation can be given. This pricing mechanism can be compared to tax brackets in which higher incomes are taxed progressively higher (Pomerleau, 2014). By choosing the price functions in this way, we get a pricing mechanism that provides an incentive to reduce the peaks. From a system perspective, optimization based on this function still leads to an approximation of the profile we would get with the quadratic cost function, albeit with slower convergence (i.e., more iterations in Fig. 1) as it only approximates the quadratic function (see Fig. 3). Note that transforming a pricing mechanism into a piecewise linear price is not a new principle and has been shown to work well (see, e.g., Li, 2008 or Park et al., 2020). Also, in other fields, similar mechanisms that use such piecewise linear functions are in place, like, e.g., the aforementioned progressive tax schemes (Blum and Kalven, 1952).

From a social perspective, this mechanism has advantages, as this mechanism can be seen as a combination of a transport tariff with peak pricing, which consumers assess as more fair than a flat rate or a complex pricing mechanism (Neuteleers et al., 2017). On the other hand, a study carried out in Great Britain indicates that consumers are still somewhat hesitant to accept time-of-use tariffs, especially when these tariffs are dynamic (Fell et al., 2015).

Moreover, Naus et al. (2015) report that people are more attracted to local solutions where social cohesion plays a role. They also found that the financial schemes need to make sense to the consumers and, therefore, preferably have only a few different tariff blocks per day. The pricing mechanism proposed in this article stems from the spatial proximity of the involved consumers, as the mechanism depends on the collective load of the set of households in a neighborhood. Furthermore, there are only a few different tariffs per day because, even though the neighborhood load S_t changes continuously over time, only when

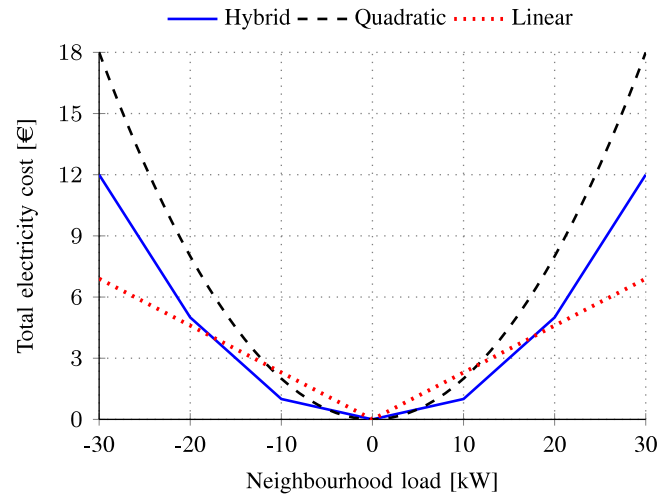


Fig. 3. An example of the proposed hybrid cost function c_t compared to a quadratic and a linear cost function.

S_t crosses a boundary b_j , the consumers experience a different price. This indicates that the proposed pricing mechanism represents a desired financial scheme such as characterized in Naus et al. (2015).

Note that in this article, we mainly propose a framework for setting up a pricing mechanism. To implement the mechanism in a community, it needs to be tailored to the neighborhood, as can be seen in the specific case of GridFlex Heeten (see Reijnders et al., 2020b).

4.2. Economic effects

One of the goals of the pricing mechanism proposed in this paper is to give the community the possibility to obtain savings on their electricity bills by using their flexibility. To implement such a mechanism, the energy community can take the role of an aggregator (or contract an existing aggregator) to supply their energy. The aggregator could then negotiate for compensation by the DSO when the community is using the network to a lesser extent and creating fewer peaks. This results in prolonging the lifetime of the assets, which is beneficial for the DSO. Furthermore, the aggregator also could get lower rates for supplying energy, as the electrical load of the community is more predictable and flatter. As already mentioned in Section 2, a flatter profile is better for a supplier, as the cost of generators rises quadratically with the load.

Another option for the aggregator is to set the prices a_i depending on the electricity market. This may be done by changing the prices within a billing period, or even daily, to better reflect the supply and demand of electricity. However, this could also lead to lower acceptance of the pricing mechanism due to the uncertainty in the costs (Neuteleers et al., 2017).

While the pricing mechanism proposed in this article is developed for residential users, including commercial and industrial users is also a possibility. However, when communities consist of different types of consumers, the prices must be set carefully to ensure that these tariffs are fair for all consumers. An alternative in such a situation would be to split up these different types of consumers in terms of pricing, while they still jointly try to flatten the peaks of their network.

The obtained savings of the energy community can either be used for a communal goal (e.g., acquiring communal PV panels or improving a neighborhood playground) or can be settled directly with the inhabitants (e.g., pro rata, or equally shared) as a deposit

for the next billing period. An example of how a community could deal with this can be found in [Reijnders et al. \(2020b\)](#), where the participants of the GridFlex Heeten project chose to use their savings to buy a defibrillator for their neighborhood and train several inhabitants in using it. More information on this project is given in the next section.

4.3. Field test results

The pricing mechanism proposed in this article was implemented within the GridFlex Heeten project. In this project, the partners aim to reduce peaks and better match supply and demand by innovative pricing mechanisms in combination with local energy production and storage ([Reijnders et al., 2018](#)). All households behind one transformer in a neighborhood in Heeten, the Netherlands, were outfitted with a home energy management system (HEMS). Additionally, batteries were installed in some of the households. The goal of this neighborhood was to keep the load at the neighborhood transformer low. The used incentive for this was the hybrid pricing mechanism, where their savings were used for a communal goal ([GridFlex Consortium, 2020](#)). This goal was chosen by the participants during co-creation sessions.

In the used implementation of the hybrid pricing mechanism, five different pieces were used in the cost function (so $m = 5$ in (2)). The participants of the project received this price information on a mobile app. Flyers explaining the mechanism were distributed to the participants, and information meetings were held to clarify the concepts. To test the understanding of consumers concerning the proposed pricing mechanism, interactive workshops with several consumers participating in the project were conducted. During these workshops, the participants indicated that they understood the idea behind the mechanism and found it suitable. These co-creation sessions were also used to tailor the mechanism and goal to the community and to increase the acceptance and effectiveness of the pricing mechanism.

4.4. Limit behavior

If sufficient flexibility is available, ideally, a pricing mechanism would stimulate consumers to create a perfectly flat electricity profile. If all customers do this, the resulting flat profile coincides with the global optimal solution of (1). In the case of the proposed pricing mechanism, it is optimal to keep the neighborhood load in that piece of the price function where $|a_i|$ is the smallest. In the example from [Fig. 3](#), this is between -10 and 10 kW. When the neighborhood load is at this global optimum, individual consumers have no incentive to change their electricity profile, as changing the load such that it would no longer be in the same piece would increase the price and, as a result, the costs for the consumer. Therefore, the only price-neutral change of the load would be within its piece. With sufficient flexibility, all time intervals have the same price, so there is no incentive to shift load between intervals. This means there is no incentive for any individual consumer to change their electricity profile, i.e., this solution is a Nash equilibrium ([Nash, 1950](#)). So with this hybrid pricing mechanism, if sufficient flexibility is present for all customers, the global optimum coincides with an optimal solution for the individual consumers, and a flat profile is obtained.

5. Implementation

The pricing mechanism specified in the previous section performs well on both social acceptance and peak shaving. To use such a pricing mechanism in a neighborhood, the inhabitants have to enable their flexibility and either activate their devices manually, or give a home energy management system (HEMS)

the possibility to automatically steer their devices. For the latter case, the pricing mechanism needs to be integrated into an algorithm. This algorithm can then, in an iterative way, determine the optimal electricity profile as already illustrated in [Fig. 1](#).

As mentioned in the previous section, a naive implementation of the hybrid pricing mechanism converges slower to the optimal electricity profile than when using a quadratic cost function. However, to speed up the convergence and have it on par with that of a quadratic cost function, we can use a result from [Schoot Uiterkamp et al. \(2022\)](#). For this, we add a small quadratic term to the cost function for the computation of the optimal solution. Note that this term only improves the convergence speed, but the solution of the optimization and, therefore, the actual costs for the consumers remain the same.

The motivation for adding this term is based on Section 5.2 of [Schoot Uiterkamp et al. \(2022\)](#). This article shows that the operation of storage devices in energy systems is an instance of a specific class of optimization problems, as long as the cost function is convex. The results in our article apply to that class of optimization problems, as our cost function c_t from (3) is convex by design. The other restrictions on the objective, constraints, and variables in [Schoot Uiterkamp et al. \(2022\)](#) also align with the optimization problem discussed in our article.

Adding a fixed quadratic part to each linear piece of the hybrid cost function c_t makes it strictly convex and even strongly convex, which we use later. Formally, for the strictly convex cost function c_t^* we get $c_t^*(\tilde{S}_t) = c_t(\tilde{S}_t) + \epsilon \tilde{S}_t^2$, with $0 < \epsilon \ll 1$. Corollary 3 of [Schoot Uiterkamp et al. \(2022\)](#) states that for the given problem, the optimal solution of the strictly convex cost function c_t^* is also optimal for the convex cost function c_t . Thus we can replace c_t by c_t^* during the optimization process to obtain the optimal solution with fast convergence. Fast convergence here means we can get a guaranteed linear convergence, which we will discuss further in the next section. With the added term, we now have a pricing mechanism that performs well in optimization, both in convergence speed and solution quality, and also in social acceptance.

6. Numerical evaluation

In the previous sections, we presented a hybrid pricing mechanism aimed at social acceptance, which also performs well in optimization. To analyze its potential compared to other types of pricing mechanisms and steering methods, we use a numerical evaluation, where we simulate a neighborhood with a HEMS and a battery in each house. Furthermore, we present an analysis of the performance of the hybrid pricing mechanism in the GridFlex Heeten project. In both cases, the goal of the households is to minimize the total electricity cost of the neighborhood with respect to a given cost function. This means that the households do not optimize their individual costs. The choice to optimize on a neighborhood level was made for several reasons. Firstly, as mentioned before, by having social cohesion on a local level and working towards a common goal, consumers are more eager to participate ([Naus et al., 2015](#)). Secondly, the energy management system is easier to implement on a neighborhood level, also resulting in faster convergence. Thirdly, as mentioned in Section 4.4, with sufficient flexibility, the neighborhood optimum coincides with the optimal solution for the individual consumers (a Nash equilibrium).

Our aim is to investigate if minimizing the costs also leads to minimizing the system-objective, namely minimizing the peaks (see (1)).

In the evaluation, we compare the effects of four types of steering methods:

- Using no steering (NO)
- Minimization of a quadratic cost function (QC)
- Minimization of the hybrid pricing mechanism (HPM)
- Using profile steering (PS)

When no steering signals (NO) are given, the batteries in the households are simply not used, and the resulting profiles are the electricity load profiles of the households without the use of a battery (reference case). The second option uses the quadratic cost function (QC) and is expected to achieve the global system optimum (as described in Section 2). The hybrid pricing mechanism (HPM) is the third option and uses the speed-up described in Section 5, while optimizing on a neighborhood level. Lastly, profile steering (PS) is a decentralized control strategy sending desired power profiles as steering signals to the households that, in turn, flatten their load based on these signals (Gerards et al., 2015). In context of Fig. 1, when creating a new aggregate profile, PS only selects the device that contributes most towards decreasing the global objective value to update its profile and then updates the desired power profile accordingly.

To implement the steering methods based on QC and HPM, we used an adapted version of the Alternating Direction Method of Multipliers (ADMM) algorithm from Rivera et al. (2016). ADMM is an iterative optimization method in which a large optimization problem (in our case: flattening the electricity profile of the neighborhood according to a cost function) is subdivided into many smaller optimization problems (flattening the electricity profile of each household according to a separate cost function) that can be solved more efficiently, while jointly solving the overall problem (Boyd et al., 2011). In context of Fig. 1, with QC and HPM all devices simultaneously are updated in each iteration, in contrast to PS.

6.1. Simulation setup

The simulations were executed using DEMKit (Hoogsteen, 2017), the decentralized energy management simulation tool. As input, we used real data from the GridFlex Heeten project (Reijnders et al., 2021). This dataset consists of 70 Dutch households, with minute-granularity data on a household level. For our base case, we use data from 45 households on the 21st of September 2019, each with a virtual battery having a capacity of 5.4 kWh and a maximum (dis)charging power of 2.7 kW. Furthermore, we assume to have perfect predictions of the neighborhood load for the next 48 h.

In each of the following subsections, we focus on one specific aspect of the base case and vary it to determine its influence on the performance of HPM by comparing it to NO, QC, and PS. First, in Section 6.2, the effect of PV production is investigated by selecting different input days. Then, in Section 6.3, we include EVs in the simulations to demonstrate the difference between charging the EVs controlled or uncontrolled. Varying the battery capacity and maximum power is considered in Section 6.4. The effects of changing the used prediction and planning procedure are discussed in Section 6.5. Furthermore, the performance of the methods when scaling up the simulations is studied in Section 6.6.

To quantify the performance of the steering methods described above, they are compared on two performance indicators: the objective value according to (1) and the total computation time. These values are calculated as averages over 25 runs with the same parameters to get a representative range of behaviors of the algorithms in DEMKit. These runs simulate a single day and only differ in the random seeds used to vary the input.

Table 1

Parameters of the different steering methods as used for the simulations.

Method	Parameter	Value
ADMM (QC and HPM)	Maximum iteration count	90
	δ	1
	μ	10
	ϵ^{pri}	4.6
	ϵ^{dual}	2.5
	τ^{incr}	2
PS	τ^{decr}	2
	Maximum iteration count	90
	Multiple commits	False
	Minimum improvement	10^{-6}

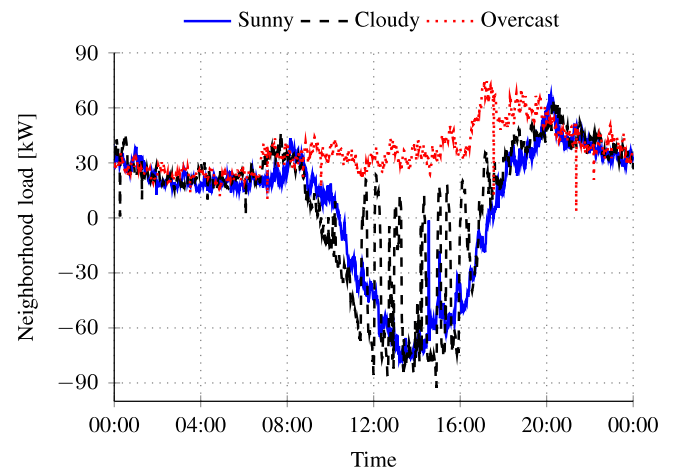


Fig. 4. Total power profiles of all households for a sunny, cloudy, and overcast day.

The base simulation without any steering (NO) takes some time to execute, therefore, we focus mainly on the added computation time of the steering methods, which is the difference between the total computation time of NO and the total computation time of the steering method. Although these computation times depend heavily on the implementation, they still provide a good impression of the performance of the different methods. The simulations were conducted on a Dell Precision 3510 with a quad-core Intel Core i7-6700HQ and 16 GB RAM. For all steering methods, we set a maximum on the iteration count (the number of convergence checks in Fig. 1 after which it is forced to “Yes”) to limit the computation times. For the ADMM algorithms of QC and HPM, we used the parameters following Rivera et al. (2016). For PS, we used the default values and model structure as mentioned in Hoogsteen et al. (2018). The overview of the chosen values for the parameters is in Table 1.

6.2. Influence of PV production

As the energy consumption profile of a household, especially when including PV, can be capricious, we first check how our method deals with different levels of volatile PV production.

To test this, we use PV profiles based on different weather types (i.e., different input days) for the simulations. The question then becomes how the other methods perform given various PV productions. We used three weather types: sunny, cloudy, and overcast. For the sunny day, we used data from the 21st of September 2019. The cloudy day was on the 2nd of October 2019, and, lastly, the overcast data is from the 18th of November 2019. The total energy profiles of all households on these days are given in Fig. 4.

As mentioned, we take the base simulation and vary only the weather type to compare the performance of the steering methods on the performance indicators. For all three weather types (sunny, cloudy, and overcast), QC, HPM, and PS perform identically in terms of the objective value (with a slight deviation for cloudy weather between PS and the others). All lead to significant improvements compared to NO, achieving a decrease of between 50.1% and 94.4% of the objective value of NO (see Table A.4 in the appendix). With overcast weather, there is hardly any PV energy to store and later use to flatten out peaks. Consequently, these objective values are the highest.

For the computation times, the results of the different weather types are comparable to each other. For all weather types, with NO, the total computation time averages around 44 s, where HPM takes around 82 s and QC approximately 92 s. PS performs the worst, ranging between 194 and 312 s. Again, see Table A.4 in the appendix for the complete table with all results.

6.3. Influence of EVs

The energy consumption of households is significantly influenced by the presence of EVs that need to charge. As the market share for EVs is quickly rising, the effects of EV charging need to be considered (Wappelhorst, 2021). Already when 20% of the households have an EV, issues in the grid arise (Nijenhuis, 2020). This stresses the importance of simulating such a case and demonstrating the effect of the steering methods on the charging of EVs.

For this, we include nine EVs in the simulation of the base case, corresponding to a penetration of 20%. All EVs are assumed to have a total capacity of 60 kWh and a charging and discharging power limit of 7.4 kW, corresponding to 32 A single phase charging with the option to use vehicle-to-grid (V2G). The EVs arrive at the households between 16:00 and 19:00, at which point the battery has between 15 and 45 kWh left and needs to be fully charged when leaving at a given time between 6:00 and 9:00 the next day. For each EV, we pick an arrival time, leftover charge, and departure time uniformly at random, independent of the other EVs.

As we want to demonstrate the effect of charging the EVs overnight, we extend the base case by one day and compare the following cases: the base case extended to two days without EVs, uncontrolled charging (charging at maximum power directly when plugged in, without batteries), and controlled charging with QC, HPM, and PS (all with batteries). Fig. 5 shows the difference between uncontrolled and controlled charging, resulting in reduced peaks of over 80%.

When adding EVs to the base case, the objective value according to (1) increases by 149%. All steering methods obtain an objective value that is immensely lower, although HPM performs slightly worse than QC and PS. For the computation times, PS is about 20 times slower than HPM and QC. This might be due to the low minimum improvement parameter of PS that causes the profile to be updated unnecessarily. The other results can be found in Table 2. Although we allowed the EVs to use V2G for all simulated cases, none of the EVs made use of this possibility. This is probably due to the available batteries discharging to charge the EV and minimizing the household peaks simultaneously.

6.4. Influence of available flexibility

One of the other aspects we can influence in the simulation is the amount of flexibility the optimization methods can utilize. As the only steerable devices in the base case of the simulation are the batteries, we provide a sensitivity analysis by varying their capacity and power. The total capacity and power of the batteries

Table 2

Objective value according to (1) and the total computation time for the profiles resulting from QC, HPM, PS, and NO with different EV setups.

EV	Method	Objective value	Computation time (s)
Controlled charging	QC	315102	151.7
	HPM	316878	133.4
	PS	315102	2736.1
Uncontrolled charging	NO	1898972	41.6
None	NO	763555	42.2

can significantly influence the time the optimization methods need to converge. Therefore, we simulated three cases: oversized, fitted, and undersized batteries within each household.

For the fitted batteries, we first needed to determine the minimal amount of flexibility required to reasonably flatten the energy consumption profile. In our case, we ended up using a 5.4 kWh/2.7 kW battery in each household. For over- and undersized batteries, we simulated a 10 kWh/5 kW and 1 kWh/0.5 kW battery in each household, respectively.

The simulations were done using the input data of the sunny day. The results here are in line with those of different PV production. The objective value is the same for all methods (QC, HPM, and PS) but, as expected, differs with the amount of flexibility. The undersized storage obtained a decrease in the objective value of 57.5% compared to NO. In contrast, the fitted and oversized storage reached a reduction of 94.4% and 99.0%, respectively (see Table A.5 in the appendix).

The total computation times for QC and HPM are similar to those of the different weather types, with HPM having a computation time of 87 s on average, about 8 s faster than QC. Both outperformed PS, which had a computation time of about 204 s with the over- or undersized storage, and 313 s with the fitted storage. For the complete table with all results, again see Table A.5 in the appendix. We note that by undersizing the batteries, insufficient flexibility is available, and therefore it can no longer be guaranteed that the global optimum coincides with a Nash equilibrium. This makes comparing HPM and QC to PS slightly unfair, as PS also optimizes the electricity profiles of the individual households.

6.5. Prediction error resilience

Up to this point, we assumed perfect predictions for testing these methods. However, in a real-world setting, this would not be the case. To solve this, the predictions can be made in a rolling horizon fashion, where once per specified time interval, an updated prediction for the next time intervals is made, based on the most recently acquired information. In our case, we updated the prediction for the next 24 h every simulated hour. More information on how these predictions are made can be found in Molderink et al. (2010) and Gerards and Hurink (2019). We evaluated the performance of the QC, HPM, and PS using this form of replanning.

For the profile steering method in DEMKit, another way of replanning is available (Hoogsteen et al., 2017). Here, the prediction is only updated when an event is triggered. These events are triggered when, for instance, the original prediction and the recently acquired information differ too much or when a storage device is almost full or empty. This way, a replanning is only made when needed.

The results of the different methods when using the prediction procedures described above can be found in Table 3. Clearly, the objective value when using a rolling horizon with replanning is significantly higher than in the case of perfect predictions. Nonetheless, the objective values when replanning are

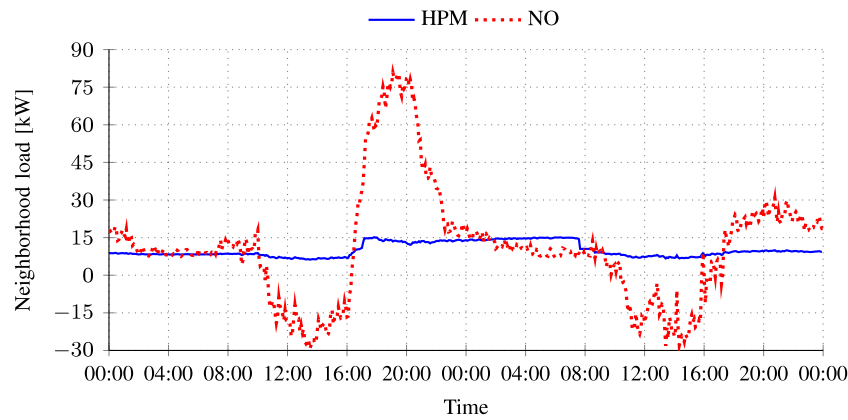


Fig. 5. Total power profiles of the simulated households with EVs using uncontrolled charging (NO) and controlled charging (HPM).

Table 3

Objective value according to (1) and the total computation time for the profiles resulting from QC, HPM, PS, and NO with different prediction and planning methods.

Predictions	Method	Objective value	Computation time (s)
Perfect	QC	20841	93.6
	HPM	20841	86.0
	PS	20841	312.7
Replanning	QC	140456	861.0
	HPM	141028	715.5
	PS	140456	902.0
Event-based	PS	141665	188.1
None	NO	375022	44.3

still considerably lower than without optimization. Interestingly, the objective value of HPM when replanning is slightly higher than for the other methods.

A drawback of replanning is that the computation times are substantially higher when compared to perfect predictions. This difference is explained by the fact that with perfect information, only one planning is made, while the replanning procedure makes one for each simulated hour. Interestingly, the event-based procedure for PS does not show an increase in computation time but even outperforms the perfect information procedure. This is because, in the event-based procedure, a swift but approximate planning is made by limiting the maximum number of iterations to convergence. The planning is then only updated when needed. However, the prize for this speed-up is an increase in the objective value, but this increase is minimal. Similar methods for QC and HPM may lead to comparable results.

6.6. Scalability

Another critical factor when using optimization methods is scalability, i.e., the change in performance when the input grows. This input growth may be either in the number of planned time intervals or in the number of households. As the compared methods operate in a rolling horizon fashion, extending the number of the simulated time intervals leads approximately to a linear growth of the objective value and the computation time. To see how the number of households influences the performance, we compared the methods when running the simulations for 1, 5, 10, 25, 45, and 70 households. The results for the total computation time can be found in Fig. 6. The computation time for NO increases linearly with time, as is expected with DEMKit. Another observation is that QC and HPM grow similarly in computation time. Except for an increment at five households, the computation

time shows quadratic growth. For PS, a trend is hard to identify. For the objective value, little valuable information is found from scaling up the number of households. The objective values attained by QC, HPM, and PS are identical for each number of households and are all significantly lower than for NO.

If we look at the scalability from a computational complexity viewpoint, the added term for the HPM, as described in Section 5, has its advantages. It is known that the convergence rate for strongly convex functions is linear when using ADMM. This holds for QC but also for our implementation of HPM. This gives our implementation of HPM a linear convergence rate (Lions and Mercier, 1979).

For each iteration of ADMM, the optimization problems in the individual households need to be solved. This is done in DEMKit with the continuous battery charging algorithm (van der Klauw et al., 2017). The computational complexity of this algorithm is $O(T^2)$ per battery, with T the amount of planned time intervals (van der Klauw et al., 2017). Furthermore, as ADMM converges linearly and is observed to have a computation time linear in the number of households H (Rivera et al., 2016), both HPM and QC have a computational complexity of $O(H^2T^2)$, which is in agreement with the results of Fig. 6. The computation time per iteration of PS typically scales linearly in the number of households. However, PS has no guaranteed convergence speed, though, in practice, the number of iterations is constant or at least bounded by $O(H)$ (Hoogsteen et al., 2018). As PS uses the same buffer optimization algorithm, its total computational complexity can also be approximated by $O(H^2T^2)$.

6.7. Real data

As mentioned in Section 4.3, the hybrid pricing mechanism was used in the GridFlex Heeten field test. The pricing mechanism used the added quadratic term from Section 5 and was implemented using the ADMM algorithm in DEMKit. The algorithm ran in real-time to directly steer the eight batteries present in the neighborhood. As the project initially intended to have more batteries placed there, the capacity and power outputs of the real batteries were doubled in DEMKit to get a realistic impression of what could have been achieved in the extended setting. Within DEMKit, a rolling horizon of 48 h was used, and the predictions were updated every 15 min. Fig. 7 shows the electricity profile of the neighborhood on the 30th of December 2020 with the hybrid pricing mechanism and without any control (corresponding to HPM and NO). It shows that the overall profile of HPM is much more flat compared to NO, and that the maximum peak was reduced from 42.4 kW to 31.1 kW. The algorithm was fast enough to keep up with steering the batteries online. The results obtained in GridFlex Heeten show the potential of using the hybrid pricing mechanism in practice.

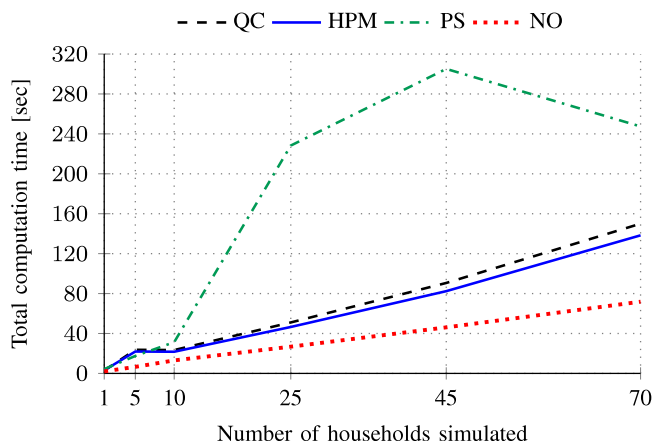
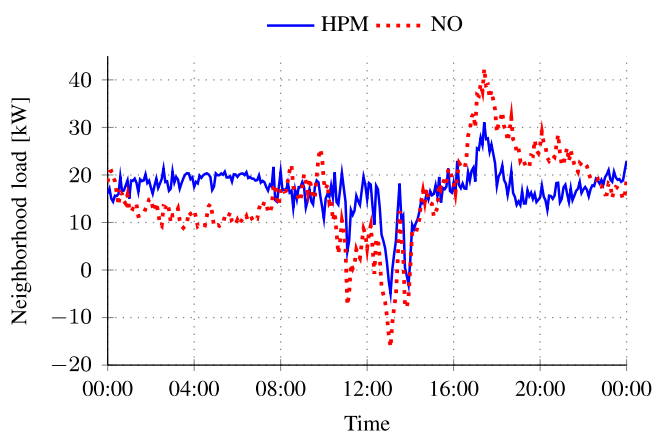
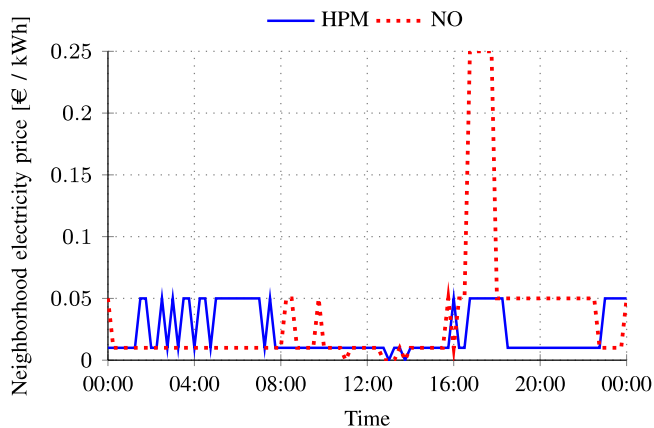


Fig. 6. Computation times for QC, HPM, PS, and NO when changing the number of households.



(a) Total power profile of the GridFlex Heeten neighborhood.



(b) Electricity prices for the GridFlex Heeten neighborhood.

Fig. 7. The effects on the GridFlex Heeten neighborhood using HPM and NO.

7. Conclusion and recommendations

This article aimed to present a framework for pricing mechanisms that are suitable for system optimization but at the same time socially acceptable. The underlying system goal is to flatten the neighborhood electricity profile. To achieve this, we proposed a hybrid pricing mechanism that uses a piecewise linear approximation of a quadratic cost function.

The presented hybrid pricing mechanism has been implemented and evaluated in a field test with an energy community, where it was observed that the consumers understood the mechanism and considered it suitable. Furthermore, the described mechanism meets several requirements from literature for social acceptance. For the implementation of the pricing mechanism in optimization algorithms, an additional term can be added to the hybrid pricing mechanism to speed up the convergence without any impact on the quality of the solution. Our numerical evaluation has shown that with this speed-up, the results of the proposed hybrid pricing mechanism are comparable with steering methods specifically designed for system optimization. Moreover, the mechanism can keep up with the online steering of batteries in terms of computation time and solution quality. This indicates that our pricing mechanism has the potential to be used in practice.

As this article only assesses the effect on peak reduction, further research has to explore if similar mechanisms exist for different system goals. Especially using the results from Schoot Uiterkamp et al. (2022) that show that different instances of similar classes of optimization problems have the same optimal solution, we may be able to link other system goals to the proposed mechanism. We also note that the hybrid pricing mechanism needs to be tailored to each neighborhood or local energy community, so future work could entail developing a method that supports the decision on specific parameters of the mechanism, i.e., deciding on the needed number of pieces m , the prices a_i and the boundaries b_j for specific communities, given their wishes and characteristics. Also, designing an event-based prediction method for the hybrid pricing mechanism could drastically reduce the computation times for realistic implementations, as was demonstrated in the numerical evaluation of profile steering. Moreover, the framework presented here could be further tailored to cases with industrial users, especially when they are in the same neighborhood as residential users. Finally, more research is needed to fully explore the effect of such mechanisms on the behavior of consumers and the social acceptance of these pricing mechanisms.

CRedit authorship contribution statement

Victor M.J.J. Reijnders: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration.
Marco E.T. Gerards: Conceptualization, Formal analysis, Writing – review & editing, Supervision, Project administration.
Johann L. Hurink: Conceptualization, Formal analysis, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Datasets related to this article can be found at <https://doi.org/10.4121/14447257.v1>, hosted at 4TU.ResearchData [53].

Acknowledgment

This research is conducted within the Grid Flex Heeten project (TEUE116230) supported by the Dutch organization RVO.

Table A.4

Objective value according to (1) and the total computation time for the profiles resulting from QC, HPM, PS, and NO under different PV production conditions.

Weather type	Method	Objective value	Computation time (s)
Sunny	QC	20841	93.6
	HPM	20841	86.0
	PS	20841	312.7
	NO	375022	44.3
Cloudy	QC	52663	92.2
	HPM	52663	81.4
	PS	52722	276.4
	NO	409032	44.7
Overcast	QC	277711	91.0
	HPM	277711	81.5
	PS	277711	194.1
	NO	556162	42.8

Table A.5

Objective value according to (1) and the total computation time for the profiles resulting from QC, HPM, PS, and NO with different amounts of flexibility.

Flexibility	Method	Objective value	Computation time (s)
Oversized	QC	3911	92.1
	HPM	3911	84.2
	PS	3911	203.7
Fitted	QC	20841	93.6
	HPM	20841	86.0
	PS	20841	312.7
Undersized	QC	159316	100.0
	HPM	159316	90.9
	PS	159316	205.0
None	NO	375022	44.3

Appendix. Additional tables

See Tables A.4 and A.5.

References

- Aljohani, T.M., Ebrahim, A.F., Mohammed, O.A., 2021. Dynamic real-time pricing mechanism for electric vehicles charging considering optimal microgrids energy management system. *IEEE Trans. Ind. Appl.* 57 (5), 5372–5381. <http://dx.doi.org/10.1109/TIA.2021.3099083>.
- Autoriteit Consument en Markt, 2016. *Besluit van de Autoriteit Consument en Markt van 21 April 2016, kenmerk ACM/DE/2016/202153, houdende de vaststelling van de voorwaarden als bedoeld in artikel 27 van de Elektriciteitswet 1998 (Tarievencode elektriciteit)*. Staatcourant.
- Blum, W.J., Kalven, H., 1952. The uneasy case for progressive taxation. *Univ. Chicago Law Rev.* 19 (3), 417–520. <http://dx.doi.org/10.2307/1597736>.
- Boyd, S., Parikh, N., Chu, E., Peleato, B., Eckstein, J., et al., 2011. Distributed optimization and statistical learning via the alternating direction method of multipliers. *Found. Trends Mach. Learn.* <http://dx.doi.org/10.1561/2200000016>.
- Celebi, E., Fuller, J.D., 2007. A model for efficient consumer pricing schemes in electricity markets. *IEEE Trans. Power Syst.* 22 (1), 60–67. <http://dx.doi.org/10.1109/TPWRS.2006.888956>.
- Dütschke, E., Paetz, A.-G., 2013. Dynamic electricity pricing—Which programs do consumers prefer? *Energy Policy* 59, 226–234. <http://dx.doi.org/10.1016/j.enpol.2013.03.025>.
- European Commission, 2008. *Energy sources, production costs and performance of technologies for power generation, heating and transport*. p. 2008, Commission Staff Working Document Accompanying the Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. *Second Strategic Energy Review. an EU Energy Security and Solidarity Action Plan*. Brussels, 13.
- Fang, M., Xiang, Y., Li, J., 2022. Locational electricity-carbon price model: Design and analysis. *Energy Rep.* 8, 721–728. <http://dx.doi.org/10.1016/j.egyr.2022.05.229>, 2022 The 4th International Conference on Clean Energy and Electrical Systems.
- Fell, M.J., Shipworth, D., Huebner, G.M., Elwell, C.A., 2015. Public acceptability of domestic demand-side response in Great Britain: The role of automation and direct load control. *Energy Res. Soc. Sci.* 9, 72–84. <http://dx.doi.org/10.1016/j.erss.2015.08.023>.
- Gerards, M.E.T., Hurink, J.L., 2019. PV predictions made easy: Flexibility through simplicity. *CIRE2019* <http://dx.doi.org/10.34890/831>.
- Gerards, M.E.T., Toersche, H.A., Hoogsteen, G., van der Klauw, T., Hurink, J.L., Smit, G.J.M., 2015. Demand side management using profile steering. In: 2015 IEEE Eindhoven PowerTech. IEEE, <http://dx.doi.org/10.1109/ptc.2015.7232328>.
- Global Smart Grid Federation, 2012. *Global smart grid federation report*. Tech. Rep., Global Smart Grid Federation, p. 15, URL https://www.smartgrid.gov/files/documents/Global_Smart_Grid_Federation_Report.pdf.
- Goulden, M., Bedwell, B., Rennick-Egglestone, S., Rodden, T., Spence, A., 2014. Smart grids, smart users? The role of the user in demand side management. *Energy Res. Soc. Sci.* 2, 21–29. <http://dx.doi.org/10.1016/j.erss.2014.04.008>.
- GridFlex Consortium, 2020. *GridFlex Heeten: Naar 'Nul op de wijktransformator'*. White Paper (September 2020), URL <https://gridflex.nl/wp-content/uploads/2020/09/267-whitepaper-v0.2.pdf>.
- Groen, M.C., 2018. *Assessing the Effect of Smart Reinforcement Alternatives on the Expected Asset Lifetime of Low Voltage Networks*. (Master's thesis). University of Twente.
- Halkin, D., 2019. Incentivizing capacity grid tariffs as a building block for the energy transition. <http://dx.doi.org/10.34890/470>, CIRE2019.
- Herter, K., 2007. Residential implementation of critical-peak pricing of electricity. *Energy Policy* 35 (4), 2121–2130. <http://dx.doi.org/10.1016/j.enpol.2006.06.019>.
- Hoenkamp, R., Huitema, G.B., de Moor-van Vugt, A.J.C., 2011. The neglected consumer: The case of the smart meter rollout in the Netherlands. *Renew. Energy L. & Pol'y Rev.* 2, 269. <http://dx.doi.org/10.2139/ssrn.1917455>.
- Hoogsteen, G., 2017. *A Cyber-Physical Systems Perspective on Decentralized Energy Management* (Ph.D. thesis). University of Twente.
- Hoogsteen, G., Gerards, M.E.T., Hurink, J.L., 2018. On the scalability of decentralized energy management using profile steering. In: 2018 IEEE PES Innovative Smart Grid Technologies Conference Europe. ISGT-Europe, IEEE, pp. 1–6. <http://dx.doi.org/10.1109/isgt-europe.2018.8571823>.
- Hoogsteen, G., Molderink, A., Hurink, J.L., Smit, G.J.M., 2017. Asynchronous event driven distributed energy management using profile steering. In: 2017 IEEE Manchester PowerTech. <http://dx.doi.org/10.1109/PTC.2017.7980986>.
- Ibars, C., Navarro, M., Giupponi, L., 2010. Distributed demand management in smart grid with a congestion game. In: *Proc. First IEEE Int. Conf. Smart Grid Communications*. pp. 495–500. <http://dx.doi.org/10.1109/SMARTGRID.2010.5622091>.
- JEM 2.0 consortium, 2018. *Jouw Energie Moment 2.0 Openbaar Eindrapport*. <https://projecten.topsectorenergie.nl/storage/app/uploads/public/5c5/abc/900/5c5abc90006ea711264881.pdf>.
- Jones, D.N., Mann, P.C., 2001. The fairness criterion in public utility regulation: Does fairness still matter? *J. Econ. Issues* 35 (1), 153–172. <http://dx.doi.org/10.1080/00213624.2001.11506345>.
- Joskow, P.L., Wolfram, C.D., 2012. Dynamic pricing of electricity. *Amer. Econ. Rev.* 102 (3), 381–385. <http://dx.doi.org/10.1257/aer.102.3.381>.
- Kim, B.-G., Ren, S., Van Der Schaar, M., Lee, J.-W., 2013. Bidirectional energy trading and residential load scheduling with electric vehicles in the smart grid. *IEEE J. Sel. Areas Commun.* 31 (7), 1219–1234. <http://dx.doi.org/10.1109/jsac.2013.130706>.
- Li, F., 2008. Continuous locational marginal pricing (CLMP). In: *Proc. IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century*. <http://dx.doi.org/10.1109/PES.2008.4596057>.
- Li, N., Chen, L., Low, S.H., 2011. Optimal demand response based on utility maximization in power networks. In: 2011 IEEE Power and Energy Society General Meeting. IEEE, <http://dx.doi.org/10.1109/pes.2011.6039082>.
- Lions, P.-L., Mercier, B., 1979. Splitting algorithms for the sum of two nonlinear operators. *SIAM J. Numer. Anal.* 16 (6), 964–979. <http://dx.doi.org/10.1137/0716071>.
- McKenna, K., Keane, A., 2014. Discrete elastic residential load response under variable pricing schemes. In: *Innovative Smart Grid Technologies Conference Europe. ISGT-Europe, 2014 IEEE PES, IEEE*, <http://dx.doi.org/10.1109/isgt-europe.2014.7028769>.
- Mohsenian-Rad, A.H., Leon-Garcia, A., 2010. Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE Trans. Smart Grid* 1 (2), 120–133. <http://dx.doi.org/10.1109/tsg.2010.2055903>.
- Molderink, A., Bakker, V., Bosman, M.G.C., Hurink, J.L., Smit, G.J.M., 2010. Management and control of domestic smart grid technology. *IEEE Trans. Smart Grid* 1 (2), 109–119. <http://dx.doi.org/10.1109/TSG.2010.2055904>.
- Morstyn, T., McCulloch, M., 2018. Multi-class energy management for peer-to-peer energy trading driven by prosumer preferences. *IEEE Trans. Power Syst.* <http://dx.doi.org/10.1109/tpwrs.2018.2834472>.
- Morstyn, T., Teytelboym, A., McCulloch, M.D., 2018. Matching markets with contracts for electric vehicle smart charging. In: 2018 IEEE Power & Energy Society General Meeting. PESGM, IEEE, <http://dx.doi.org/10.1109/pesgm.2018.8586361>.

- Nash, J.F., 1950. Equilibrium points in n-person games. *Proc. Natl. Acad. Sci.* 36 (1), 48–49. <http://dx.doi.org/10.2307/j.ctv173f1fh.6>.
- Naus, J., van Vliet, B.J.M., Hendriksen, A., 2015. Households as change agents in a dutch smart energy transition: On power, privacy and participation. *Energy Res. Soc. Sci.* 9, 125–136. <http://dx.doi.org/10.1016/j.erss.2015.08.025>.
- Neuteleers, S., Mulder, M., Hindriks, F., 2017. Assessing fairness of dynamic grid tariffs. *Energy Policy* 108, 111–120. <http://dx.doi.org/10.1016/j.enpol.2017.05.028>.
- Nijenhuis, B., 2020. *Electric Vehicle Charging in the Dutch Low-Voltage Grid (Master's thesis)*. University of Twente.
- Park, L., Yoon, Y., Cho, S., Choi, S., 2020. Prosumer energy management considering contract with consumers under progressive pricing policy. *IEEE Access* 8, 115789–115799. <http://dx.doi.org/10.1109/access.2020.3004643>.
- Piotrowski, K., Geers, M.P.A., Garrido, D., Chen, J., Peralta, J.J., Casaca, A., Gerards, M.E.T., 2018. Balancing energy production and consumption in energy efficient neighborhoods. In: 2018 IEEE International Energy Conference. ENERGYCON, IEEE, <http://dx.doi.org/10.1109/energycon.2018.8398801>.
- Pomerleau, K., 2014. *2015 Tax brackets*. Tax Foundation.
- Rajasekhar, B., Pindoriya, N., Tushar, W., Yuen, C., 2019. Collaborative energy management for a residential community: A non-cooperative and evolutionary approach. *IEEE Trans. Emerg. Top. Comput. Intell.* 3 (3), 177–192. <http://dx.doi.org/10.1109/tetci.2018.2865223>.
- Reijnders, V.M.J.J., Gerards, M.E.T., Hurink, J.L., 2019. Pricing mechanism based on losses using grid topology. In: 2019 IEEE Milan PowerTech. IEEE, <http://dx.doi.org/10.1109/ptc.2019.8810436>.
- Reijnders, V.M.J.J., Gerards, M.E.T., Hurink, J.L., 2020a. A hybrid pricing mechanism for joint system optimization and social acceptance. In: 2020 6th IEEE International Energy Conference. ENERGYCON, IEEE, pp. 900–905. <http://dx.doi.org/10.1109/energycon48941.2020.9236603>.
- Reijnders, V.M.J.J., Gerards, M.E.T., Hurink, J.L., 2021. Energy Consumption Data of the Gridflex Heeten Project. 4TU.ResearchData, <http://dx.doi.org/10.4121/14447257.v1>.
- Reijnders, V.M.J.J., Gerards, M.E.T., Hurink, J.L., Smit, G.J.M., 2018. Testing grid-based electricity prices and batteries in a field test. In: CIREN Workshop 2018: Microgrids and Local Energy Communities. p. 0500. <http://dx.doi.org/10.34890/219>.
- Reijnders, V.M.J.J., van der Laan, M.D., Dijkstra, R., 2020b. Energy communities: A Dutch case study. In: Behind and beyond the Meter. Elsevier, pp. 137–155. <http://dx.doi.org/10.1016/b978-0-12-819951-0.00006-2>.
- Rivera, J., Goebel, C., Jacobsen, H.-A., 2016. Distributed convex optimization for electric vehicle aggregators. *IEEE Trans. Smart Grid* 8 (4), 1852–1863. <http://dx.doi.org/10.1109/tsg.2015.2509030>.
- Schoot Uiterkamp, M.H.H., Gerards, M.E.T., Hurink, J.L., 2022. On a reduction for a class of resource allocation problems. *INFORMS J. Comput.* 34 (3), 1387–1402. <http://dx.doi.org/10.1287/ijoc.2021.1104>.
- Sharma, S., Abhyankar, A.R., 2017. Loss allocation of radial distribution system using Shapley value: A sequential approach. *Int. J. Electr. Power Energy Syst.* 88, 33–41. <http://dx.doi.org/10.1016/j.ijepes.2016.11.015>.
- Siano, P., 2014. Demand response and smart grids—A survey. *Renew. Sustain. Energy Rev.* 30, 461–478. <http://dx.doi.org/10.1016/j.rser.2013.10.022>.
- Sovacool, B.K., 2014. What are we doing here? Analyzing fifteen years of energy scholarship and proposing a social science research agenda. *Energy Res. Soc. Sci.* 1, 1–29. <http://dx.doi.org/10.1016/j.erss.2014.02.003>.
- Stoll, P., Brandt, N., Nordström, L., 2014. Including dynamic CO2 intensity with demand response. *Energy Policy* 65, 490–500. <http://dx.doi.org/10.1016/j.enpol.2013.10.044>.
- Stromback, J., Dromacque, C., Yassin, M.H., 2011. The potential of smart meter enabled programs to increase energy and systems efficiency: A mass pilot comparison. Vaasa ETT Global Energy Think Tank.
- Tushar, M.H.K., Assi, C., 2017. Optimal energy management and marginal-cost electricity pricing in microgrid network. *IEEE Trans. Ind. Inf.* 13 (6), 3286–3298. <http://dx.doi.org/10.1109/tii.2017.2712652>.
- van der Klauw, T., Gerards, M.E.T., Hurink, J.L., 2017. Resource allocation problems in decentralized energy management. *OR Spectrum* 39 (3), 749–773. <http://dx.doi.org/10.1007/s00291-017-0474-2>.
- Wang, M., Song, Y., Sui, B., Wu, H., Zhu, J., Jing, Z., Rong, Y., 2022. Comparative study of pricing mechanisms and settlement methods in electricity spot energy market based on multi-agent simulation. *Energy Rep.* 8, 1172–1182. <http://dx.doi.org/10.1016/j.egy.2022.02.078>, 2021 International Conference on New Energy and Power Engineering.
- Wappelhorst, S., 2021. *On the electrification path: Europe's progress towards clean transportation*. European Alternative Fuels Observatory. March.
- Wesseh, P.K., Lin, B., 2022. A time-of-use pricing model of the electricity market considering system flexibility. *Energy Rep.* 8, 1457–1470. <http://dx.doi.org/10.1016/j.egy.2021.12.027>.
- Woo, C.-K., 1990. Efficient electricity pricing with self-rationing. *J. Regul. Econ.* 2 (1), 69–81. <http://dx.doi.org/10.1007/bf00139363>.
- Xia, Y., Xu, Q., Qian, H., Cai, L., 2022. Peer-to-peer energy trading considering the output uncertainty of distributed energy resources. *Energy Rep.* 8, 567–574. <http://dx.doi.org/10.1016/j.egy.2021.11.001>, 2021 The 8th International Conference on Power and Energy Systems Engineering.