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Local electricity market pricing mechanisms' impact on welfare distribution, privacy and transparency

Marthe Fogstad Dynge [a,*], Kjersti Berg [a], Sigurd Bjarghov [b], Ümit Cali [a]

[a] Department of Electric Energy, Norwegian University of Science and Technology, Trondheim, Norway
[b] Department of Energy Systems, SINTEF Energy Research, Trondheim, Norway

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ABSTRACT

Local energy communities and electricity markets have emerged as possibilities for interaction among prosumers. A substantial effort has been invested into creating efficient pricing mechanisms for various market arrangements, all of which take into consideration distinct characteristics of local electricity trading. However, since they are all evaluated in terms of various systems and market conditions, it is challenging to directly compare the mechanisms. In this research, three well-established pricing mechanisms from the literature are systematically compared and evaluated under identical settings on their influence on welfare distribution across various market participant groups, privacy protection, transparency and complexity level. According to the findings, the supply–demand ratio pricing system leads to the lowest costs for consumers and is also the most privacy compliant and transparent. Furthermore, prosumers obtain the highest cost-savings through the consensus alternating direction method of multipliers pricing mechanism, whereas the equilibrium pricing mechanism performs best regarding economic fairness. The aim of this article is to provide insight into the performance of different pricing mechanisms to energy regulators and local electricity market facilitators. The comparative analysis should aid in making informed decisions on the implementation of local electricity markets.

1. Introduction

Following the global commitment to the United Nations Sustainable Development Goals, the world's energy sector is undergoing a vast transition towards decarbonisation. Consequently, investment costs for rooftop photovoltaic (PV) panels have fallen steeply over the last decade [1] and they are now becoming affordable to households. Thus, previously passive consumers can now take a more active role in their energy behaviour as *prosumers*. With the simultaneous maturing of information, communication and digitalisation tools, a closer interaction between grid operators, end users and other system agents is allowing a more consumer-centric energy system. Local energy communities have emerged as a promising concept for better coordinating this interaction [2,3], where members can collaborate to ensure common economic, environmental, and social benefits while also providing system services [4].

Upon the realisation of local energy communities, mechanisms for fair distribution of internal resources and the determination of the related prices should be established. This could be accomplished by forming local electricity markets with custom trading schemes [5,6]. Although surveys of German and Dutch households indicate that environmental benefits and the ability to share electricity are the primary motivations for participating in local trading schemes [7,8], the community trading price has a strong influence on the participants' trading behaviour [9,10]. In order for local energy communities and electricity markets to become widely accepted real-world phenomena, a consistent pricing mechanism that is perceived as fair by all market participants must therefore be in place.

Furthermore, according to a survey conducted in several European countries, potential market participants consider a lack of trust in the trading system to be a major risk [11]. This includes the expected lack of transparency and explainability of the algorithms, as well as concerns about data anonymisation. Transparency relates to both explainability and interpretability and refers to any decisions made by the algorithm or the users that can affect the market outcome [12]. It is critical for promoting user satisfaction, autonomy, and informed decision-making. A lack of transparency undermines trust both among market participants and between market participants and market operators [13]. This is evident in today's retail electricity markets, where a lack of relevant and transparent information about the electricity market and prices, combined with a high level of market complexity, are significant barriers to consumer engagement [14]. The European Network of

* Corresponding author.
E-mail address: marthe.f.dynge@ntnu.no (M.F. Dynge).

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Transmission System Operators for Electricity (ENTSO-E) addresses the issue by publishing fundamental information on European electricity markets via its transparency platform [15]. According to the association, transparency is critical for the creation of efficient, liquid, and competitive markets, as well as for avoiding potential market power abuse [16].

As local electricity markets are likely to be realised through digital platforms, they must adhere to regulations like the European Union's Digital Services Act (Regulation 2022/2065) [17], which states that the platform must provide a level of transparency that allows market participants to make informed decisions. Transparency extends beyond simply making known the method used, as the methods can range from simple rule-based mechanisms to complex mathematical models. However, if the mechanism's complexity level is high and the pricing mechanism is difficult to understand, the degree of transparency will not always aid in market players' acceptance.

The inclusion of households in such markets can also lead to the sharing and misuse of potentially sensitive information, thus privacy concerns should be carefully considered [18]. Further, the competitive nature of a market environment necessitates privacy in order to ensure healthy and fair competition. Unlike traditional electricity markets, local electricity markets accommodate private market participants with little or no market knowledge rather than professional market participants. It is thus commonly assumed that market activity is conducted through a third party, such as an aggregator, energy service provider, or community manager, who is in compliance with data protection regulations such as the European General Data Protection Regulation (GDPR) [19]. However, despite the fact that numerous regulations and legal frameworks exist to protect privacy and transparency, they are not always effective in practise [12]. As a result, data protection should be built into the algorithmic and systematic design, and a third-party consumer agreement should include a mapping of how privacy is protected and what information is shared. Furthermore, market participants should be informed of the trade-off between privacy and market efficiency [20]. Thus, implementable pricing mechanisms should be as transparent and privacy-preserving as possible.

Mechanisms for determining the internal local electricity market price proposed in the literature are manifold, taking into account various factors such as product differentiation [21], heterogeneous agent preferences [22] and willingness to pay [23]. However, the analyses of these techniques have been conducted on distinctive case studies, with varying assumptions about market conditions [24]. As a result, comparing and evaluating the most suitable strategy for real-world deployment is difficult. Some studies compare pricing mechanisms that share the same general principle, such as rule-based [25,26], game-theoretic [27,28] and auction-based [29] methods. However, no research has been found that compares mechanisms across these main categories. With the diversity of pricing mechanisms proposed in the literature, a thorough comparison of these different overall principles is needed. To make a properly informed decision when implementing a pricing mechanism in a real-life local electricity market, the following questions must be answered:

- How do different pricing mechanisms influence the welfare distribution in local electricity markets?
- Which pricing mechanism is most beneficial for prosumers, and which one is most beneficial for consumers?
- How do the different pricing mechanisms compare with respect to privacy, transparency, and complexity?

2. Literature review and contributions

A general assumption when determining the local trading price is that it should reflect the energy balance within the local electricity market. Additionally, to maintain stable market conditions, the price should be higher than what the prosumers can sell their excess energy for in the traditional market and lower than what consumers would otherwise pay in the wholesale market. With these assumptions, various mechanisms have been proposed in the literature, which in general can be categorised into rule-based, auction-based, game theory-based and optimisation-based methods. More specifically, in this study, mechanisms based on rules, distributed optimisation and equilibria are analysed. Since auction-based mechanisms require that market participants have knowledge of their bidding curves, they have not been included.

2.1. Rule-based pricing

The general characterisation of rule-based pricing mechanisms is that a set of rules sets the market price, usually applied exogenously to the main market clearing mechanism. The prices are often set post-event, meaning that the costs are distributed in the community after the actual trading has taken place. This removes the need for negotiation between the market participants and can be combined with a variety of market clearing structures.

Bill sharing and mid-market rate are two rule-based mechanisms that have become widely used in the literature [30]. The bill-sharing mechanism is a pro-rata scheme based on the individual contribution to the energy balance of each prosumer, while the mid-market rate sets the price to be the average between the wholesale buying and selling price. A third popular mechanism used in the literature is the supply–demand ratio, proposed by [31]. The main idea is that the local market price should reflect the energy balance within the energy community. Thus, the proportion between supply and demand is used to linearly set the price between an upper and lower bound, typically the buying and selling price of the wholesale market. The authors emphasised that the advantage of the supply–demand ratio mechanism is that market participants only need to share the measured net consumption with the market operator. The three mechanisms were compared in [25,26], showing the best overall performance and the highest social welfare among the market participants when using the supply–demand ratio mechanism. Many versions of the mechanism have been proposed in the literature, with extensions such as preferred participation level [31], compensation rates [30], donation systems [32], alternative pricing boundaries [33] and other incentive mechanisms [34]. There are also several examples of how this simple rule-based method can be combined with more complex market clearing algorithms, such as game-theoretic markets [35] and distributed optimisation [36].

Although many of these studies showcase the increased social welfare for the energy community as a whole, few analyse the welfare distribution between consumers and prosumers. Ref. [34] found that the basic supply–demand ratio mechanism is most beneficial to consumers, while adding a fixed premium to the pricing rule moves the advantage to the prosumers. Ref. [35] analysed the impact of different constellations of participants and found that prosumers with a high degree of self-sufficiency have a negative cost reduction when the amount of prosumers (i.e., energy surplus) increases in the local market when using the supply–demand ratio pricing mechanism. The benefits to the consumers do, however, increase with the number of prosumers.

2.2. Distributed optimisation-based pricing

The distributed nature of local electricity markets is often used as inspiration to clear the market in a similarly distributed fashion. Often reasoned through privacy-related considerations, the general motivation is to decompose the market clearing problem into individual optimisation problems for each market participant. Thus, different approaches to distributed optimisation are popular among the pricing mechanisms proposed in the literature. Here, versions of the alternating direction method of multipliers (ADMM) algorithm are reoccurring, most commonly the consensus ADMM (CADMM), where market participants seek consensus on price and/or quantity within the local electricity market. The dual version of the problem, exchange ADMM, is also frequently used in the literature [21,36], resembling a Walrasian auction. In this paper, the CADMM approach is chosen, as the price settlement itself is the main focus. For further details on ADMM, readers are referred to [37].

Ref. [38] tested the CADMM algorithm on different communication structures of a local electricity market, concluding that the average price remains the same for both direct peer-to-peer and community-based structures if the economic input parameters of the market are equal. The algorithm was compared to a centralised market clearing approach in [39,40], where the dual variable of the market balancing constraint is interpreted as the local trading price. The results show how the CADMM algorithm reaches the same optimal solution as the centralised approach, though with a lesser amount of information shared. Ref. [41] used the CADMM mechanism to achieve a Nash equilibrium for the local electricity price, while including individual utility functions to capture the levels of personal satisfaction of the market agents. The differences in cost distribution between prosumers and consumers were addressed by [42], indicating a slight advantage to the consumers when solving a market problem based on optimal power flow with the CADMM algorithm.

Disregarding the use of distributed ledger technology, none of the articles reviewed in this section have addressed the transparency of the ADMM algorithm. Most of them justify the use of the algorithm for pricing based on privacy preservation, but few discuss the topic beyond this initial reasoning. Ref. [39] stated that the market participants only have to share their local exchange profile with a supervisory node, not with the other agents. Common for the studies is that only direct buyer-to-seller information is shared among the agents, as this is a consensus variable. Still, individual preferences and more sensitive information can be shared with a third party.

2.3. Equilibrium-based pricing

With the liberalisation of energy markets, the ability to accurately model the price and quantity equilibria influenced by the different decision-makers in the market has become increasingly important [43]. Equilibrium- and complementarity-based problems have proven to be particularly effective in modelling the markets' ability to manipulate both physical (primal) and economic (dual) variables [44]. These characteristics are also valid for local electricity markets, with multiple potentially strategic agents participating. However, to ensure an optimal social welfare distribution among the market participants, the local electricity market should preferably be subject to perfect competition. This can be obtained by inserting all the entities' Karush–Kuhn–Tucker (KKT) conditions into a mixed complementarity program [43]. The local electricity market price can then be deducted from the dual of the market balancing constraint. The approach was demonstrated in [45], where a peer-to-peer market subject to capacity tariffs was modelled as a mixed complementarity program.

In the literature, these kinds of models are frequently used as the lower level of a Stackelberg game or bilevel optimisation problem, where the mixed complementarity program or equilibrium model is parameterised by the decision variables of the upper level (leader) [22]. This is to simulate the response from a perfect market to signals sent by a third party, typically the distribution system operator (DSO) or an aggregator [46,47]. Ref. [48] modelled the interaction between a local electricity market and the DSO. The agents in the market were assumed price-takers, responding to signals from the cost-recovering DSO. A community welfare-maximising mixed complementarity program was formulated as the lower level in [22], responding to an upper level that determined the dynamic participation of agents in the local electricity market. A set of fairness factors indicated a medium degree of allocation fairness, which were improved when adding more demand to the local market (i.e. better supply–demand balance).

However, equilibrium problems are often considered computationally intractable to solve, and many reformulate the problem into equivalent optimisation problems [49]. This was demonstrated in [50], where a multi-player equilibrium model of the local electricity market was solved through its equivalent optimisation model. The equivalence was proved by demonstrating that the KKT conditions of the equilibrium problem are identical to those of the optimisation problem. This also suggests that the desired market properties, such as market efficiency and revenue adequacy, are preserved. The possibility of reformulating equilibrium problems into equivalent single optimisation problems is, however, only possible in the case of markets with perfect competition [44]. Although equilibria are used to a smaller extent as a pricing mechanism for local electricity markets compared to the other mechanisms reviewed in this paper, the approach is included in the form of a mixed complementarity program as it illustrates general price formation under perfect competition.

2.4. Contributions of this paper

The aim of this article is to provide energy regulators and local electricity market facilitators insight into the distributional effects of three common local electricity market pricing mechanisms, as well as an assessment of their privacy and transparency characteristics. For this purpose, we compare how the supply–demand ratio, CADMM and equilibrium pricing mechanisms impact local electricity market participants. By applying each mechanism to the same case study, the effect on welfare distribution among the different participant groups can be measured. Privacy preservation is an essential aspect of implementing such markets, but the pricing mechanisms' explicit impact on this is scarcely discussed in the reviewed literature. Further, apart from the emphasis on the simplicity of the supply–demand ratio, none of the reviewed studies have discussed the mechanisms' level of transparency explicitly. Comparative analyses of the mechanisms' functionalities can yield insight into their ability to preserve privacy, as well as their complexity and transparency levels. Thus, the contributions of this paper are as follows:

- A comprehensive comparison between different local electricity market pricing mechanisms, subject to identical market conditions.
- A demonstration of how the pricing mechanisms influence the welfare and resource distribution between prosumers and consumers.
- A qualitative analysis of the mechanisms' privacy and transparency characteristics.

3. Methodology

This section describes the three different pricing mechanisms which will be compared: the supply–demand ratio, the CADMM, and an equilibrium approach. The basic principles of the three methods are shown in Fig. 1. It is assumed that there is a local electricity market for an energy community, where each house communicates with the community manager. One main difference between the methods is that supply–demand ratio prices are calculated ex-post from measured data, while the price in the other two mechanisms is determined ex-ante from committed demand and generation. It is assumed that the houses can purchase and sell electricity to both the local electricity market and the wholesale market. The communication between the community manager and the market platform and/or the wholesale market is however not considered in this article.

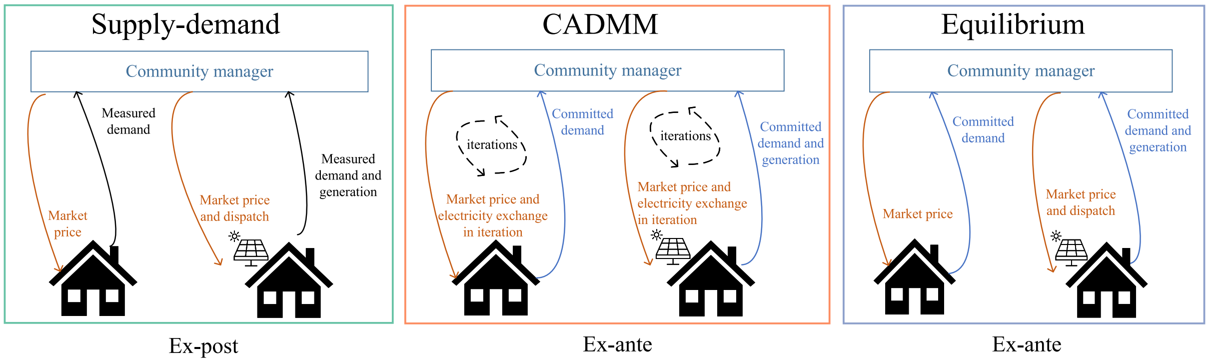

Fig. 1. Information exchange in pricing mechanisms.

3.1. Underlying market clearing problem

The local electricity market in this study is cleared as a peer-to-peer market regardless of pricing mechanism, which means that bilateral trades between each market participant are settled in the clearing. To be able to compare the pricing mechanisms on a fair basis, the market is assumed to be cleared based on the same linear program. The objective of the market clearing is to minimise the total local electricity market costs of the energy community. From an overall local market perspective, the internal trading costs should equal zero, as the costs of buying and selling in the local market should be the same. Thus, the objective on a local electricity market level is to minimise the costs of importing, g_{ht}^{imp}, and exporting, g_{ht}^{exp}, to the wholesale market for all time steps t and all houses h, as described in (1). These costs are considered as the upper and lower bounds, respectively, for the internal local electricity market price regardless of pricing mechanism in this study.

$$\min \quad \sum_{h} \sum_{t} \left(\left(C_t^{spot} + C^g\right) \cdot g_{ht}^{imp} - C^{FiT} \cdot g_{ht}^{exp} \right) \tag{1}$$

The costs of procuring from the wholesale market are here assumed to equal the day-ahead spot price, C_t^{spot}, and the additional tariffs related to grid and taxes, C^g. The price at which the prosumers sell their excess electricity to a retailer is assumed to equal the feed-in-tariff, C^{FiT}. All variables in the model are non-negative.

The internal local market trades are balanced under the constraint of (2), where the amount house h procures from peer p, i_{hpt}, should be equal to the amount peer p sells to house h, x_{pht}, in time step t.

$$i_{hpt} = x_{pht}, \qquad \forall p \neq h, \forall ht \tag{2}$$

Furthermore, the total amount purchased, i_{ht}^{LM}, or sold, x_{ht}^{LM}, by house h in timestep t should be equal to the sum of its bilateral trades, as defined in (3) and (4).

$$i_{ht}^{LM} = \sum_{p \neq h} i_{hpt} \qquad \forall ht \tag{3}$$

$$x_{ht}^{LM} = \sum_{p \neq h} x_{pht} \qquad \forall ht \tag{4}$$

Finally, the energy balance of each house h in time step t is controlled by (5), with the respective dual variable μ_{ht}^{eb}, which represents the shadow price of one additional kilowatt-hour of electricity. This dual will later be used for formulating the Nash game in Section 3.4. The balance also includes parameters that represent the demand, D_{ht}, and PV generation, PV_{ht}, of each house.

$$g_{ht}^{imp} + i_{ht}^{LM} + PV_{ht} = D_{ht} + x_{ht}^{LM} + g_{ht}^{exp} \quad (\mu_{ht}^{eb}) \quad \forall ht \tag{5}$$

3.2. Supply–demand ratio

The supply–demand ratio pricing mechanism settles the internal local electricity market prices after the actual trades have taken place. The overall idea is that the price should reflect the amount of surplus available in the local market, relative to the demand. Assuming that the market is settled by the linear programming problem described in Section 3.1, and assuming that the trades have been conducted accordingly, the supply–demand ratio, s_t, is then defined by (6).

$$s_t = \frac{\sum_h \left(g_{ht}^{exp} + x_{ht}^{LM}\right)}{\sum_h \left(g_{ht}^{imp} + i_{ht}^{LM}\right)} \qquad \forall t \tag{6}$$

The uniform local electricity market price, λ_t, is defined in (7) as a convex combination of s_t and the upper and lower bounds, here assumed to be the buying and selling price of the wholesale market, respectively.

$$\lambda_t = s_t \cdot C^{FiT} + (1 - s_t) \cdot (C_t^{spot} + C^g) \quad \forall t \tag{7}$$

If $s_t = 0$, meaning that there is no surplus available in the local electricity market, the local price equals the upper bound, $\lambda_t = (C_t^{spot} + C^g)$. If there is an abundance of surplus in the local electricity market, hence $s_t \geq 1$, the local electricity price reaches its lower bound, thus $\lambda_t = C^{FiT}$. Fig. 1 illustrates the settlement process of the supply–demand ratio pricing mechanism. The pricing mechanism itself only requires information exchange between the market participants and the community manager consisting of net measurements of supply and demand to the local electricity market.

3.3. Consensus alternating direction method of multipliers

The second pricing mechanism analysed in this study is the settlement of local electricity market prices through the CADMM. Unlike the supply–demand ratio pricing mechanism, local electricity market prices are set in the market clearing process and are therefore committed day-ahead. The market is settled by decomposing the central optimisation problem into individual sub-problems for each of the peers. The complicating constraint of the central problem is (2), as it couples together the peers' decisions. This constraint is thus embedded in the individual objective function, with an aim of reaching a consensus on the two variables through the iterative solving process. The individual objective function is represented by the augmented Lagrangian in (8), where γ is the penalty factor that determines the step size for each iteration.

$$\begin{aligned} \min \quad & \sum_{t} \Big(\left(C_t^{spot} + C^g\right) \cdot g_{ht}^{imp} - C^{FiT} \cdot g_{ht}^{exp} + \lambda_{pt} i_{hpt} - \lambda_{ht} x_{pht} \\ & + \gamma \| i_{hpt} - \bar{x}_{pht}^{\nu-1} \|^2 + \gamma \| x_{pht} - \bar{i}_{hpt}^{\nu-1} \|^2 \Big) \end{aligned} \tag{8}$$

The sub-problems are additionally subject to restrictions (4)–(5). To avoid simultaneous sales and purchases from the same agent, additional binary constraints as defined in (9) are added.

$$\begin{cases} g^{imp}_{ht} = 0 \quad \text{and} \quad i^{LM}_{ht} = 0 \quad \text{if} \quad u_{ht} = 0, \quad u_{ht} \in \{1,0\} \quad \forall ht \\ g^{exp}_{ht} = 0 \quad \text{and} \quad x^{LM}_{ht} = 0 \quad \text{if} \quad u_{ht} = 1, \quad u_{ht} \in \{1,0\} \quad \forall ht \end{cases} \tag{9}$$

As the prices are assumed to be between the buying and selling price of the wholesale market, the local prices are initialised by (10) at the beginning of the procedure.

$$\lambda_{ht} = \frac{C^{spot}_t + C^g + C^{FiT}}{2} \quad \forall ht \tag{10}$$

Between each iteration of trying to reach a consensus, the local electricity prices are updated depending on their primal residual, as defined in (11) and (12).

$$r_{ht} = i^{LM}_{ht} - x^{LM}_{ht} \quad \forall ht \tag{11}$$

$$\lambda^{(\nu+1)}_{ht} = \lambda^{\nu}_{ht} + 2 \cdot \gamma \cdot r_{ht} \quad \forall ht \tag{12}$$

In practise, this means that if a consensus is not reached in iteration ν, the prosumers must lower their offered prices and the consumers must increase theirs. This iterative process is repeated until $\sum_h \sum_t r_{ht} < \epsilon = 0.01$. The iterative process is illustrated in Fig. 1. The only information from the market participants to the community manager is the committed volumes sold and purchased for each iteration. In turn, the community manager sends back updated local market prices and shares information about the average amount bought and sold by each peer with the other peers.

3.4. Equilibrium approach

The competitive local electricity market game is modelled using an equilibrium approach. This is formulated by deriving the KKT conditions of the original problem. This results in a mixed complementarity program, with an additional market clearing constraint. The mixed complementarity program can be solved directly using the PATH solver [51], reformulated as a mixed integer linear program using the "Big M" method, or by using special order sets [52]. The linearity of the problem ensures that the KKT conditions are necessary and sufficient for optimality.

The solution to the mixed complementarity problem provides a Nash equilibrium in which no market participants may improve by changing their decisions, mimicking perfect market competition. This is beneficial when market operators advertise the market clearing scheme to the consumers, due to the implicit economic fairness inferred from the perfect competition. First, the market clearing constraint is given by (13), clearing the local electricity market price λ_t, which is now considered in the objective of each consumer.

$$\sum_h (i^{LM}_{ht} - x^{LM}_{ht}) = 0 \quad \perp \lambda_t \quad \forall t \tag{13}$$

The consumer objective from (1) can now be further derived to (14), which contains the costs and revenues related to trading in the local electricity market. In addition, a small administration cost C^a is added to purchasing of electricity, representing an envisioned cost of facilitating trade, while also avoiding model issues related to multiple optimal solutions.

$$\min \quad \sum_t \left(g^{imp}_{ht} \cdot (C^{spot}_t + C^g) - g^{exp}_{ht} \cdot C^{FIT}_t + (i^{LM}_{ht} - x^{LM}_{ht}) \cdot \lambda_t + i^{LM}_{ht} \cdot C^a \right) \tag{14}$$

From this basis, the KKT conditions can be derived to represent the local electricity market competitive game (15)–(19). All variables are still nonnegative, with the exception of the duals related to the equality constraints, which are free.

$$C^{spot}_t + \mu^{eb}_{ht} + C^g \geq 0 \perp g^{imp}_{ht} \geq 0 \quad \forall ht \tag{15}$$

$$-C^{FiT}_t - \mu^{eb}_{ht} \geq 0 \perp g^{exp}_{ht} \geq 0 \quad \forall ht \tag{16}$$

$$\lambda_t + \mu^{eb}_{ht} + C^a \geq 0 \perp i^{LM}_{ht} \geq 0 \quad \forall ht \tag{17}$$

$$-\lambda_t - \mu^{eb}_{ht} \geq 0 \perp x^{LM}_{ht} \geq 0 \quad \forall ht \tag{18}$$

$$g^{imp}_{ht} + i^{LM}_{ht} + PV_{ht} - D_{ht} - x^{LM}_{ht} - g^{exp}_{ht} = 0 \perp \mu^{eb}_{ht} \quad \forall ht \tag{19}$$

3.5. Fairness indicators

Measuring how fair a market is perceived to be by its participants is a complicated task, especially when subject to preferences as diverse and irrational as in local electricity markets. In order to address the pricing mechanisms' impact on welfare and resource distribution, fairness is in this paper defined as just that: economic fairness. Three indicators have gained momentum in the literature in assessing the economic fairness of local electricity markets, as demonstrated in [36,22], e.g. The first one, *quality of service*, measures the allocation fairness and is based on Jain's index [53].

$$\text{Quality of service}_t = \frac{\left(\sum_h \left(x^{LM}_{ht} + i^{LM}_{ht}\right)\right)^2}{H \cdot \sum_h \left(x^{LM}_{ht} + i^{LM}_{ht}\right)^2} \quad \forall t \tag{20}$$

A quality of service value of 1 indicates that all the market participants get an equal share of the resources traded within the market. This is not necessarily a relevant outcome for a local electricity market, as the participants' demands naturally vary. However, it may give an indication if the market is subject to particularly impactful participants and thus of the market's robustness against strategic behaviour [36].

The next indicator, *quality of experience*, measures the deviation in observed costs within the local market. The observed electricity cost of each market participant is defined in (21).

$$q_{ht} = \frac{g^{imp}_{ht} \cdot (C^{spot}_t + C^g) - g^{exp}_{ht} \cdot C^{FIT}_t + \lambda_t \cdot (i^{LM}_{ht} - x^{LM}_{ht})}{D_{ht} - PV_{ht}} \quad \forall ht \tag{21}$$

The quality of experience indicator is then defined as the ratio between the standard deviation of the perceived prices, σ, and the maximum deviation, $\sigma^{max}_t = (C^{spot}_t + C^g) - C^{FiT}$.

$$\text{Quality of experience}_t = 1 - \frac{\sigma_t}{\sigma^{max}_t} \quad \forall t \tag{22}$$

The quality of experience indicator gets a value of 1 if the perceived prices are equal for all participants. Lastly, the *minimum–maximum fairness* indicator indicates the difference between the minimum and maximum import from the wholesale market.

$$\text{minimum-maximum}_t = \frac{\min_h(g^{imp}_{ht})}{\max_h(g^{imp}_{ht})} \quad \forall t \tag{23}$$

With a minimum–maximum value of 1, all the participants are equally dependent on the system outside the local electricity market.

4. Case study

To properly compare the three pricing methods, it is essential that they are tested under the same conditions. Thus, two case studies were designed in order to capture the mechanisms' behaviour when subject to low and high amounts of available surplus within the local electricity market. The cases are illustrated in Fig. 2, where Case 1 includes 30% prosumers and Case 2 includes 60% prosumers. All prosumers in both cases are equipped with 3 kWp rooftop PV panels. For both cases, the penalty parameter γ of the CADMM mechanism is empirically set to 0.15, after testing the convergence of different values. A business-as-usual (BAU) reference scenario is also included, where there is no local electricity market, the consumers cover their demand by procuring from the grid and the prosumers sell all their surplus to a retailer for a feed-in-tariff. The feed-in-tariff used is set to the German 2020 value of 8.16 €c/kWh [54] and the administration cost C^a is set to 0.01 €c/kWh.

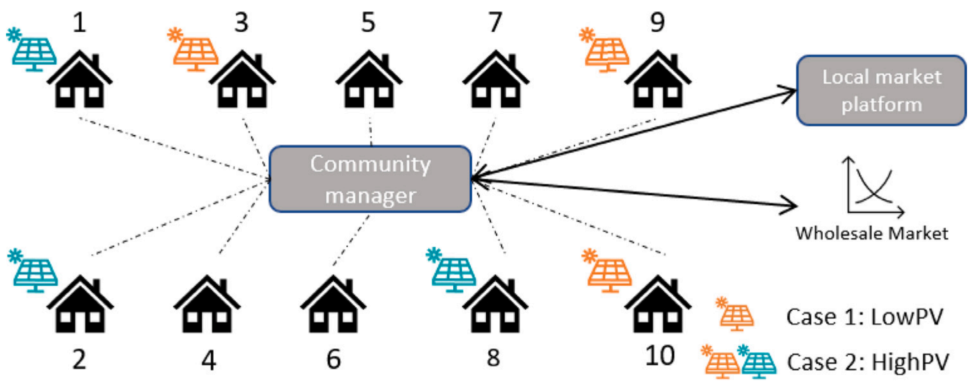

Fig. 2. Illustration of the case study setup.

Table 1
Annual demand of each house.

	House nr.									
	1	2	3	4	5	6	7	8	9	10
Demand [kWh]	3527	2341	3433	2203	2476	3350	2933	2948	3565	3366

All simulations were run on a Lambda Quad RTX 2080 Ti, with an Intel Core i9-9920X @ 3.5 GHz, 128 GB RAM (Ubuntu 18.04.6 LTS).

All input data are equal across the case studies and pricing mechanisms. This includes hourly time series for the German electricity day-ahead prices from 2020 retrieved from NordPool. A markup of 3 €c/kWh is added to simulate the perceived electricity price for households purchasing electricity through a retailer in Germany [55]. Additionally, costs related to grid fees, taxes, and other surcharges are added as a fixed value of 23.88 €c/kWh throughout the year, according to German levels from 2020 [55]. PV production profiles were retrieved through the open-source tool Renewable Ninja [56], and were generated through the NASA MERRA-2 meteorological database [57] for a location in southern Germany. The load profiles of each household are generated through the Artificial Load Profile Generator developed by [58], replicating the consumption profiles of various types of Dutch households, assumed to be similar to the German consumption profiles.[1] The annual demand of each house is shown in Table 1, while the total load and PV production are shown in Fig. 3.

5. Results and discussion

The main results for the three pricing mechanisms are presented and discussed in this section. First, an overview of the local electricity market prices and welfare distribution is given, as well as an evaluation of the mechanisms' performance in terms of economic fairness. Second, the privacy concerns, information sharing, transparency and complexity of the different pricing mechanisms are discussed.

5.1. Local electricity market prices and welfare distribution

This section shows the results for Case LowPV and Case HighPV. First, we investigate the market clearing of the different price mechanisms for one specific day to understand how the prices are determined and how it affects each household in the community. Second, we summarise the overall local electricity market price, total costs and welfare distribution for each household, and evaluate the fairness of the pricing mechanisms through the indicators introduced in Section 3.5.

[1] In accordance with the household categories defined by this tool, the following are used for this case study: one SingleWorker, two SingleRetired, one DualWorker, one part-time DualWorker, two DualRetired, two FamilyDualWorker and one part-time FamilyDualWorker.

5.1.1. Case LowPV

Fig. 4 illustrates the behaviour of the three mechanisms on a representative example day in February. As the market is cleared with the linear program introduced in Section 3.1 for the central market clearing applied together with the supply–demand ratio pricing mechanism, the objective is to minimise total community costs. Thus, the trades are distributed accordingly and assigned to whichever prosumer contributes to lowering the community costs in a said hour. House 3 sells most of its surplus this day. Note that the supply–demand ratio pricing mechanism can be combined with a variety of market clearing algorithms, and the central market clearing used in this paper is just one example. As the market dispatch is determined by the market clearing and not the pricing mechanism, it is not necessarily a general result for the supply–demand ratio pricing mechanism. However, this clearly differs from the market dispatch assigned through the CADMM approach, where priority is given to the prosumer who offers the lowest price. The price level corresponds to the amount of surplus, so that the prosumer with the highest surplus offers the lowest price. For this particular day, house 10 sells most of its surplus within the local electricity market, while the other prosumers sell theirs to the retailer. In contrast to the supply–demand ratio dispatch, house 3 exchanges almost no energy within the local electricity market. An even distribution of traded volumes is observed in the equilibrium approach which represents a more "compromise-oriented" market outcome compared to the two former approaches.

Fig. 5 offers a closer look at the prices set by the three mechanisms for the whole year, sorted by the volume exchanged for the price. The equilibrium pricing mechanism models prices endogenously, which means that the prices are determined by the alternative prices that the agents observe. The alternative prices in this case study are the wholesale price and feed-in-tariff, resulting in an "either/or" distribution of the prices between the two bounds. While the available surplus within the local electricity market is lower than the demand, the local price stays close to the value of the retailer buying price. When the local market reaches its saturation point, i.e. the surplus exceeds the demand, the local price drops to the feed-in-tariff level. This also happens for the prices set by the supply–demand ratio pricing mechanism. However, unlike the equilibrium pricing mechanism, the price only equals the wholesale price when no trade occurs within the local electricity market and is otherwise linearly set between the two bounds depending on the extent to which the surplus covers the local demand. For the CADMM algorithm, the local prices are initialised to be in the middle of the buying and selling price of the outside market. The effect of this initialisation can be clearly observed in Fig. 5 as the prices remain at this level independently of the volume traded. With only inflexible solar production present in the local electricity market, the procedure requires relatively few iterations to reach a consensus, and the effect of the adjustments made by (12) is minimal. The penalty factor γ is also relatively low, empirically set for the sake of convergence, and thus the adjustments are small. It should be noted that the CADMM

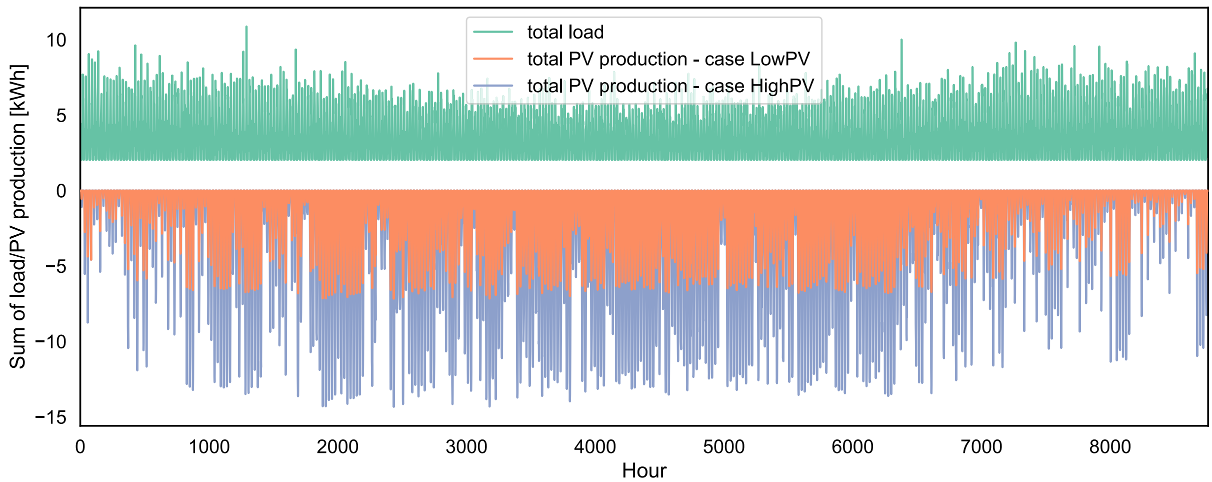

Fig. 3. Total PV and load for both cases.

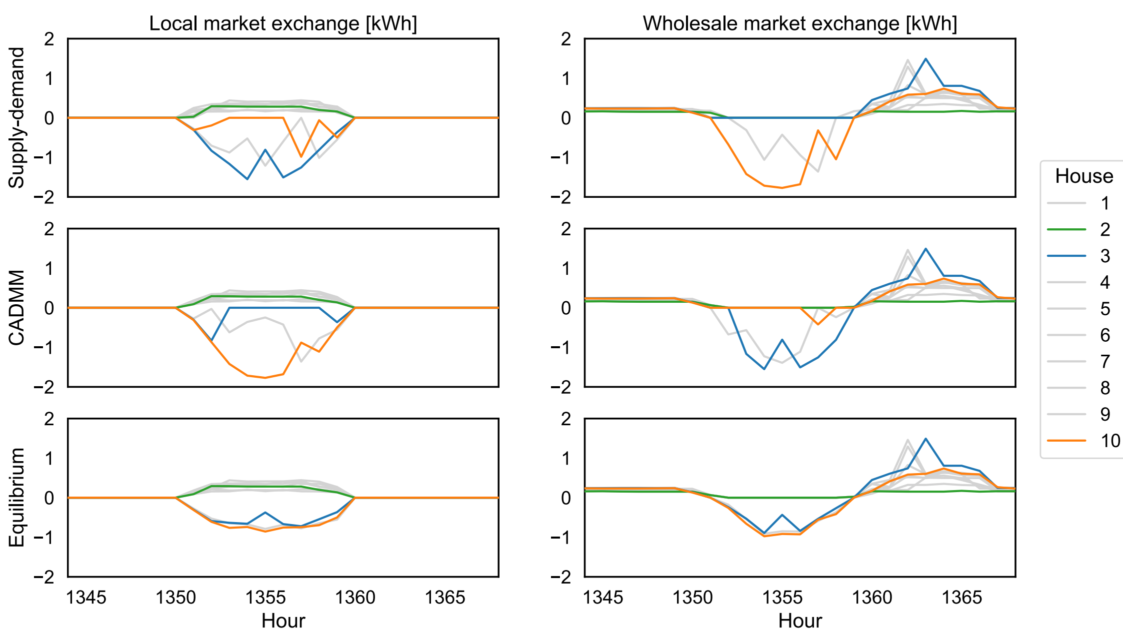

Fig. 4. Exchange example for one day (February 25) Case LowPV. Houses discussed in the text are highlighted for increased readability.

prices presented in this section are the mean of the individual prices obtained. The individual differences are minimal, again due to the low penalty factor and number of iterations, and thus the mean value offers an adequate impression of the price levels of the mechanism.

The same effects are further highlighted by the duration curve in Fig. 7. Here, the prices are sorted in descending order over the year. The prices obtained through the CADMM mechanism clearly follow the initial value, with a stable level between the buying and selling price throughout the year. The price levels of the other two mechanisms are more equal, but with slightly lower prices with the supply–demand ratio mechanism when there is activity in the local market without saturation ($0 < s_t < 1$).

Combining market insights and pricing behaviour, the welfare distribution between market participants can be analysed. Fig. 6 shows how much each of the market participants saves in annual costs for the three mechanisms, compared to the BAU scenario. Prosumers are marked by PV illustrations underneath the x-axis. The prices of the CADMM mechanism never reach the lower bound, and thus the method is more beneficial for prosumers than consumers. However, due to the "winner-takes-all" outcome of the market clearing, the extent of the benefits varies among the prosumers. On the other side, due to its low prices, the supply–demand ratio mechanism yields the highest cost savings for consumers, but the lowest cost savings for the prosumers. The equilibrium mechanism results in the most even cost distribution for all participants. The total costs of the different market participant groups are summarised in Table 2. The prosumers' collective advantage with the CADMM pricing mechanism is further highlighted, as well as the consumers' advantage with the supply–demand ratio mechanism.

Table 2
Total costs [€] Case LowPV.

Customer type	BAU	Supply–demand	CADMM	Equilibrium
Prosumers	1391	1301 (−7.5%)	946 (−32.0%)	1148 (−17.5%)
Consumers	5966	5109 (−14.4%)	5464 (−8.4%)	5262 (−11.8%)
Total	7357	6410 (−12.9%)	6410 (−12.9%)	6410 (−12.9%)

5.1.2. Case HighPV

In the case of high PV generation, the level of self-sufficiency in the local electricity market is naturally improved. Thus, despite the

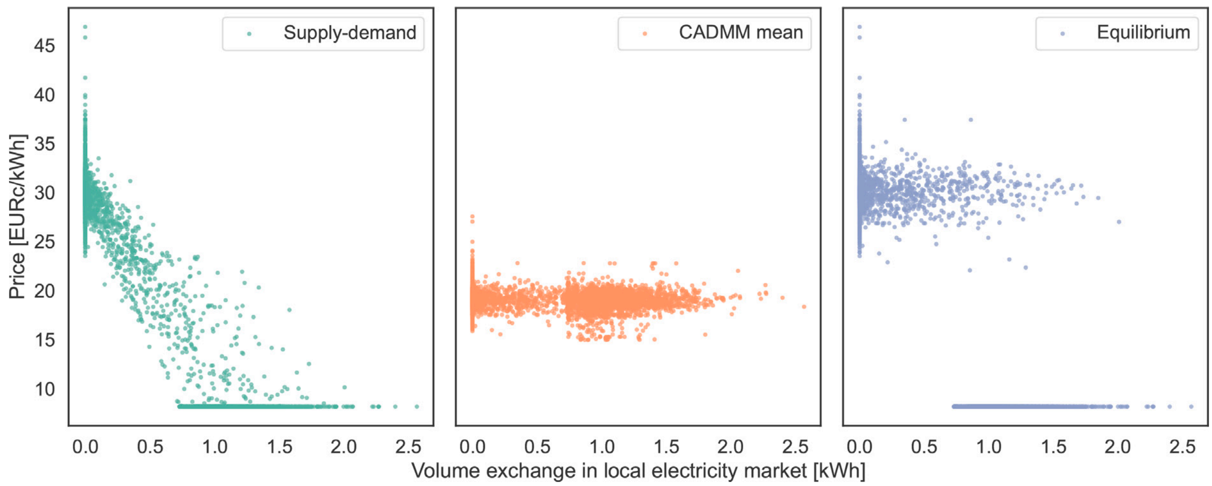

Fig. 5. Scatter plot of local electricity market prices with respect to volume exchanged in market Case LowPV.

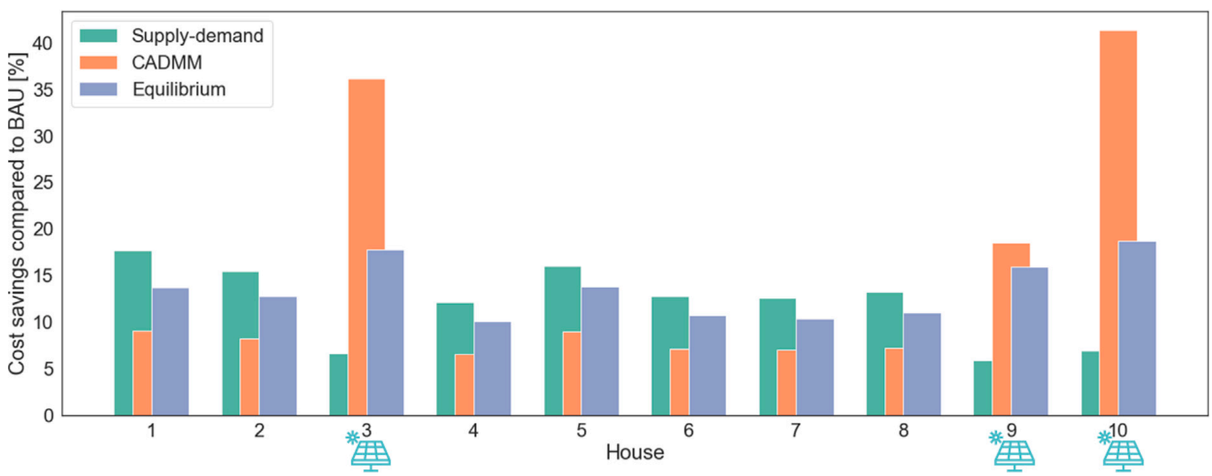

Fig. 6. Cost savings compared to business as usual Case LowPV.

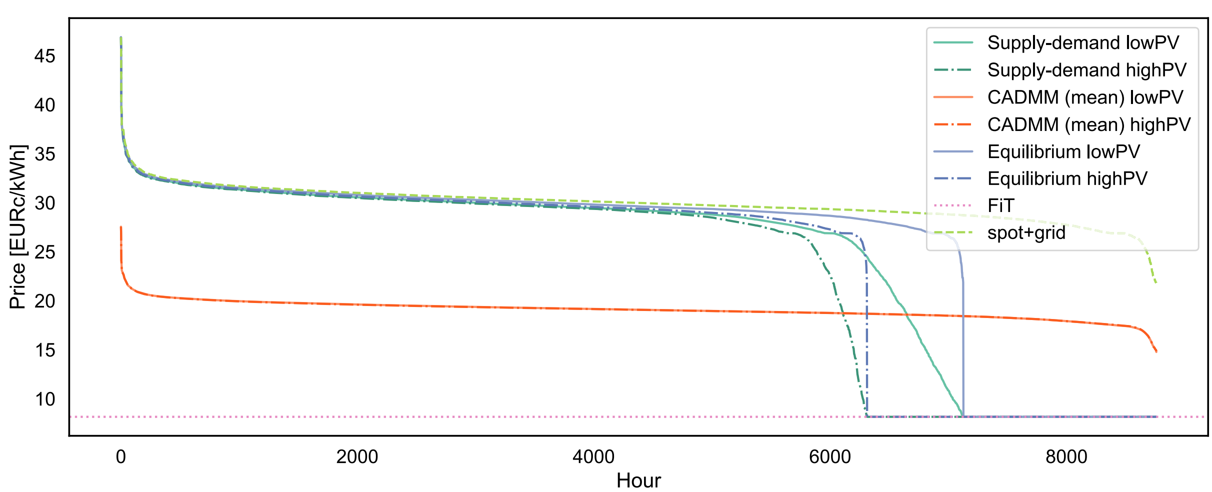

Fig. 7. Local electricity market price duration curve in all cases. Upper and lower bounds are shown as "spot+grid" and "FiT", respectively.

increase in the number of prosumers, the amount exchanged within the local market decreased as the net demand of the neighbourhood decreased. This is illustrated in Fig. 8. Still, the same dispatch behaviour is observed for all three mechanisms, with an arbitrary distribution by the supply–demand ratio approach, a single assignment to house 2 by the CADMM and an even allocation by the equilibrium mechanism. Compared to Fig. 4, house 2 has taken over from house 10, and dominates the market for this day. In Case LowPV, house 10 was the

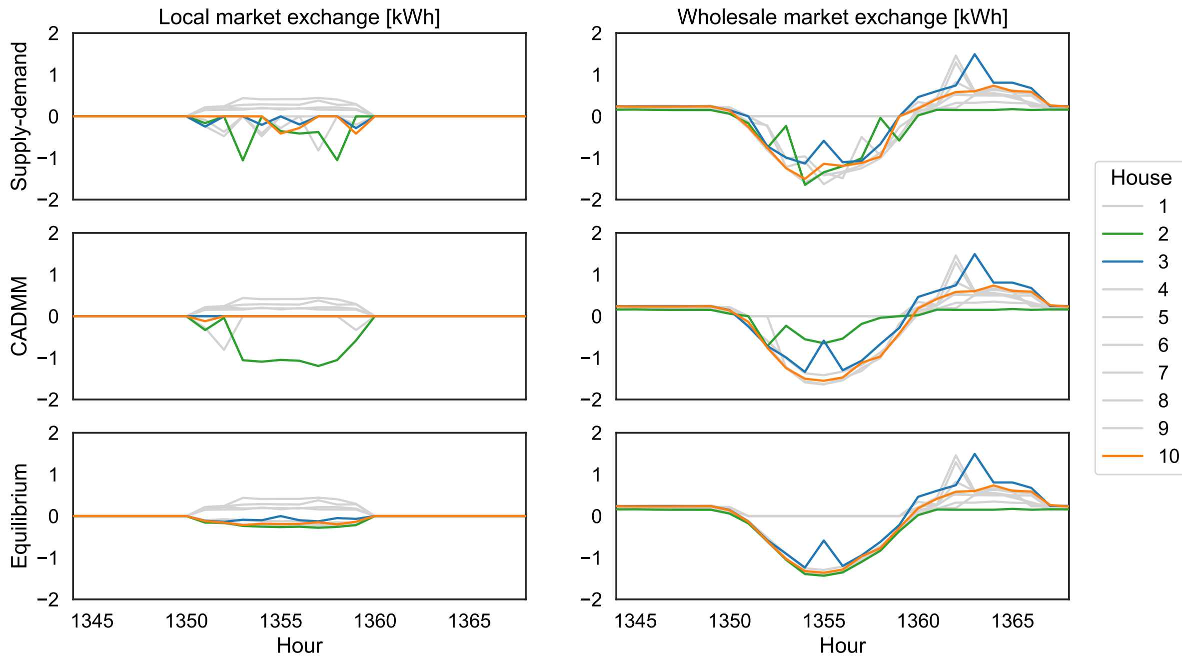

Fig. 8. Exchange example for one day (February 25) Case HighPV. Houses discussed in the text are highlighted for increased readability.

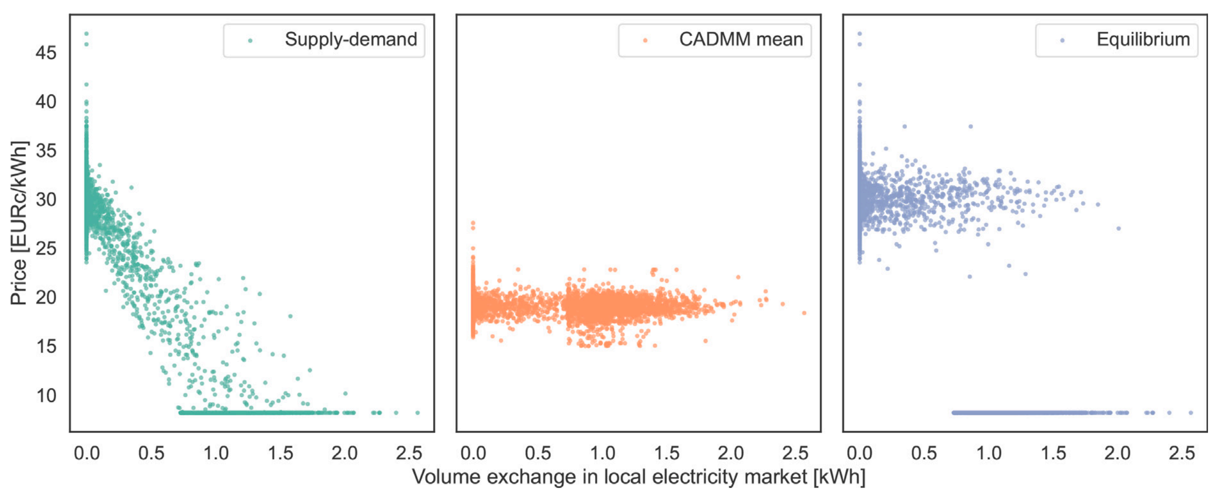

Fig. 9. Scatter plot of price in local electricity market vs. volume exchanged in the market Case HighPV.

prosumer with the highest net production, which is surpassed by house 2 in Case HighPV. This indicates that the CADMM pricing mechanism prioritises the prosumer that offers the highest volume to the market.

The prices follow the same tendencies as in Case LowPV, but with less density between the two bounds for the supply–demand ratio and the equilibrium mechanisms (Fig. 9). This is due to the high share of PV production compared to the community demand, thus reaching a market saturation level and the lower pricing bound more frequently than in Case LowPV. However, the prices of the CADMM mechanism are unaffected by this situation and are similar to the ones obtained for Case LowPV. The duration curve in Fig. 7 further confirms this, as the CADMM prices are still at a steady level at the middle of the buying and selling prices of the outside market. Here, one can also observe how the two other pricing mechanisms reach the lower bound quicker than in the previous case, at 6311 hours compared to 7126 hours at this point for Case LowPV.

With the reduced demand within the local electricity market, higher competition and the prices being pushed down towards the feed-in-tariff, the benefits to the prosumers are considerably reduced in Case HighPV, as seen in Table 3. Consumers still have lower costs with the supply–demand ratio mechanism, and prosumers still have lower costs with the CADMM mechanism, but the differences between the pricing mechanisms and the BAU scenario are reduced for all. The new energy balance in the market has also affected individual revenues, as shown in Fig. 10. Looking at house 10 in Figs. 6 and 10, the loss of market share has remarkably reduced the annual cost savings, thus limiting the incentives to participate in the local electricity market. Houses 2 and 8, with the highest net production among the prosumers, are prioritised by the CADMM mechanism to trade within the local electricity market and are still able to secure some revenue compared to the other pricing mechanisms. This implies that an investment in production capacity in a local electricity market with a supply–demand ratio or equilibrium pricing mechanism implemented limits the profitability for all prosumers in the market, while investing in the largest capacity can still be beneficial through the CADMM mechanism.

The aggregated costs for each of the market participant groups are summarised in Table 3 and confirm the trends observed in Fig. 10. The total cost is naturally reduced for all mechanisms due to the higher

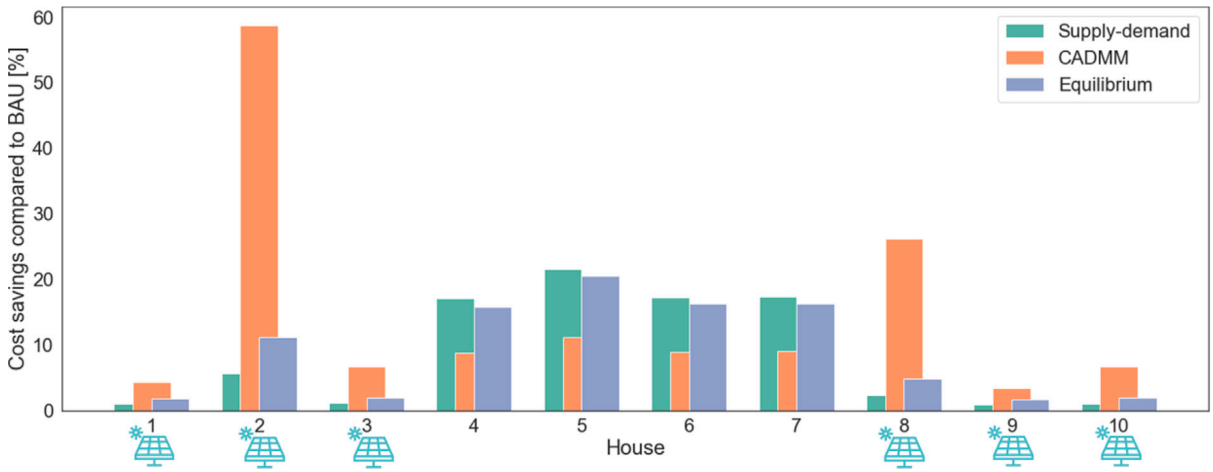

Fig. 10. Cost savings compared to business as usual Case HighPV.

Table 3
Total costs [€] Case HighPV.

Customer type	BAU	Supply demand	CADMM	Equilibrium
Prosumers	1396	1383 (−0.9%)	1318 (−5.6%)	1371 (−1.8%)
Consumers	4344	3716 (−14.5%)	3781 (−13.0%)	3728 (−14.2%)
Total	5740	5099 (−11.2%)	5099 (−11.2%)	5099 (−11.2%)

degree of self-sufficiency. The prosumers' costs have also increased for all cases, partly due to a higher number of participants within this group, but the differences between the mechanisms have significantly decreased compared to Case LowPV. The values are also very close to the BAU prosumer cost value. As most prosumers are forced to sell a high share of their surplus to the retailer instead of within the local electricity market, the impact of the local pricing mechanism is diminished. The same can be observed for the consumers, but with a higher benefit of participating in the local electricity market compared to the BAU scenario.

5.1.3. Fairness evaluation

For a deeper investigation of the pricing mechanisms' impact on the perceived fairness among participants in the local electricity market, the fairness indicators quality of service, quality of experience and minimum–maximum fairness, introduced in Section 3.5 are applied to both case studies. It should be noted that only the quality of experience indicator is directly related to pricing mechanisms. The other two assess the allocation fairness of the underlying market mechanism, which cannot be used to draw general conclusions about the supply–demand ratio pricing mechanism as the market dispatch is determined by its underlying market clearing, not the pricing mechanism. However, they can serve as comparative indices for the CADMM and equilibrium market dispatches, as well as validation for the generalisability of the examples in Figs. 4 and 8. The mean value of each indicator for all three mechanisms is presented in Table 4, along with its standard deviation. All values are calculated based on the hours of the year when there is activity in the local electricity market, which in total is 3040 and 3307 hours for cases LowPV and HighPV, respectively.

For Case LowPV, the quality of service is almost equal for the supply–demand ratio and CADMM mechanisms (0.57 and 0.58, respectively). A value of 1 would indicate that all the market participants get an equal share of the volume traded within the local electricity market. This is consistent with the behaviour seen in Fig. 4, which shows an uneven distribution of trades among the market participants for both mechanisms. Furthermore, the balanced dispatch of the equilibrium observed in the same figure results in a higher quality of service (0.69). In Case HighPV, increasing the number of prosumers improves the equilibrium pricing mechanisms' quality of service because more of the neighbourhood residents can participate in the local market with a relatively even distribution of traded volumes. Still, for both cases, the equilibrium pricing mechanism results in slightly higher standard deviations than the other mechanisms, indicating a larger hourly variation in the quality of service throughout the year. The quality of service of the supply–demand ratio pricing mechanism is almost unaffected by the change indicating a similar dispatching behaviour regardless of the energy balance within the local electricity market. In contrast, the quality of service is significantly reduced for the CADMM pricing mechanism. The indicator has clearly captured how the market is dominated by some players, as indicated in Figs. 6 and 10. The quality of service values obtained in both cases are consistent with the values obtained in both [36], where the market is cleared using an ADMM approach, and [22], where it is cleared using an equilibrium approach.

The minimum–maximum indicator is primarily used in markets where arbitrage is permitted [59], and therefore the information it can provide in this study is limited. The low values for all cases and pricing mechanisms do, however, indicate a relatively large difference between market participants' need to import from the market, which is not uncommon in a local electricity market context due to typically high shares of local generation and variations in demand. With energy storage available in the local electricity market, a value of 1 would imply that some prosumers purchase energy from the wholesale market without the need to do so, before reselling it to other community members, thus contributing equally to the total community imports from the retailer [36]. This would in turn increase the disparities in the individually perceived electricity prices, i.e., lowering the fairness of the local electricity market.

According to the quality of experience values in Table 4, the individually perceived prices are quite homogeneous for all of the pricing mechanisms examined in this study. A value of 1 indicates that all market participants get the same perceived price in all time steps. For the equilibrium pricing mechanism, the indicator has a mean value of 1 throughout the year, with no deviation, implying a 100% fair market in terms of the participants' economic satisfaction. The equilibrium-based market in [22] only obtained a quality of experience of around 60%–70%, depending on the case study. However, the prices were distorted by adding a willingness-to-pay for each of the market participants, and are thus not directly comparable to the outcome of this study. As this mechanism determines the prices based on the alternative costs, the perceived prices for all participants, whether they participate in the market or not, would be the same. As the prices of the supply–demand ratio pricing mechanism, especially in Case HighPV, frequently hit the upper or lower bound, and therefore effectively obtain a similar effect as the equilibrium mechanism, the quality of experience for

Table 4
Fairness indicators.

		Quality of Service		Quality of Experience		Minimum–maximum	
		Mean	St.dev.	Mean	St.dev.	Mean	St.dev.
Case LowPV	Supply–demand	0.57	0.17	0.94	0.09	0.33	0.24
	CADMM	0.58	0.16	0.86	0.06	0.28	0.25
	Equilibrium	0.69	0.19	1.00	0.00	0.33	0.24
Case HighPV	Supply–demand	0.58	0.16	0.98	0.06	0.35	0.23
	CADMM	0.45	0.17	0.82	0.04	0.26	0.25
	Equilibrium	0.78	0.21	1.00	0.00	0.35	0.23

this mechanism is also high. When there is market activity without saturation, i.e., $0 < s_t < 1$, the price is set somewhere between the limits and the perceived prices differ between those who participate in the local market and those who do not. As a result, the annual mean quality of experience is slightly lower than that of the equilibrium mechanism. The CADMM pricing mechanism has a lower quality of experience than the other mechanisms and is the only one that decreases in Case HighPV, compared to Case LowPV. This is due to the slight difference in the individual local electricity prices, and the constant difference between the local and wholesale prices. The values are, however, even lower than those obtained from the ADMM-based market in [36]. This may be due to the use of exchange ADMM instead of CADMM or differences in the underlying market conditions and parameters.

In this study, the three fairness indicators are used to evaluate the post-market clearing performance on the economic fairness of the three pricing mechanisms. For further development of the algorithms towards real-life implementation, criteria for maximising economic fairness could to a larger extent be embedded into the algorithms. One approach would be to incorporate similar indicators as used in this study into the objective function, but this would necessitate complex decisions on how to weight the various indicators. Another approach is to formulate them as constraints, but this can make the optimisation problem intractable. Adding fairness considerations into the optimisation process rather than post-optimisation evaluation also necessitates a stricter definition of what constitutes economic fairness as well as a more rigorous prioritisation of which aspects to include. Additionally, adding more complexity to the pricing mechanisms may affect the mechanisms' scalability. As the purpose of this study is to evaluate existing mechanisms, the implementation of such alterations is beyond the scope but should be investigated in further research.

In summary, the equilibrium pricing mechanism appears to perform the best regarding economic fairness. Because the mechanism assumes perfect competition, it should achieve competitive fairness in theory. However, these indicators only provide limited insight into the market participants' actual experiences when subject to the pricing mechanisms and only assess the purely economic aspects of the local electricity market. Thus, further evaluation of other aspects of perceived fairness is required, as well as practical assessments of participants' responses.

5.2. Information sharing and privacy concerns

In this section, the information sharing and privacy concerns raised by each of the pricing mechanisms are discussed. Only the aspects related to the mechanisms themselves are considered, and other privacy-preserving tools that could be added to a potential local electricity market framework, such as distributed ledger technology, are excluded. Table 5 summarises the required amount of information shared by each of the three pricing mechanisms.

The supply–demand ratio pricing mechanism necessitates the least amount of information sharing and thus offers the best privacy protection of the three pricing mechanisms investigated. Not only is there a minimal requirement for information sharing, but there is also no requirement to share any information with other market participants. This is true for the pricing mechanism itself, not the central market clearing used in this study. Furthermore, the price is determined ex-post, which means that no information must be shared in real-time. Instead, after the market period has ended and the prices have been cleared, net-metered consumption data are sent. By using advanced techniques, net-metered consumption can be translated into detailed information on what type of components a specific market participant has, and when they are used. This could provide competition-disturbing insight, or even more invasive, provide information about the market participants' whereabouts.

Table 5
Information shared in the three pricing mechanisms.

Characteristic	Supply–demand	CADMM	Equilibrium
Net metered load	Yes	No	Yes
Trading volumes	No	Yes[a]	Yes
Objective/preferences	No	No	Yes
Asset type and specifications	No	No	Yes
Asset demand	No	No	Yes

[a]Only the average traded volumes are shared with other market participants

The CADMM pricing mechanism requires market participants to share their market position in order to reach an ex-ante consensus. A participant's market position is here defined as the offered volume traded for a certain price. Because the method relies on market participants reaching consensus iteratively, information must be exchanged back and forth. However, only market positions must be shared, not detailed consumption and production data. This adds an additional layer of privacy since no information on asset demand, specifications, or preferences need to be exchanged. The central entity receives each participant's market position and then conveys the average market position of all market participants back to each individual participant, ideally resulting in market clearing convergence. As only the average market position of each participant is exchanged, the CADMM approach provides an extra layer of privacy compared to standard ADMM, in which the market position of each individual participant is shared [36]. However, due to the slow convergence of these methods, some insight into participants' private information may occur [60]. The CADMM model in this study took 2300 seconds of CPU time, compared to 86 and 1200 seconds for the supply–demand ratio and equilibrium models, respectively. The CADMM solvability could have been improved by parallelisation or other accelerating methods [61], which would have resulted in a shorter computational time. Still, the computational burden of this and the equilibrium model may cause issues with both privacy and scalability. Moreover, adversarial models or inverse optimisation techniques may be used to reconstruct the individual optimisation problems or parameters [62].

Third and last, the equilibrium pricing mechanism necessitates extensive data sharing ex-ante. In order to clear the market, detailed specifications and consumption data (if applicable) for specific assets must be provided in addition to forecasted net demand. As a result, of the three suggested methods, the equilibrium pricing mechanism has the greatest need for data sharing. Similar to the supply–demand ratio pricing mechanism, data must be shared with a central entity and not with other market participants. However, because the equilibrium approach necessitates complete knowledge of each participant's data,

Table 6
Privacy and transparency characteristics of the three pricing mechanisms.

Characteristic	Supply–demand	CADMM	Equilibrium
Information shared with	Central entity	Central entity and market participants[a]	Central entity
Detail level of sharing	Low	Medium	High
Method complexity level	Low	High	Medium
Transparency on daily price	Yes	Yes, but complicated[b]	Yes[b]

[a] Only the average traded volumes are shared with other market participants.
[b] At the cost of privacy.

it has the most serious consequences in the event of a breach. This problem has been the motivation for anonymised auctions [63], but these come at the expense of less efficient markets. As indicated in the literature review in Section 2.3, solving mixed complementarity problems directly may not be a realistic option for real-life implementation of local electricity pricing mechanisms. Still, many of its optional transformations, such as central mixed integer linear programs, have the same requirements for information sharing.

As summarised in Table 6, the three mechanisms have in common that information is shared with a responsible third party, to various degrees. This is not unique to local electricity markets and is a situation that is generally accepted in other sectors. With the widespread use of social media, most people already accept the collection of sensitive data about them, both intentionally and unintentionally, and without necessarily being aware of the full extent [18]. This suggests that privacy preferences are highly subjective and that the amount of information that someone is willing to share can vary among the participants [64].

5.3. Transparency and complexity

The last aspect to be evaluated in this study is the level of transparency and complexity of the pricing mechanisms. It should be noted that only the transparency of the pricing mechanisms is discussed, not the transparency that can be provided by other tools such as distributed ledger technology. As the market participants should be able to understand both the logic behind the pricing mechanism and the resulting daily prices, we distinguish between transparency and complexity in these two elements. A summary of the transparency and complexity of the three pricing mechanisms is provided in Table 6.

5.3.1. Transparency and complexity of the pricing mechanism

The supply–demand ratio pricing mechanism is straightforward and does not raise significant transparency concerns. Because the method is rule-based, it should be understandable to the majority of market participants. The upper and lower bounds of the market price should be thoroughly explained, ensuring that market participants understand between which two points the price will move. The ex-post nature of the supply–demand ratio pricing mechanism has some drawbacks, as market participants will not know the local market price when planning their demand, adding some complexity to daily operations. However, with knowledge of the upper and lower bounds, participants have an indication of the local price on which to base their operational decisions.

The CADMM pricing mechanism is far more complex and raises a number of transparency and complexity concerns. First, the method is based on advanced mathematical formulations and optimisation problems, which are hardly comprehensible to most individuals. Second, the optimisation problem is decomposed and solved using a distributed optimisation method which has issues with convergence and frequently necessitates empirical adjustments to the step size parameters. As implied by the results in this study, this parameter alteration also influences the market price, which may lead to a conflict of interest.

The equilibrium pricing mechanism is also complex in the sense that it relies on advanced optimisation techniques. However, under the assumption of convexity and sufficient scalability, the pricing mechanism can guarantee a Nash equilibrium solution, which may be a more comprehensible concept. Perfect competition is a well-established concept in economics, and the method can be explained using popular thought experiments such as the Prisoner's Dilemma. Scalability remains an issue, which might require transformation into more scalable methods as mentioned in Section 2.3.

5.3.2. Transparency of the daily market price

Transparency on price formation is simple under the supply–demand ratio pricing mechanism because price formation only requires aggregated net-metered data to be determined. This is more difficult under the CADMM approach because the method is not only advanced but also based on iterative negotiations that are tuned by a series of adjustable parameters. Nonetheless, the market operator could go beyond sharing only the average market position to sharing each market participant's market position in each iterative step, which would only slightly violate the market participants' privacy. Furthermore, information about the CADMM algorithm's adjustable parameters could be provided, but these are difficult to interpret. As previously stated, the values of these parameters are empirically determined for numerical convergence, which has little meaning for most market participants. As they in turn affect the daily market price to such a large extent, as seen in this study, it can be difficult to convince the participants of the reasoning behind the outcome. Lastly, the effect of the starting point of this algorithm, where the price is initiated to be in the middle of the buying and selling price of the wholesale market, is found to be significant. As seen in this study, with so few iterations the final price rarely deviates significantly from the initial price, possibly leading some to argue that the price is predetermined by the market operator. The logic behind this may be difficult to explain to the market participants. This issue may change if flexibility or other dispatchable sources are introduced into the market, necessitating more iterations to reach a consensus and thus reducing the effect of the starting point.

Still, both the supply–demand ratio and CADMM pricing mechanisms are more privacy-preserving than the equilibrium pricing mechanism, in which price formation can only be explained by sharing the full information of every market participant. However, because the price often equals the lower or upper bound (assuming no storage or other flexibility is available), net metered data indicating whether or not the market has a surplus of generation may be sufficient to explain the price.

6. Conclusion

In this study, three principally different pricing mechanisms for local electricity markets have been compared. A vast number of mechanisms are proposed in the literature, each tailored to different market conditions and participant characteristics. Thus, for well-informed decisions in future implementations, a comprehensive analysis of the mechanisms' behaviour when applied to the same case study is required. The supply–demand ratio, CADMM and equilibrium-based pricing mechanisms were all tested in two different case studies, with a low and high share of PV generation available in the local electricity market.

Investigating the welfare distribution among the two market participant groups, consumers and prosumers, it was observed that consumers

Table 7
Nomenclature.

Sets		
$t \in T$	Hours t in time horizon T	hours
$h, p \in H$	Peers h and p in houses H	–
Scalars		
C^g	Energy term of grid tariff	EURc/kWh
C^a	Administration cost	EURc/kWh
C^{FiT}	Feed-in-Tariff	EURc/kWh
γ	Penalty factor	–
Parameters		
D_{ht}	Demand of house h in time step t	kW
PV_{ht}	Electricity production from PV of house h in time step t	kW
C_t^{spot}	Wholesale spot price for electricity from the grid in time step t	EURc/kWh
s_t	Supply–demand ratio	–
r_{ht}	Primal residual of CADMM	kWh
Variables		
g_{ht}^{imp}	Grid import to house h in time step t	kWh
g_{ht}^{exp}	Export to grid from house h in time step t	kWh
i_{hpt}	Electricity purchase of house h from peer p in time step t	kWh
x_{pht}	Electricity sold by house h to peer p in time step t	kWh
i_{ht}^{LM}	Electricity purchase of house h in time step t from local market	kWh
x_{ht}^{LM}	Electricity sold by house h in time step t from local market	kWh
u_{ht}	Binary variable for CADMM	$\{0, 1\}$
λ_{ht}/λ_t	Local electricity market price	EURc/kWh
μ_{ht}^{eb}	Market balance dual	EURc/kWh
q_{ht}	Perceived price by house h in time step t	EURc/kWh
σ_t	Standard deviation of perceived prices in time step t	EURc/kWh
σ_t^{max}	Maximum deviation in perceived price in time step t	EURc/kWh

obtained the lowest costs through the supply–demand ratio pricing mechanism because of its low prices. In contrast, prosumers benefited the most from the CADMM pricing mechanism because of its consistently high price level compared to the other mechanisms. These trends were the same regardless of the market's energy balance, i.e. the two case studies. The supply–demand pricing mechanism excels in simplicity, privacy and transparency, and should hence be an attractive candidate in early-stage local electricity market adoption. As local electricity markets mature and gain more trust, the equilibrium approach is superior in terms of economic efficiency and is a clear long-term candidate. However, the privacy-related issue of the mechanism must be solved. The CADMM pricing mechanism has privacy benefits but suffers from convergency issues and reliance on adjustable parameters, as well as raising transparency and complexity concerns. As a result, the mechanism is less practically realisable than the other two mechanisms.

The conclusions of this research should serve as inspiration for future comparative assessments of pricing mechanisms, and help in the making of informed decisions about the establishment of local electricity markets. Since this research only investigated three of the different pricing mechanisms available, future studies should broaden their scope to cover additional pricing mechanisms. Other characteristics, such as a more in-depth analysis of the fairness aspect or computational tractability, might be incorporated in more detailed comparisons. Moreover, further research should be conducted to examine how pricing mechanisms compare when there is flexibility in the local electricity market and the potential for strategic behaviour emerges. Finally, interdisciplinary aspects of energy and social-political decisions may be coupled with the demonstrated framework, which may aid decision-makers and policymakers in making the best available decisions when designing the boundaries of future local electricity markets.

CRediT authorship contribution statement

Marthe Fogstad Dynge: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Project administration. **Kjersti Berg:** Conceptualization, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Sigurd Bjarghov:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Ümit Cali:** Conceptualization, Resources, Writing – review & editing, Supervision.

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

Data will be made available on request.

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Appendix. Nomenclature

See Table 7.

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