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P2P trading of heat and power via a continuous double auction

Timothy D. Hutty, Solomon Brown *

Department of Chemical and Biological Engineering, University of Sheffield, UK

HIGHLIGHTS

- Simulation of peer-to-peer (P2P) energy trading via a continuous double auction
- Heat and power both considered, with fuel cells and heat pumps coupling these
- Auction format allows flexible devices to plan schedules in advance
- With electricity trading, higher load factor for fuel cells, cuts reliance on grid
- Heat trading brings extra technical benefits though cost savings are not certain

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ABSTRACT

Peer-to-peer (P2P) energy trading, whereby customers can trade energy with one another rather than the energy supplier only, has the potential to save money for consumers whilst also incentivising more efficient and environmentally beneficial behaviour. Many existing models for P2P only consider a real-time or hour-ahead market, which does not allow proper scope for the planning of flexible demand or for energy storage. Accordingly, in this model we employ a day-ahead continuous double auction (CDA), in which all the upcoming timeslots are simultaneously open for trading. This allows schedules for device dispatch to be developed properly. We consider the flexibility and interdependence of bidding across different timeslots and develop strategies to address this. Furthermore, we consider the trade of heat as well as power, via a low temperature heat network. Heat and power trading interact due to the use of air source heat pumps (ASHPs) as well as reversible solid oxide cells (rSOCs), which can provide combined heat and power, or alternatively produce hydrogen via water electrolysis. In our case study, the P2P market is simulated with 25 houses participating, for two week-long periods in different climate conditions. P2P electricity trading is found to bring a marked reduction in reliance on grid electricity, and a reduction in peak grid load. This is brought about mainly by the incentive for rSOCs to generate at a higher average load factor, and the average house makes savings of ca. £10 / week in winter weather. Heat trading brings a further decrease in reliance on grid electricity, and largely eliminates the use of inefficient resistive heat. However, the heat trading may not be financially worthwhile in all conditions.

1. Introduction

As the world seeks to decarbonise its energy systems, some of the changes will be seen at a local and household level. These changes will be felt across the key sectors of power, transport and heat. They include the growth of embedded generation, both solar PV and combined heat and power (CHP) systems [1], the proliferation of electric vehicles (EVs) [2], and the decarbonisation of heating systems. Peer-to-peer (P2P) energy trading, whereby consumers are able to trade energy with one another, rather than the energy supplier only, can help to incentivise the efficient use of these new technologies [3,4]. For instance, P2P can incentivise the synchronisation of flexible loads with surpluses in renewable generation; a simple example of this is the scheduling of EV charging to make use of a peer's surplus solar power. The net effect is increased local self-sufficiency in energy, decreased environmental impact and a reduction in bills [4]. Although market regulations in many countries do not yet support P2P trading, interest is growing, with companies including Centrica and EDF carrying out trial schemes in recent years [5,6].

A continuous double auction (CDA) is a particularly interesting structure for a P2P market, since it closely resembles the continuous

* Corresponding author.
E-mail address: s.f.brown@sheffield.ac.uk (S. Brown).

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Nomenclature and terminology.

Acronyms

ASHP Air source heat pump
CDA Continuous double auction
CHP Combined heat and power
COP Coefficient of performance (of heat pump)
EV Electric vehicle
G_ONLY Market paradigm where only grid trade of electricity is available.
LHV Lower heating value
MILP Mixed integer linear programming
P2P Peer-to-peer
P2P_P Peer-to-peer market allowing trading of electrical power only
P2P_H_P Peer-to-peer market allowing trading of both heat and power
rSOC Reversible solid oxide cell
SOEC Solid oxide electrolyser cell [mode of rSOC]
SOFC Solid oxide fuel cell [mode of rSOC]
TES Thermal energy storage
TR Truthful [bidder]
V2X; V2H; V2G Vehicle to anything; vehicle to house; vehicle to grid
ZI[P] Zero intelligence [plus]

Symbols

Symbol (Unit) Description
t (–) Timeslot, typically in {1…24}
t_{last} (–) Final timeslot, typically 24.
Δt (s) Duration of a timeslot.
b (–) Binary variable
v_{V2X} (£/kWh) Estimated financial benefit of 1 kWh charged to the EV battery for V2X.
C (kWh/K) Heat capacity
C_{EV} (kWh) Capacity of EV battery
c_{V2X} (£/kWh) Estimated cost of discharging 1 kWh from the EV battery for V2X.
c_{rapid} (£/kWh) Cost of rapid charging.
D Set of devices owned by auction participant
p (£/kWh £/kg) Price; £ / kWh for energy, £ / kg for H_2.
p_{cl} (£/kWh) Clearing price for double auction
H (kWh) Thermal energy
H2 (kg) Hydrogen
K (kW/K) Thermal transfer coefficient
E (kWh) Electrical energy
E_{min_final} (kWh) Minimum kWh for the final storage state of the EV battery.
P (kW) Power
PEN (£) Penalty term in objective function
T (°C) Temperature
VAL (£) Valuation of a device's stored energy
η_{inv} Efficiency of inverter
η_{SOFC} (kWh/kg$_{H2}$) For rSOC in SOFC mode, kWh electricity generated per kg H_2.
η_{SOFCth} (kWh$_{th}$/kg$_{H2}$) For rSOC in SOFC mode, kWh heat generated per kg H_2.
η_{SOEC} (kWh/kg$_{H2}$) For rSOC in SOEC mode, kWh electricity consumed per kg H_2.

Subscripts

buy Energy to buy via future trades
sell Energy to sell via future trades
bought Energy already bought via successful offers
sold Energy already sold via successful asks
imp Imported
exp Exported
cl Cleared in auction
P2P peer-to-peer
res reserve price
rh resistive heat
st energy storage
tes Thermal energy storage
grid_retail Grid retail tariff for electricity import
grid_FI Grid feed-in tariff for electricity export

trading that takes place, for instance, in stock and currency markets - as well as wholesale electricity markets such as the UK intraday markets. In a CDA, buyers and sellers are both in direct competition, and this competition drives the variation in the energy price. Previous work on CDA has generally assumed, with only rare exceptions [7,8], that only a single timeslot of energy exchange is open for trading at any one time, for instance in an hour-ahead fashion. A more versatile model allows trading in all future timeslots up to a certain horizon; this allows scheduling of flexible devices and energy stores to be developed, since P2P bids for these devices introduce interdependence between the timeslots of the market. In this work, we introduce a day-ahead CDA where energy trading proceeds in all 24 upcoming timeslots simultaneously, and we present an agent-based model for such a market.

Decarbonisation of heat, which is often neglected in studies of P2P trading, can lead to additional motivations to trade energy [9,10]. For instance, air source heat pumps (ASHPs) can make use of peer's surplus electricity generation, storing heat either in the fabric of buildings or in dedicated thermal storage. Meanwhile, CHP systems which typically produce heat and power in a fixed ratio [11], can benefit by exporting surplus power to peers while tracking heat demand. The possibility of local trading in heat between peers, rather than power only, has received a limited amount of attention in the literature. Such trading requires connection to a heat network, likely operating at a moderate temperature [10]. In theory, this enables the extra flexibility to procure heat from different sources, depending on what is most cost-effective at a given time, achieving additional savings. Accordingly, the CDA model introduced in this work allows for trading in heat as well as electricity.

2. Literature review

2.1. P2P trading and double auctions

By enabling peers to trade with one another, rather than the energy supplier, P2P trading can be advantageous for both consumers and generators (often termed 'prosumers'); for electricity, trades agreed at prices between the grid retail cost and the feed-in tariff (if any) are profitable to both parties [12]. Even in the absence of flexible demand, generation or energy storage, P2P can be profitable, as it simply provides fairer recompense for energy that would be physically shared anyway – as in [13]. The real power of P2P, however, lies in its ability to incentivise smart coordination of flexible devices between peers, where these incentives do not exist under the traditional market paradigm. For instance, this can include the scheduling of a flexible load, or energy storage, to absorb surplus solar generation from a peer [3,14]. It is this aspect of P2P which can bring technical and environmental benefits, rather than financial only [4].

P2P energy trading can encompass a range of market designs. It is important to note that P2P can encompass markets where trading is fully bilateral between peers, and also markets where peers trade via a centralised market mechanism. For instance, real-life schemes such as the Brooklyn microgrid have employed auction markets similar to utility power markets [15]; whereas pilot P2P projects such as those by EDF and Centrica have employed Blockchain or similar technologies to enable the market to be processed in a distributed fashion [5,6]. Some schemes have taken a very simple pricing approach with a constant P2P tariff for trading, e.g. [16]; these schemes are designed predominantly for the sale of PV power and may not be suitable for a future scenario with a more complex mix of generation and flexibility.

Existing literature on P2P includes both a variety of market structures, and a variety of approaches to their simulation and study. In some cases, flexible devices and energy sharing transactions are optimised centrally [17–19] although for real-world implementations this would often be unviable, due to the computational burden as well as concerns surrounding the privacy and autonomy of peers [8]. Central optimisation methods can be re-posed as distributed optimisation problems, with the alternating method of mixed multipliers (ADMM) a popular approach, as in [20]. Game theoretic approaches are frequently seen, as in [21–25]; and many researchers have considered various forms of iterative market, where peers repeatedly adjust their strategies on the basis of feedback from the previous iteration, until convergence is achieved [3,4,26,27].

In this work the focus is on a **double auction** as the basis of the P2P market; this is an auction where buyers and sellers of a commodity are simultaneously in competition. One of the merits of this approach is the analogy with the operation of utility scale markets [28], as well as existing P2P schemes like the Brooklyn microgrid [13]. Participants submit bids to buy or sell consisting of a volume of energy and a reserve price; an equilibrium price is established and as many trades are cleared as possible. There is a symmetry between buyers and sellers which is absent from single-sided auctions or fixed price schemes. The clearing of the market may be one-off, as in [21], or may happen on a rolling basis as in [29,30]; the latter case is termed a continuous double auction (CDA). CDA has the advantage of avoiding the need for sophisticated price forecasting, as prices can be discovered in real time as the auction proceeds; small quantities of energy can be traded initially to elicit information from other traders [31,32].

There is a reasonable amount of previous work on double auctions for P2P energy trading, covering such issues as secure, distributed implementation [33], use of Blockchain [30], and comparison of price setting strategies [13]. Chen et al. [34] used a data-driven machine learning method to integrate price predictions with the strategy formation of auction participants in a CDA electricity market; the focus here was on the benefits to the single prosumer using the machine learning method, rather than the benefits of the market overall. Thakur et al. [35] consider a novel distributed double auction market in which any peer can act as the auctioneer; the focus here is on the reduction of computational overhead via use of the distributed algorithm, and flexible load / generation appears not to have been considered. Haggi et al. [36] consider a hierarchical double auction, with nodal, zonal and distribution network stages. The auction mechanism is able to ensure that physical network constraints are not violated; again, flexible load / generation is not considered, and only one timeslot is settled at a time. Zhang et al. [31] present an iterated double auction wherein agents may adjust their prices to increase profits with successive rounds; again, flexible loads and forward trading are not considered.

2.2. Flexible devices

The inclusion of flexible devices / energy storage in P2P markets brings particular challenges, owing to the coupling that these devices introduce between different timeslots. For instance, a battery may seek to buy additional energy at 12 pm, contingent on being able to sell this energy at 7 pm; an EV may prefer to charge at 6 pm *unless* cheaper energy will be available at 11 pm. El-Baz et al. [8] note that these issues mean that the real-time or hour-ahead trading most commonly seen in literature is not adequate when flexible devices and energy storage are involved. It is important that multiple timeslots of an upcoming day are simultaneously available for trading.

For a one-off, sealed-bid auction (such as the day-ahead utility scale markets for electricity) some of these issues can be addressed by submitting details of flexibility to the market operator. Zhang et al. [37] use such an approach, with shiftable / adjustable loads (including EVs) sending information on flexibility to the market operator, which then matches loads to PV generation. Similarly, utility day-ahead markets can allow for complex bids which encode flexibility information: these include linked block orders, flexible hourly orders and exclusive block orders [28]. In this case, the complex task of scheduling flexible loads is passed to the market operator, and the auction-clearing mechanism (which runs only once) may have to be rather complex, and may resemble global optimisation of the system.

By contrast, continuous trading cannot typically allow for complex bids, as only a few bids are typically being matched at one time, and the auction clearing mechanism must run many times. Instead, the problems of flexibility and interdependence between bids at different times must be addressed by the strategies of bidders as they engage in trading. Typically, bidders will acquire (or sell) energy gradually over the duration of the auction, and may revise strategies repeatedly in response to the evolving situation on the market. As noted in [32], the incremental trading of small quantities of energy can assist with discovering prices and forming strategies. Whilst the majority of auction models for P2P energy trading have energy traded in only one timeslot at a time (e.g. [10,20,24,25,31,34]–[36,38]) El-Baz et al. [8] present a rare double auction model in which agents can engage in forward trading in any of the upcoming timeslots, up to gate closure. The model in this present work is constructed on a similar basis. An important addition in this work is the allowance for arbitrage and consideration of arbitrage bidding strategies (whereas in [8] energy storage devices are used only to buffer the demand, or as a backup to ensure the trading position can be met). The addition of a second energy vector (heat) in the model adds further complexity to bidding strategies owing to interdependence between the desired quantity and price for heat and power bids.

2.3. Heat and power

The consideration of heat in studies of P2P energy trading can take two forms. Firstly, without actual trading of heat, but with consideration of household devices that couple electricity and heat demand: that is, principally heat pumps or CHP. Secondly, with P2P trading of heat as well as power. In the first category, Gan et al. [39] considered P2P electricity trading between multiple energy ‘hubs’ equipped with 200 kW CHP generators; an increase in profits of up to 19% was obtained. Zhu et al. [9] studied synergies between power, heat and hydrogen energy flows, with only power traded; P2P trading and hydrogen storage were both found to be important in cutting costs. The work of Nguyen et al. [20] is particularly relevant to the present work, as it involves P2P power trading between fuel cells providing CHP. The motivation to trade stemmed partly from the variable efficiency of the fuel cell at different partial loads. Heat from the fuel cells was used for DHW tanks – this system was the sole flexible device involved in the trading. Detailed consideration of bill savings was not included.

Trading of heat in DHNs has received somewhat less attention than the equivalent for electricity. One reason for this is that heat networks in many countries are vertically integrated, with the network itself owned by the same entity as the main heat generation; these networks thus form natural monopolies, and competitive markets have no applicability [40]. Government regulation is typically needed in order to ensure that consumers are not exploited by the monopoly owner [41]. Conversely, liberalisation of market regulation requires that there is competition on the heat side of the market, as demonstrated by experience in Sweden [41]. 4th generation DHNs operating at lower flow temperatures may help to diversify the supply side and help to motivate new market structures [42].

In the second category, Davoudi et al. [7] considered a trading of both heat and power, albeit with the price for heat assumed to be fixed and constant. An iterative approach was employed where peers had the ability to form both fixed-price and variable-price contracts. The P2P market was found to be profitable with respect to grid trading. Shi et al. [43] studied an integrated energy system with trading in heat, power and hydrogen. ADMM was used to optimise transactions between peers, and it was found that P2P together with a demand response programme was more profitable than either in isolation. Jing et al. [44] considered the trading of heat and power between commercial and residential prosumers, with an emphasis on finding fair prices for transactions – although they do not appear to have allowed the P2P prices to vary across timeslots. Daryan et al. [45] consider trading of heat and power between Smart Energy Hubs; the settlement of trading is broken down into optimisation of the trades which should take place, followed by identification of fair prices to incentivise these trades; the total social cost sees a 14% reduction. Block et al. [46] contrived a two-dimensional auction for heat and power, allowing for dependency between bids in the two energy types. Finally, Wang et al. [10] employed coalition game theory to study a double auction market for heat and power. Trading was motivated by slightly undersized heat pumps in dwellings, the varying COPs of these, and varying willingness to compromise on comfort.

2.4. Contribution of this work

In this work, we consider a CDA for P2P trading of both power and heat in a small residential community. The CDA is chosen as one of the most simple, generic and flexible forms of market [34], and because of its resemblance to utility scale markets. A separate double auction is provided for each timeslot of the upcoming day, and trading takes place in all timeslots simultaneously. This is in contrast to the majority of comparable literature on double auction for P2P: for instance references [10,20,24,25,31,34]–[36,38] all have auctions that operate one timeslot at a time, to the exclusion of forward trading (see Table 1). Of all extant work, the CDA markets proposed by El-Baz et al. [8] and Davoudi et al. [7] resemble the current work most closely; this work differs in certain important ways: the inclusion of strategies for arbitrage, and the inclusion of multiple energy markets (heat and power). In particular, this work addresses the interdependence between bids in the market, for instance to charge and discharge storage, as well as the flexibility to spread bids across more timeslots than ultimately required, aspects which are not included in [8] [7]. Furthermore, pricing in this model is fully competitive, contrasting the fixed heat prices of [7].

Our approach is fundamentally an agent-based one, with the bidders in the market being the main agents. As noted by Schimeczek et al. [47], agent-based models provide an approach to the analysis of energy markets which is less idealised (than optimisation models, for instance) and can capture sub-optimal markets with sub-optimal behaviours and inhomogeneity between bidders.

In summary, the present work addresses the following gaps:

- A double auction model wherein energy is traded simultaneously in all upcoming timeslots, allowing flexible devices and energy storage to engage in forward trading to develop schedules ahead of time.
- Strategies for agents to address the flexibility of their bidding, and the potential interdependence between bids, including for arbitrage applications.
- CDA markets for both heat and power, interacting via ASHP and reversible solid oxide cell (rSOC) devices.

The remainder of this document is structured as follows. In Section 3, the P2P CDA model is presented, including details of the proposed market mechanism, as well as the simulated bidding strategies of peers. In Section 4, results from the model are presented, showcasing the impact of the market on energy flows and techno-economic metrics. Discussion of the results may be found in Section 5 along with proposals for future work, and conclusions are drawn in Section 6.

Table 1
Summary of related literature.

	Market			Modelling approach				Features					
Reference	P2P market	Single-sided auction	Double auction	ABM	Central optimisation	Distributed optimisation	Game theory	Flexible devices	Energy storage	Forward trading	Heat demand	Heat trading	Pricing strategy
[45]	✓				✓			✓	✓		✓	✓	optimised for fairness
[43]	✓					✓		✓	✓		✓	✓	fixed proportion of retail price
[24]	✓						✓		✓				mid-market rate
[22]	✓						✓	✓	✓				(custom)
[38]	✓						✓	✓	✓		✓		
[39]	✓						✓	✓	✓		✓		
[10]	✓			✓				✓			✓	✓	
[30]	✓		✓	✓									
[33]	✓		✓	✓									adaptive aggressive
[35]	✓		✓	✓									fixed
[36]	✓		✓	✓									‘random’
[31]	✓		✓	✓									(custom)
[34]	✓		✓	✓				✓	✓				ZI, bid-as-predicted
[37]	✓	✓			✓			✓	✓		✓		(custom)
[8]	✓		✓	✓				✓	✓	✓	✓		(custom)
[7]	✓			✓				✓	✓	✓	✓	✓	constant heat price
current work	✓		✓	✓				✓	✓	✓	✓	✓	ZIP, truthful

3. Method

3.1. Overview

The P2P energy market consists of a CDA for each timeslot of the upcoming day, and where applicable each energy type (electricity and heat). Fig. 1 gives a high-level overview of this, and a simplified view of household strategy. Trading takes place simultaneously for all upcoming timeslots, so that schedules for flexible devices and energy stores can be planned effectively.

In principle, bidders could use arbitrary strategies to engage with the market. Here, bidding strategies are developed using a combination of (1) MILP optimisation, and (2) various rules that determine the prices submitted, and generate alternative bids or address possible interdependence between bids. Strategies may be revised repeatedly as the rounds of the market continue, responding to changing price profiles and to the success/failure of trading so far. Essential issues that need to be considered include the following:

- flexibility of bids in time
- interdependence of bids between energy types (e.g. sale of both heat and power from the rSOC)
- interdependence of bids between timeslots (as for energy storage charge and discharge)

The CDA market structure does not allow 'complex' bids with inherent interdependence or flexibility in time, and so here, these issues have to be handled by the strategies of the bidders. To facilitate this, it is enforced that the auctions for different timeslots and energy types never clear simultaneously; thus, participants always have the opportunity to respond to their success or failure in a particular auction by adjusting bids in other auctions.

The following conventions are adopted for terminology: **Bid** – any order whether to buy or sell energy. **Offer** – a bid to buy energy. **Ask** – a bid to sell energy. **Timeslot** – A future time period during which power is traded, typically half an hour or one hour in duration. **Round** – an iteration of the market wherein CDA's are cleared for every timeslot for both heat and power. We define D to be the set of devices available to an auction participant. 'Device' is to be interpreted broadly, as for instance the inflexible electrical load of a house and the space heating demand are both regarded as 'devices'.

MILP optimisations are carried out using Pyomo [48] with the GLPK solver [49]; all other aspects of the market simulation are modelled in AnyLogic software [50].

3.2. Markets

Offers and asks are not submitted to the auctions in truly continuous time, but rather in a sequence of rounds, similar to the markets in El-Baz et al. [8,51]. Multiple bids will typically arrive at each auction every round, after which the auction is cleared. The separate auctions for different timeslots clear in chronological order every round, with the auction for heat following the auction for power, for each timeslot, where applicable. Auction clearing entails ordering the offers in descending order of the submitted price, and the asks in ascending order. Offers are matched to asks until either the current ask price exceeds the current offer price, or there are no more asks to process, or there are no more offers to process. The clearing price p_{cl} is midway between the price of the final ask and offer to be cleared. Typically, either the final offer or final ask is only partially fulfilled. The auctions implement a 'pay-as-cleared' rule, meaning that all the cleared trades are transacted at the same price p_{cl}. Fig. 2 illustrates how the auction is cleared, showing the supply / demand curves as a function of price, with the intersection of these curves giving the clearing price.

3.3. Determination of bidding strategy

A bidding strategy is defined as the full set of asks and offers that a

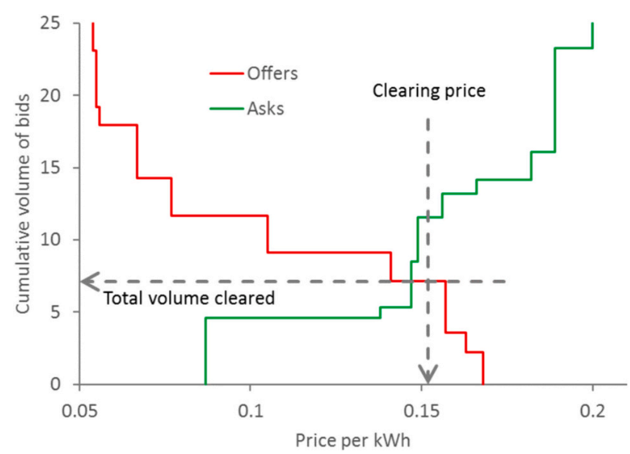

Fig. 2. Illustrates how the clearing price is found when a double auction is resolved. Note that each vertical step corresponds to a bid.

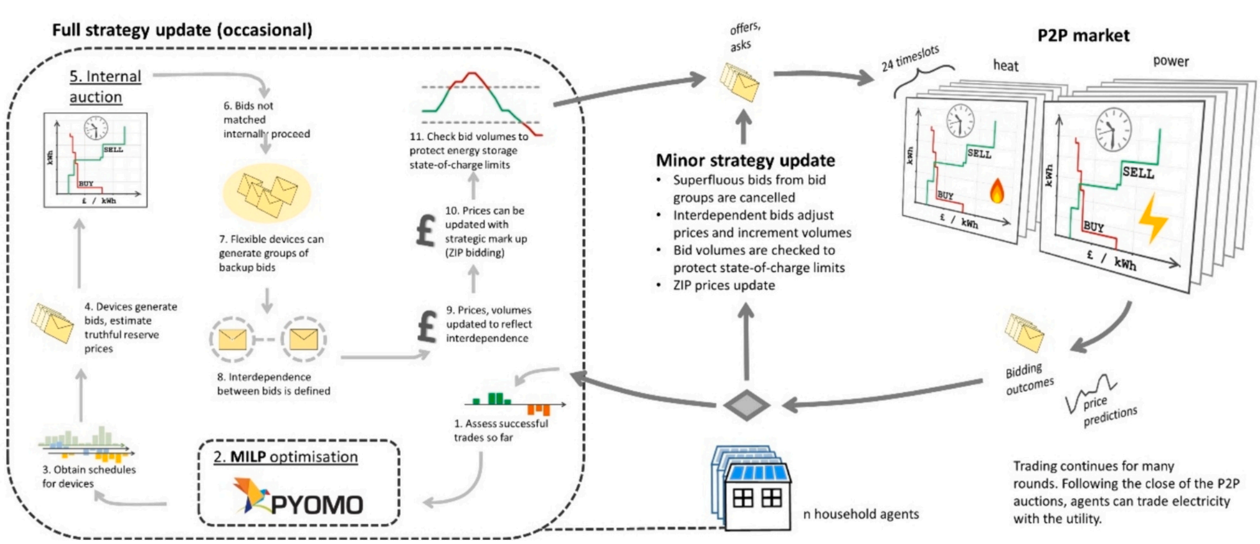

Fig. 1. A simplified overview of the market structure and household strategisation process.

participant wishes to submit, across all timeslots of the auction, incorporating both the quantities to trade and the reserve prices. Participants may theoretically update strategies at any time; for the purposes of this work, full strategy updates only take place between rounds, and in general only every few rounds. Smaller adjustments may be made more frequently; these adjustments typically arise from the interdependence of bids (see Section 3.3.4) – and could involve the activation / deactivation / cancelling of bids, as well as adjustments to reserve prices.

When the final round of auctions is completed, all households optimise their devices one final time, with respect to the trades they have successfully closed. Grid prices are available for further trade of power; further trade of heat is not allowed, as a 'utility' heat provider is not considered.

3.3.1. Categories of bid

Bids are categorised according to the device that generated the bid and the intended use of the energy; categories are shown in Table 2.

3.3.2. Price prediction

For simplicity, the initial price prediction

at the start of trading is equal to the mid-market rate halfway between grid retail and feed-in price. Initial heat price predictions are £0.10 / kWh or £0.08 / kWh, dependent on season, where this is based on experience running the model. A truer picture of prices emerges after a few rounds of bidding. Subsequent price predictions at each timeslot are the mean of the two most recent clearing prices. If no trading is occurring for the timeslot in question, the price predictions start to 'decay' exponentially towards limiting prices given by top-of-book prices, if outstanding bids exist, or otherwise the utility prices. A decay constant of 0.22 is used based on experience. Note that in the absence of trading, price predictions can still improve if top-of-book prices improve. The price of hydrogen is considered fixed, at least over the one-day time horizon of an auction.

3.3.3. Optimisation and internal auction

A full update to bidding strategy employs MILP optimisation of a household's energy flow, combined with rules to generate additional back-up bids. Decision variables for the MILP describe the load points for flexible devices and energy storage, as well as temperatures in the building and the TES; see the Appendix.

Electricity purchased to charge the EV battery may be required either for essential travel, or for V2H / V2G, and this affects the valuation per kWh. To enable these bids to be separated, the optimiser runs twice, with V2X disabled the first time.

Table 2
Categories of bids.

Name	Description
Offers (power)	
INFLEXIBLE_LOAD	Standard electrical load of the house, assumed inflexible
EV_ESSENTIAL	EV charging that is essential for travel.
EV_ARBITRAGE	EV charging for V2X, or to carry energy into the next day.
ASHP_BUY	Power required for the ASHP to meet the heat demand
ASHP_FOR_TES	Power required for the ASHP to charge thermal storage.
ASHP_FOR_EXPORT	Power required for the ASHP to export heat (P2P_H_P only)
RESISTIVE_BUY	Power for resistive heat
RSOC_BUY	Power required to run SOEC mode of the rSOC
Asks (power)	
PV_EXPORT	Exported solar PV power
EV_V2X	Power exported from the EV battery
RSOC_SELL	Power from SOFC mode of the rSOC
Offers (heat)	
HEAT_DEMAND	Heat required to meet household demand
HEAT_FOR_TES	Heat to charge thermal storage
Asks (heat)	
HEAT_FROM_RSOC	Heat from the rSOC
HEAT_FROM_ASHP	Heat from the ASHP
HEAT_FROM_RH	Heat from the resistive heater

For each timeslot t the MILP optimisation receives information on the energy that has already been traded, i.e. $E_{bought,t}$, $E_{sold,t}$, $H_{bought,t}$, and $H_{sold,t}$, as well as the latest price forecasts for each timeslot. The optimiser calculates schedules for all devices and the amount of energy to be imported / exported. At each timeslot, the net energy required by the devices must balance with the energy already bought / sold, and the energy to be bought / sold in the future, as expressed in Eqs. 1–2.

$$E_{sold,t} - E_{bought,t} = -E_{sell,t} + E_{buy,t} + \sum_{d\in\mathscr{D}} \left(E_{gen,d,t} - E_{cons,d,t}\right) \tag{n. 1}$$

$$H_{sold,t} - H_{bought,t} = -H_{sell,t} + H_{buy,t} + \sum_{d\in\mathscr{D}} \left(H_{gen,d,t} - H_{cons,d,t}\right) \tag{n. 2}$$

Note that the left-hand side of each equation consists of fixed parameters, whereas the right-hand side consists of non-negative decision variables.

For simplicity, P2P trades that have previously been made are not reversed: i.e. participants do not sell / buy back energy that they have previously bought / sold. Thus, participants will never have both asks and offers agreed for the same energy type at the same timeslot. The exception is at the very end of the trading, when trade with the utility electricity supplier, at retail tariff, may be used to reverse P2P trades if wished. Accordingly, the following constraints apply:

$$\begin{cases} E_{bought,t} > 0 : E_{sell,t} = 0 \\ E_{sold,t} > 0 : E_{buy,t} = 0 \end{cases} \tag{3}$$

$$\begin{cases} H_{bought,t} > 0 : H_{sell,t} = 0 \\ H_{sold,t} > 0 : H_{buy,t} = 0 \end{cases} \tag{4.}$$

The objective function for the household optimisation is given as the net earnings, with the value attached to any energy stored at the close of the day, minus any penalty terms arising from individual device models. Note that this is expressed as a maximisation problem:

$$\begin{aligned} obj = & \sum_t \left(E_{sell,t} \bullet p_{power,exp,t} - E_{buy,t} \bullet p_{power,imp,t}\right) \\ & + \sum_t \left(H_{sell,t} \bullet p_{heat,exp,t} - H_{buy,t} \bullet p_{heat,imp,t}\right) \\ & + p_{H2,exp} \sum_t H2_{sell,t} - p_{H2,imp} \sum_t H2_{buy,t} \\ & + \sum_{d\in\mathscr{D}} VAL_{d,t_{last}} - \sum_{d\in\mathscr{D}} \sum_t PEN_{d,t} \end{aligned} \tag{5.}$$

The variables, constraints and penalty terms that describe the specific behaviour of each device $d \in \mathscr{D}$ are given in the Appendix. In practice, two sub-models give rise to penalty terms; the rSOC model introduces a penalty term for switching between modes, and the space heating model introduces penalties for any infringement of thermostat settings.

The optimisation model is expressed in terms of net energy generation / consumption; thus it does not explicitly specify which devices in a house share energy with each other, nor which devices are assigned to use (supply) energy previously bought (sold) on the P2P market. However, for the assignment of reserve prices in the P2P market, it is necessary to allocate each P2P bid to a device, since the reserve prices for devices differ as shown in Table 3. Therefore, before bids are submitted to the P2P auctions, the devices in each household participate in an internal auction. Each device places offers for the amounts $E_{cons,d,t}$ and asks for the amounts $E_{gen,d,t}$; these may be broken down into separate bids with differing reserve price. Prices submitted to the internal auction are always truthful (see Table 3). Additionally, the amounts $E_{bought,t}$ and $E_{sold,t}$ enter the internal auction respectively as asks and offers; they are assigned respectively very low and very high prices, to ensure that they are cleared. The internal auctions are cleared in identical fashion to the P2P auction (see Section 3.2). Bids cleared in the internal auction are stamped with a nominal valuation that corresponds either to the current predicted P2P price (when the bid has been matched with another

Table 3
Truthful reserve prices (i.e. limit prices) assumed for different applications.

Category	Truthful reserve price (£/kWh)
Offers to buy power	
INFLEXIBLE_LOAD	p_{grid_retail}
EV_ESSENTIAL	p_{grid_retail}
ASHP_BUY	p_{grid_retail}
ASHP_FOR_EXPORT	$COP \bullet \tilde{p}_{heat}$ where $\tilde{p}_{heat}$ is the predicted price to sell heat
RESISTIVE_BUY	p_{grid_retail}
RSOC_BUY	$min\left(p_{grid\_retail}, \frac{p_{H2} \bullet \eta_{inv}}{\eta_{SOEC}}\right)$
EV_ARBITRAGE	**For an amount corresponding to the EV_V2G bids that have been matched (internally or externally) at an average value of p_{V2X}:** $(p_{V2X} - c_{V2X}) \bullet \eta_{inv}^2 \bullet \eta_{st}$ **For a further amount not exceeding 10% of battery capacity in each auction round:** $\left(\tilde{p}_{V2X} - c_{V2X}\right) \bullet \eta_{inv}^2 \bullet \eta_{st}$ (where $\tilde{p}_{V2X}$ is the *predicted* average value of corresponding EV_V2X.)
Asks to sell power	
PV_EXPORT	p_{grid_FI}
RSOC_SELL	**No heat trading:** ***For the power corresponding to heat used in the house:*** $\frac{p_{H2}}{\eta_{SOFC} \bullet \eta_{inv} + \eta_{SOFCth}}$ ***For any further power:*** $\frac{p_{H2}}{\eta_{SOFC} \bullet \eta_{inv}}$ **With heat trading:** ***Where corresponding heat is unmatched:*** $\frac{p_{H2}}{\eta_{SOFC} \bullet \eta_{inv}}$ ***Where corresponding heat is matched at price p_{heat}:*** $\frac{p_{H2}}{\eta_{SOFC} \bullet \eta_{inv}} - \frac{p_{heat} \bullet \eta_{SOFCth}}{\eta_{SOFC} \bullet \eta_{inv}}$
EV_V2G	**For an amount corresponding to the EV_ARBITRAGE bids that have been matched (internally or externally) at an average value of p_{ARB}:** $\frac{p_{ARB}}{\eta_{inv}^2 \bullet \eta_{st}} + c_{V2X}$ **For a further amount not exceeding 10% of battery capacity in each auction round:** $\frac{\tilde{p}_{ARB}}{\eta_{inv}^2 \bullet \eta_{st}} + c_{V2X}$ where $\tilde{p}_{ARB}$ is the average predicted price of the EV_ARBITRAGE bids not yet matched.
Offers to buy heat	
HEAT_DEMAND	$min\left(\tilde{p}_{power}, p_{heat,marginal}\right)$ where $\tilde{p}_{power}$ is predicted power price and $p_{heat,marginal}$ is the price to generate more heat locally.
Asks to sell heat	
HEAT_FROM_RSOC	***Where corresponding power is unmatched:*** $\frac{p_{H2}}{\eta_{SOFCth}}$ ***Where corresponding power is matched at price p_{power}:*** $\frac{p_{H2}}{\eta_{SOFCth}} - \frac{p_{power} \bullet \eta_{SOFC} \bullet \eta_{inv}}{\eta_{SOFCth}}$
HEAT_FROM_ASHP	***Where corresponding power has not been obtained:*** $\frac{p_{grid\_retail}}{COP}$ ***Where corresponding power has been obtained at price p_{power}:*** $\frac{p_{power}}{COP}$

household device) or, if matched with a previously successful P2P bid, the traded price of this bid. Bids not cleared in the internal auction proceed to the P2P auction.

3.3.4. *Interdependence of bids*

As has been already mentioned, bids to buy and sell energy can be interdependent in two ways. Firstly, in the heat and power market, there is interdependence between bids for the two types of energy. For the rSOC (in SOFC mode) to export both heat and power at a particular timeslot, it is fundamentally required that:

$$\eta_{SOFC} \bullet \eta_{inv} \bullet p_{power} + \eta_{SOFCth} \bullet p_{heat} \geq p_{H2} \tag{n. 6}$$

Where heat (power) from the rSOC is matched in the internal auction, the corresponding power (heat) can immediately be assigned a reserve price and sent to the P2P market. The P2P reserve price in this case is obtained by substituting the valuation assigned by the internal auction into Eq. 6. Where neither heat nor power are matched in the internal auction, so that both are to be sold to peers, the following approach is taken:

1. The bulk of the energy for export is assigned a reserve price that guarantees a profit, i.e. p_{H2}/η_{SOFCth} for heat and p_{H2}/η_{SOFC} for power.
2. Incremental amounts of heat / power corresponding to 10% of the rSOC capacity are assigned more aggressive reserve prices that still mutually satisfy Eq. 6.
3. Whenever a P2P bid to sell rSOC heat or power is matched, the corresponding quantity of power / heat receives a new price obtained by substituting the clearing price into Eq. 6.
4. When the aggressively priced incremental amounts are matched, they are replaced, until there is no more capacity to sell, or the auction ends.

For the ASHP to import power in order to export heat, it is required that:

$$COP \bullet p_{heat} \geq p_{power} \tag{n. 7}$$

This is addressed in a similar manner to the rSOC. Where power is to be imported in order to export heat, only 10% of the ASHP capacity is entered into the P2P electricity auction at one time. This is priced at $COP \bullet \tilde{p}_{heat}$ where $\tilde{p}_{heat}$ is the predicted price to sell heat. 100% of the ASHP thermal capacity can be entered into the P2P heat market with a price of p_{grid_retail}/COP, as the grid retail price is guaranteed to be available. If a bid to buy power is matched, the price of the corresponding heat can be updated as p_{cl}/COP. Note that the incremental bidding of 10% capacity prevents excessive purchase of electricity when the sale of corresponding heat may not be achieved.

The second type of interdependence is between bids to charge and discharge energy storage. For instance, for the EV, the fundamental requirement in order to buy energy at t_1 and sell at t_2 is:

$$\eta_{inv}^2 \bullet \eta_{st}\left(p_{power,t_2} - c_{V2X}\right) \geq p_{power,t_1} \tag{n. 8}$$

where c_{V2X} represents the cost of cycling the EV battery, η_{st} is the DC round-trip battery efficiency, and η_{inv} is the inverter efficiency. As with the ASHP and rSOC, the approach is to only allow small increments of energy to be submitted to the P2P auction at one time. For the EV, the total volume of bids to charge the storage (i.e. type EV_ARBITRAGE) should not exceed the volume of matched V2X energy by >10% of battery capacity. Conversely, the total volume of bids to discharge storage does not exceed the volume of matched EV_ARBITRAGE bids by >10%. As with the interdependence of heat and power bids, matching of a P2P bid to charge / discharge the EV will trigger adjustment of the price for a corresponding volume of discharged / charged energy. Bids to charge and discharge the TES are dealt with in analogous fashion.

It is worth noting that the model also allows heat energy to be stored in the fabric of the house, by exceeding the minimum thermostat demand temperature. The interaction of timeslots induced by this energy storage is handled by the optimiser, but we have not attempted to explicitly address it in the bidding strategy and reserve prices.

Interdependent bids are updated after the clearing of every timeslot in every round, even if the house does not perform a full strategy update that round.

3.3.5. Pricing strategy

3.3.5.1. Truthful reserve prices.. It is important for bidders to possess a truthful valuation of the energy they are seeking to trade. This can be variably termed a reserve price, a limit price, or an indifference price, and gives the minimum acceptable price for asks and a maximum acceptable price for offers. The assumptions made for these reserve / limit prices are shown in Table 3. In some cases, establishing reserve prices is straightforward (e.g. for PV export). Where there is interdependence between bids, limit prices are also interdependent on the prices and volumes achieved by the connected bid, as detailed in Section 3.3.4 above.

3.3.5.2. ZIP bidding. Some auction participants submit their truthful valuations (or 'limit' prices) with their bids, as per Table 3. This is termed an 'aggressive' strategy, since it maximises the chance of making a trade, possibly at the expense of obtaining a less favourable price. Other participants bid using a 'ZIP' ('zero intelligence plus') strategy. This entails seeking a price better than the truthful limit price. This should not necessarily be seen as un-altruistic; as noted by Glismann, strategic markup can be an important coordination mechanism; ultimately, traders leveraging their market power means that prices will more properly reflect supply and demand [32]. ZIP bidders submit a reserve price uniformly distributed between their truthful reserve price and an upper or lower bound price. For bids to buy power, this means:

$$p_{res} \sim U\left(p_{grid\_FI}, p_{tr}\right) \tag{n. 9}$$

For bids to sell power:

$$p_{res} \sim U\left(p_{tr}, p_{grid\_retail}\right) \tag{n. 10}$$

For bids to buy heat:

$$p_{res} \sim U(0, p_{tr}) \tag{n. 11}$$

For bids to sell heat:

$$p_{res} \sim U\left(p_{tr}, p_{grid\_retail}\right) \tag{n. 11b}$$

3.3.6. Flexible bidding by the EV

For the charge and discharge of the EV battery, it is assumed that bidding can be more flexible than the strategy dictated by optimisation. The timeslots are partitioned into availability periods A_i representing distinct periods when the vehicle is available (long availability periods may also be subdivided). The amount to buy or sell from the battery is then calculated for the period as a whole, using the optimisation output, as per Eqs. 12 and 13:

$$E^{A_i}_{buy,EV} = \sum_{t \in A_i} E_{buy,EV,t} \tag{n. 12}$$

$$E^{A_i}_{sell,EV} = \sum_{t \in A_i} E_{sell,EV,t} \tag{n. 13}$$

The bidder then places a 'group' of offers or asks across multiple timeslots of the availability period. These include the bids specified by the optimiser, as well as backup bids with a total volume of up to $r_{bu} \bullet E^{A_i}_{buy,EV}$ or $r_{bu} \bullet E^{A_i}_{sell,EV}$ where r_{bu} is a backup ratio randomly chosen by each auction participant. Since the total volume of the bids is now greater than required, superfluous bids must be cancelled once the targeted amount is secured for the availability periods. Because the timeslots of the auction are settled sequentially, there is opportunity after the settlement of each timeslot to make these adjustments. Note again that the market does *not* allow the submission of bids that are flexible by time. Instead, the flexibility is achieved entirely by the bidder's strategy of placing additional bids and cancelling those which become superfluous.

Since the 'backup' bids have not been specified by the optimiser, the headroom to charge or discharge the battery has to be checked at each timeslot, against any bids to buy or sell that have already succeeded, and any energy planned to exchange between EV and house.

3.3.7. Protecting state-of-charge limits

Bids to supply energy from energy storage (the EV battery or TES) may be contingent on bids to buy energy at a separate timeslot. If only a subset of the bids placed are successful, then the state-of-charge limits of the storage could be infringed (in practice this could be prevented via last-minute trading at the grid tariffs, but this would be financially unattractive). To avoid this situation, the volume of bids can be trimmed to ensure that the future state-of-charge remains within limits.

Following the settlement of the internal auctions, the 'achieved' storage profile $\widehat{E}_{stored,t}$ is obtained for the EV battery (or any other energy storage device). That is, the profile achievable with energy already bought / sold on the P2P market, and energy shared within the house, that the internal market has assigned to the storage. $\widehat{E}_{cons,d,t} \in \left(0, E_{cons,d,t}\right)$ and $\widehat{E}_{gen,st,t} \in \left(0, E_{gen,d,t}\right)$ are respectively the amounts of power consumption and generation cleared by the internal auction for the storage device d. The achieved storage profile is then defined as follows:

$$\widehat{E}_{stored,\hat{t}} = E_{stored,0} + \sum_{t=1}^{\hat{t}} \left\{ \eta_{inv} \bullet \eta_{st} \bullet \widehat{E}_{cons,d,t} - \frac{1}{\eta_{inv}} \widehat{E}_{gen,d,t} + E_{drive,t} - E_{drive,t} \right\} \tag{n. 14}$$

Before the auction for timeslot t is settled, each participant checks the headroom for charge and discharge:

$$BUY_{max} = \min_{\hat{t} \geq t} \left(C_{st} - \widehat{E}_{stored,\hat{t}}\right) \bullet \frac{1}{\eta_{inv} \bullet \eta_{st}} \tag{n. 15}$$

$$SELL_{max} = \min\left(\min_{\hat{t} \geq t} \left(\widehat{E}_{stored,\hat{t}}\right), \widehat{E}_{stored,t_{last}} - E_{min\_final} \right) \bullet \eta_{inv}$$

Note that, if there is a constraint E_{min_final} on the final amount of energy stored, this must also be factored in. The volume of bids for energy to charge the storage are then compared to the value of BUY_{max} and reduced if necessary; asks are compared to $SELL_{max}$ in the same way. Conversely, bids that were previously reduced in this way may be restored to their original value following the success of 'dependent' bids. Bids with volume reduced to zero are not submitted to the auction, but still retained in case they can be activated in future rounds.

4. Results

4.1. Case study

To investigate the efficacy of the P2P market, we employ a case study of 25 houses, containing various devices (see Fig. 3). These are assumed to share the same circuit in the electrical distribution grid. Where heat trading is considered, the houses are assumed linked by a small 4th generation heat network. Results are also presented for a case with 1000 houses, in order to verify the computational scalability of the approach.

The energy sharing neighbourhood is notionally located in south-east England with climate data drawn from UKECN [52] and inflexible load data from UKPN [53]. 15 houses are randomly assigned to have 6 kW_p solar PV systems; these are evenly split between east-, south- and west-facing systems. Generation is calculated from irradiance data and the azimuth and tilt of the panels, using the model reported in [54].

All houses have one EV, with a trip schedule drawn from the UK National Travel Survey 2017–2019 [55]. The fuel economy of the vehicles is assumed to depend strongly on outdoor temperature; for more details of the data sample and EV model, see [4]. EV chargers have 7 kW

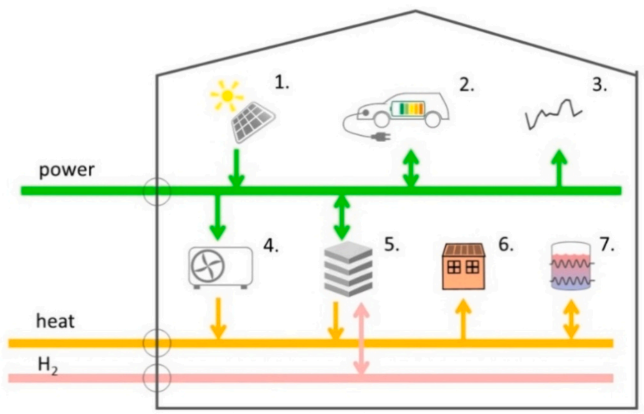

Fig. 3. Shows the possible devices included in houses (not all houses contain all devices). 1. PV generation. 2. EV. 3. Inflexible electric load. 4. ASHP. 5. rSOC. 6. Heat demand model. 7. TES. 25 houses with varying devices are included in the case-study.

capacity and for simplicity are assumed operable at any partial load. Furthermore, the possibility to discharge the EV battery V2H or V2G is always permitted.

Heat demand is modelled by adopting the CREST building archetype for improved semi-detached buildings, with building parameters varied by ±20% for additional diversity [56]. Space heating demand temperatures are uniformly distributed between 17.5 °C and 22 °C; 50% of houses are assigned morning and evening heating patterns, while 50% are assigned all day heating patterns. 13 houses are assigned to have ASHP heating systems, and 12 have rSOCs. ASHPs have capacity 3 kW$_e$; COP is assumed to be 38% of the ideal COP operating between the outdoor air temperature and a flow temperature of 55 °C, an assumption based on reference [57]. The heat pumps are assumed to be accompanied with TES consisting of 300 l of hot water, operating between an upper temperature of 80 °C and a minimum usable temperature of 40 °C. Insulation is 10 cm thick with conductivity 0.03 W/mK; thermal losses are assumed to flow into the internal node of the space heating model; see also the MILP model in the Appendix.

The rSOC is assigned a capacity in SOFC mode of 2.5 kW$_e$. We assign η_{SOFC} as 16.7 kWh$_e$/kg$_{H2}$ and η_{SOFCth} as 13.3 kWh$_e$/kg$_{H2}$, for a total CHP efficiency of 90%$_{LHV}$. η_{SOEC} is assigned as 48 kWh$_e$/kg$_{H2}$, so that used as an energy storage device, the rSOC has round-trip efficiency of just under 35%. Capacity in SOEC mode is taken as 7.5 kW$_e$. In both modes, the rSOC is assumed to have a partial load range of 10–100%. The rSOC is sized as a compromise between the peak electrical load and the peak space heating load of around 5 kW; for peaks in heat demand, either resistive heat or the heat network connection must be employed. See also the MILP rSOC model in the Appendix.

Simulations were run over the duration of one week. The first week simulated was a shoulder (spring) week with moderate heat demand and moderate solar resource; the second was a winter week with high heat demand and low solar resource. See Table 4 and Fig. 4 for the specifics. Note that a 'heating degree day' (HDD) is calculated as the gap between a day's mean temperature and 15.5 °C.

Three scenarios are considered: G_ONLY, where only grid trade of electricity is possible, and no trading in heat; P2P_P, where P2P trading of power only occurs, using the double auction approach detailed in the previous section; and P2P_H_P, where P2P trading of both heat and power is available.

The grid retail tariff in this work is assumed to be a constant £0.28 / kWh [58]; the grid feed-in tariff is £0.075 / kWh [59]. The cost of rapid charging for EVs is set at £0.446 / kWh [60,61]. The price of hydrogen is assumed to be fixed in the case study, at £3.50 / kg [62,63].

Table 4
Climate weeks for simulation.

Season	Sample week start date	Mean GHI (W/m^2)	Mean HDD (°C)
Winter	9th Jan 2013	22.1	14.5
Spring	2nd April 2013	159.2	12.7

4.2. Results

We focus initially on the **spring / shoulder** week in order to explore the functioning of the market. Fig. 5 shows the volume of (a) power and (b) heat traded on April 2nd under P2P_H_P. The day's timeslots are shown vertically, and the rounds of the auction horizontally. Importantly, trading comes to an end after finite time; this is expected, since re-trading of energy already bought / sold is not considered for this work. Most trading has ceased by 200 rounds; a similar outcome was observed for all days and seasons. It is noticeable that heat trading lags behind power trading; one reason for this is that ASHP heat becomes available on the market *after* the corresponding power has been acquired. Fig. 6 (a) shows progress of the market in power for a particular timeslot (10–11 am for Thursday of the spring week). Price is rather volatile, averaging £0.179 / kWh, with 53 kWh eventually traded for the timeslot. 6 (b) shows progress of the same market with 1000 peers rather than 25. Price is less volatile, which is an expected 'law of large numbers' effect; trading comes to an end after a similar amount of time.

The computational burden of the P2P market is incurred more by strategy formation of the peers than by the clearing of the auction itself. In the case with 25 peers, strategisation involved on average 11.9 s of computation per peer per day. This is assumed to be acceptable, given that these computations would be parallelised in any real application. Clearing of the auction involved only 1.7 s of computation (ca. 4 ms per round). To ascertain the scalability of the approach, the size of the study was increased to 1000 peers. In this case, strategisation required 10.6 s per peer per day, whilst the auction clearing required 61.1 s per day, which is considered to be entirely practicable.

For the spring week under P2P_P, 9400 bids to trade power were matched by the P2P auction, representing a turnover of 2.95 MWh, with an average price of £0.220 / kWh. Fig. 7 (a) shows the diurnal P2P price variation, with heat demand and inflexible electrical load shown for comparison. The variation in electricity price is relatively modest; the price peak is roughly coincident with peak inflexible demand at 7 p.m., whilst availability of solar power depresses the price during the daytime.

Figs. 8 (a) and 8 (b) respectively show the volume of offers and asks matched by the P2P_P market, by category, averaged over the spring week. The purchase of power for EV charging clearly peaks during the lowest priced period, particularly for the non-essential ('arbitrage') charging. ASHPs also purchase power to charge TES during the low price period. Transactions to supply inflexible load and essential EV charging continue all day, with generation from the rSOC dominating the supply side. Fig. 9 shows the energy flows for P2P_P in the second column. When comparing with G_ONLY, the following observations can be made:

1. The quantity of grid imports is greatly reduced, with generation from the rSOC filling the gap.
2. Use of the rSOC's SOEC mode is decreased. Houses with solar surpluses find it more profitable to sell power to peers rather than manufacture H_2.
3. EV charging increases during the peak in solar generation, replacing the SOEC use.
4. Use of resistive heat is decreased. This is because the rSOCs in SOFC mode can now follow their household heat load, exporting the corresponding power to peers.

For the spring week under P2P_H_P, 9100 bids to trade power were successful, representing a turnover of 3.6 MWh; for heat, 8200 bids representing 2.9 MWh were matched (compare the total heat demand of

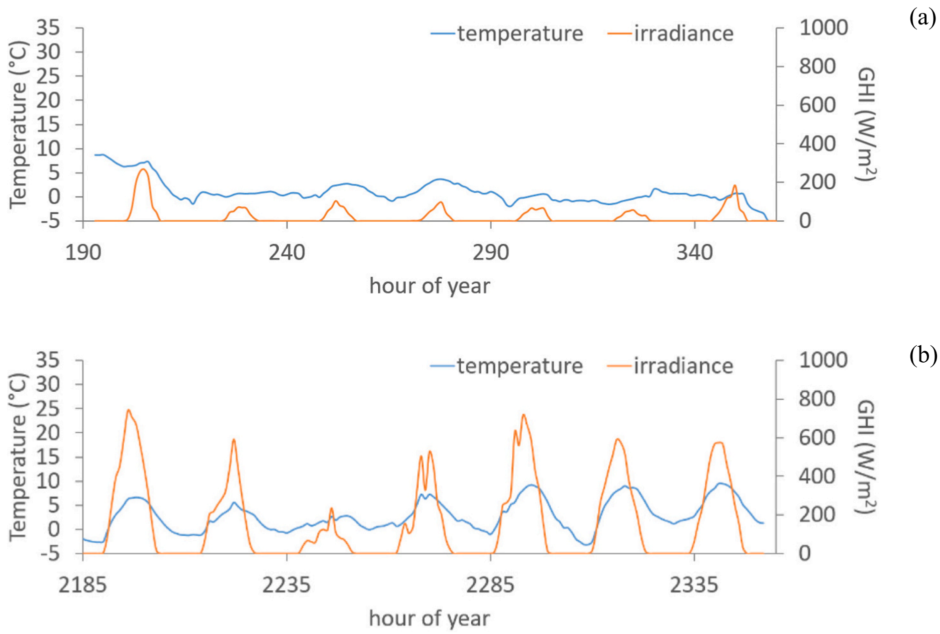

Fig. 4. Irradiance and temperature for (a) the winter week and (b) the spring week.

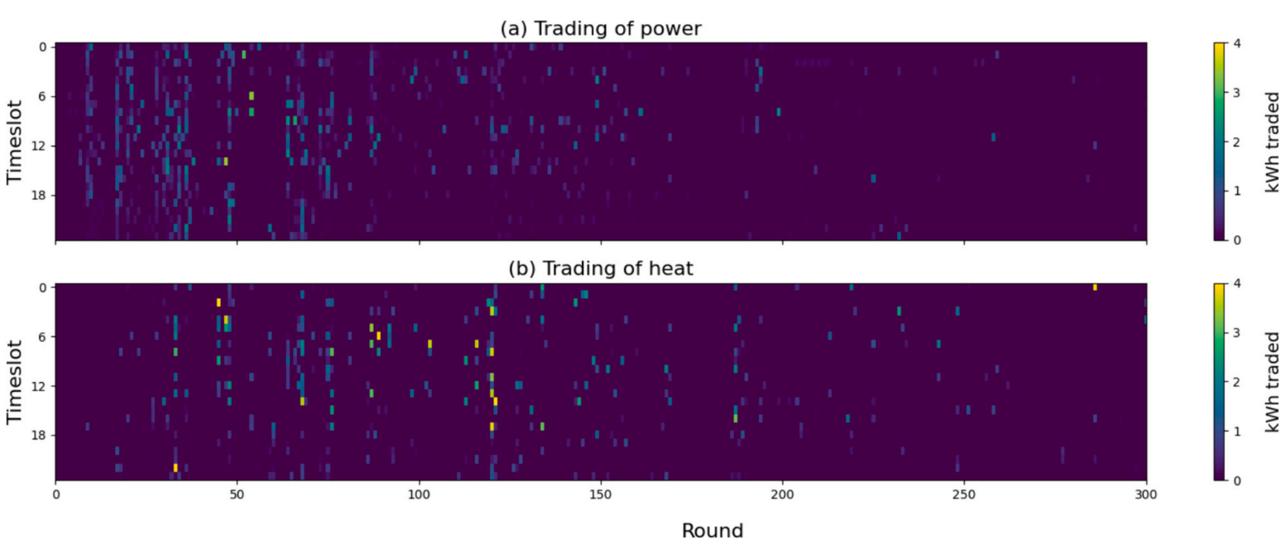

Fig. 5. Heat plot showing progress of the double auction for April 2nd, the first day of the spring week, under P2P_H_P, with the colour scale showing the quantity of energy cleared. Rounds of the auction are shown left to right, and timeslots of the day from top to bottom. (a) power trading; (b) heat trading. Timeslot 0 corresponds to 5 a.m. For clarity, only 300 of the rounds are shown.

5.9 MWh). The average price of power was virtually unchanged from P2P_P at £0.226 / kWh; the average heat price was £0.078 / kWh. Fig. 7 (b) shows the diurnal price variation for P2P power and heat; variations in heat price clearly respond to the demand.

Figs. 8 (c) – (f) show the volume of successful asks and offers under P2P_H_P. As before, EV charging increases in response to peak solar generation. Large amounts of power are purchased by ASHPs in order to re-export the heat. ASHP dominates the supply side of heat market during the day, whereas rSOCs are more likely to export heat at night when (a) COP is lower for the ASHPs, making them less competitive and (b) local heat demand is more likely to be low. 1.97 MWh of ASHP heat was exported overall, at an average price of £0.077 / kWh; for rSOC the corresponding figures were 0.90 MWh, and £0.081 / kWh. Note that the cost of rSOC heat is well below the cost of the corresponding hydrogen, which is possible thanks to the high average value (£0.228 / kWh) of the corresponding power on the P2P market. Some import of heat in order to charge TES occurs during price troughs; this heat is always discharged locally, as no heat is observed to be sold back to the network. The impact of heat trading on the energy flows can be seen in Fig. 9; the most significant impact is that the use of resistive heat now almost completely ceases, as heat that cannot be generated locally can instead be imported. Heat trading also appears to have enabled increased V2X discharge from the EVs, the reasons for which are not wholly clear. Use of TES is decreased, as exporting heat P2P may be more profitable than storing it.

4.3. Savings and participant willingness

We now evaluate the economic advantages of the P2P markets; results from both spring and winter are considered. Fig. 10 gives the average net bill for houses over (a) the winter week, and (b) the spring week; net bills comprise net P2P payments, net grid payments, and net hydrogen payments. Both trading systems enable the average house to

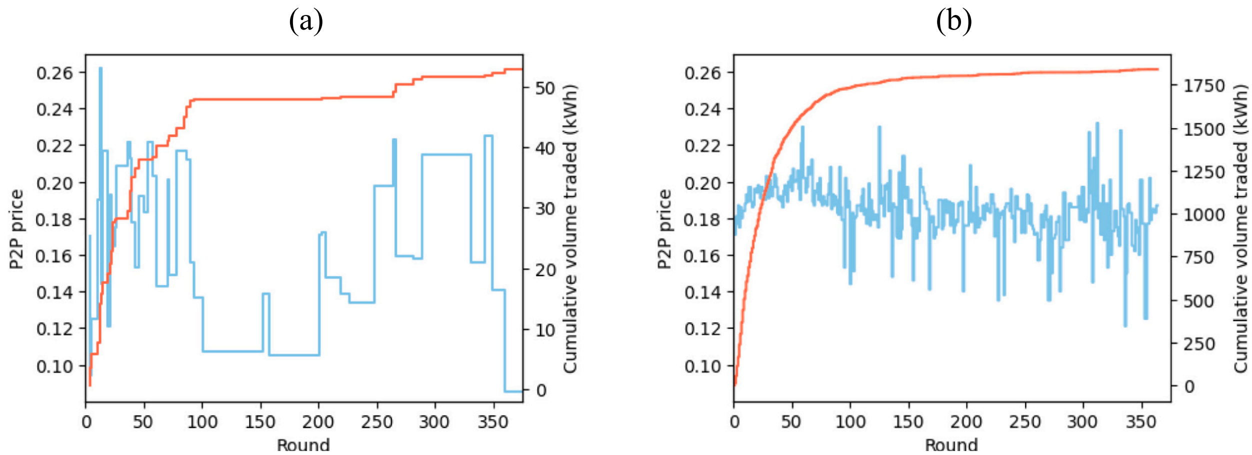

Fig. 6. Shows progress of the double auction in **power** for one particular timeslot (10–11 am). (a) with 25 peers (b) with 1000 peers.

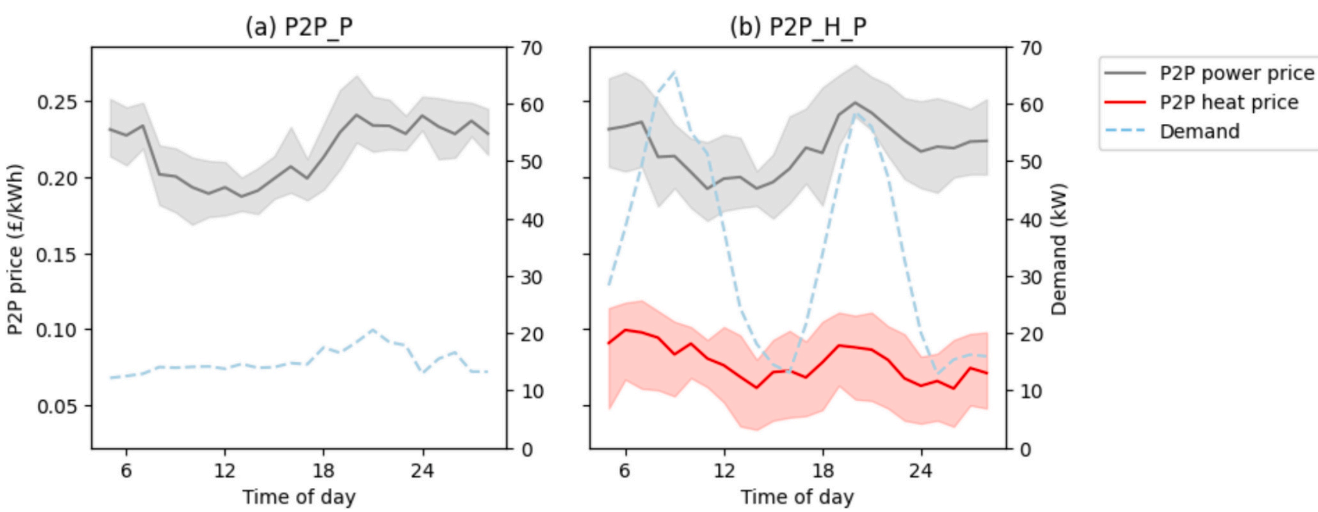

Fig. 7. Daily P2P price variations averaged across the spring week. (a) P2P_P (b) P2P_H_P. The mean P2P transaction price is shown for each time of day, with the interquartile range shaded. Demand is shown for context (inflexible electricity demand in (a) and heat demand in (b)).

save money relative to G_ONLY. For the winter week, the mean saving is £9.52 under P2P_P and £19.59 under P2P_H_P, and participant willingness is 84% and 88% respectively (where participant willingness is defined as the proportion of participants who profit, relative to the baseline G_ONLY – see Fig. 11). rSOC houses appear to enjoy the greater financial benefits, but ASHP houses also profit. For the spring week, the mean saving is £16.99 under P2P_P and £16.69 under P2P_H_P, with participant willingness of 100% and 84%. From this it appears that the possibility to trade heat may not achieve additional financial savings during the spring weather conditions, although there may still be technical benefits.

4.4. Technical and environmental impact

Fig. 13 shows the impact of the trading systems on the load duration curve for electrical grid interaction. For both winter and spring, P2P_P achieves a notable decrease in peak load, and P2P_H_P achieves a further reduction. Specifically, under G_ONLY, grid imports peak at 44.5 kW in winter and 35.3 kW in spring. P2P_P sees decreases of 20% (to 35.5 kW) and 44% (to 20.0 kW) for winter and spring respectively. P2P_H_P sees decreases of 44% (to 24.8 kW) and 66% (to 12.0 kW) for winter and spring respectively. Conversely, export of electricity to the grid becomes somewhat more common under P2P trading. This is especially the case under P2P_H_P, where for the rSOC, the opportunity to earn money by exporting heat P2P means that exporting power at the feed-in tariff is more viable. Under P2P_P the export of power to grid is more questionable and may indicate imperfections in houses' bidding strategies.

Note that grid interaction is a relatively small proportion of overall energy flow (see Fig. 9); energy is principally obtained from hydrogen. P2P trading increases the usage of hydrogen, as the rSOCs are able to export energy to peers, and therefore run at a higher average load factor (see Figs. 9, 12 (a)). The UK marginal GHG intensity for grid electricity is estimated at 0.269 $kgCO_2e$ / kWh for 2022 [64]. Under the assumption that all hydrogen purchased is green hydrogen, the GHG emissions for the 25 houses are proportional to the grid imports. The highest GHG intensity occurs during the winter week under G_ONLY, averaging 5.93 $kgCO_2e$ per house per day. P2P_P cuts this to 2.81 $kgCO_2e$ (−53%), P2P_H_P to 1.88 $kgCO_2e$ (−68%). The respective figures for spring are 3.29 $kgCO_2e$ under G_ONLY; 0.447 $kgCO_2e$ (−86%) and 0.134 $kgCO_2e$ (−96%).

5. Discussion and future work

The advantages of the P2P power trading market (P2P_P) are clear from these results, with the average house making significant weekly savings in both the climate weeks. Whilst PV and EVs play a part (see Fig. 9) the rSOC is clearly the driving force, consuming more hydrogen in order to export power to peers at the P2P market price. The merits of

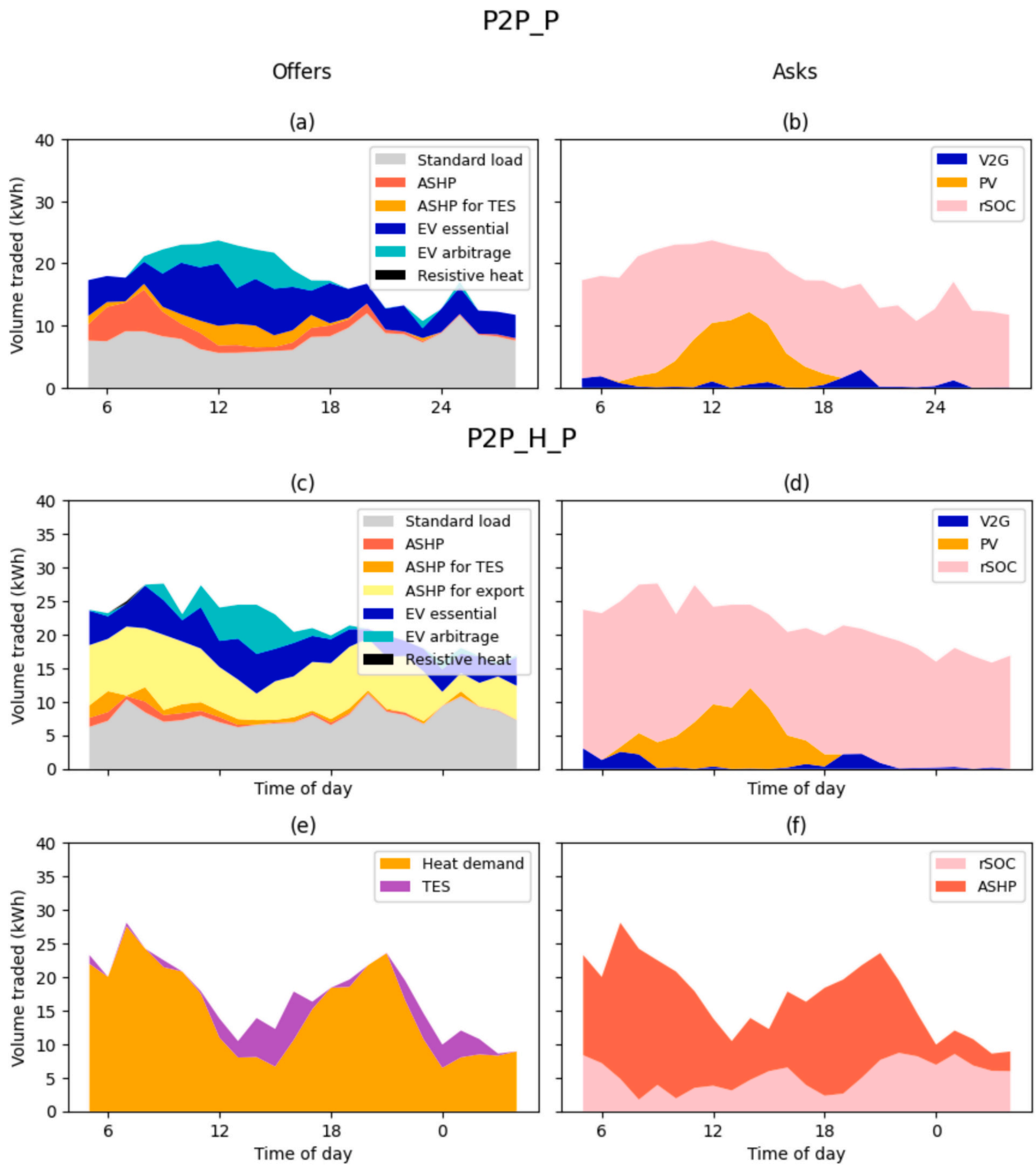

Fig. 8. Volume of P2P trades matched during the spring week, by category and time of day. Volume of trades is shown averaged across the week to obtain a daily profile. (a) and (b): electricity traded under P2P_P. (c) and (d): electricity traded under P2P_H_P. (e) and (f): heat traded under P2P_H_P. Note that 5 a.m. corresponds to timeslot 0 in the market.

the heat trading are more nuanced. In the cold winter week, P2P_H_P almost doubled the savings of an average house compared to P2P_P; however, in the spring week additional savings were not obtained. On the other hand, the burden on the grid connection was reduced both in terms of total and peak energy import.

Participant willingness for engagement with the P2P market was generally under 100% (Fig. 11), indicating that it was possible for households to lose money via their attempts to trade energy. This possibility is somewhat inevitable, given that actual clearing prices may always differ from predicted prices. Also, whenever passive bidding takes place, there is the possibility of sub-optimal outcomes – for instance, an offer of type ESSENTIAL_LOAD could be outbid by an offer of type EV_ARBITRAGE. More sophisticated price prediction could help with participant willingness, and it may be that the bidding and pricing strategies could be further improved. A possible extension of the model could see the CDA preceded by a one-off sealed-bid double auction, allowing complex orders as found on the Nordpool and EPEX exchanges.

It is worth noting that the P2P power market in this work experienced almost universal 'seller's market' conditions, indicating an overall scarcity of power, and resulting in a P2P price closer to the retail tariff than the feed-in tariff. 6 kW_p PV generation in houses was clearly insufficient to cause major downward pressure on prices, despite the 6 kW_p figure being towards the upper end of what is viable for average UK housing stock (the actual average is 3 kW_p [1]). The addition of wind

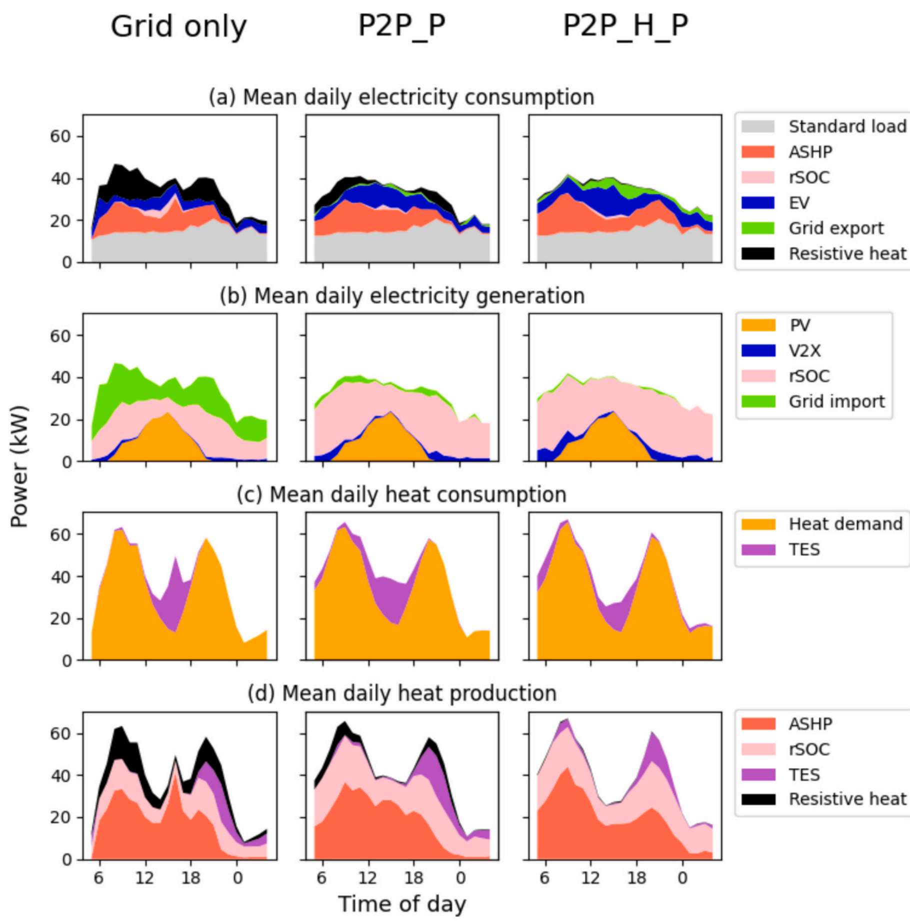

Fig. 9. Average daily energy flow during the spring week, for G_ONLY (left), P2P_P (centre) and P2P_H_P (right). Shown are the generation and consumption of both heat and electricity. Note that 5 a.m. corresponds to timeslot 0 in the market.

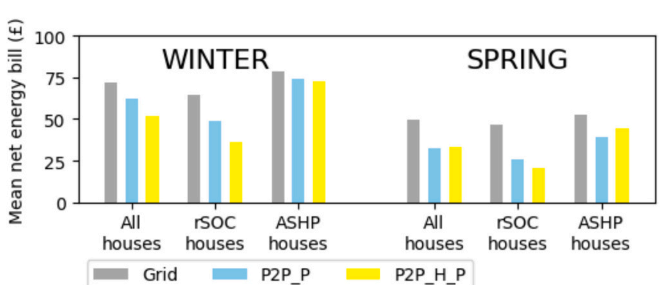

Fig. 10. Average net household bills for the winter week (left) and the spring week (right); these consist of net P2P payments, net grid payments, and net hydrogen payments.

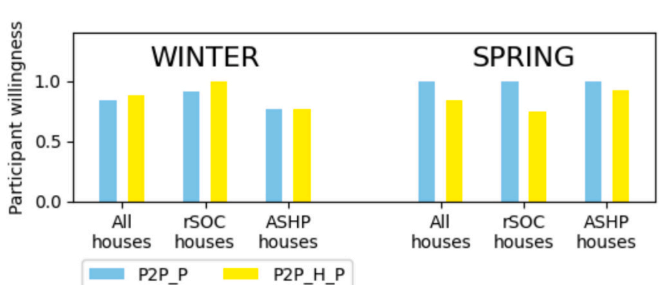

Fig. 11. Participant willingness for the winter week (left) and the spring week (right).

power into the generation mix might add interesting dynamics to the market – however, wind power is not generally very feasible in proximity to the built environment. Perhaps of more interest would be to use a variable grid tariff (the grid tariff was constant in this work) which could reflect the abundance of wind power on the wider electricity network.

A related issue to the prevailing seller's market conditions was the negligible use of SOEC mode of the rSOC. For manufacture of hydrogen to be optimal, there needs to be an abundance of cheap energy generation. For the spring week under G_ONLY, only 2.6 kg of hydrogen was produced via water electrolysis, compared to 133 kg consumed by SOFC mode. With the introduction of P2P trading, even this hydrogen production was mainly eliminated, as it became more profitable to export energy surpluses to peers. Even when the model was run for a high irradiance summer week with negligible heat demand, demand for hydrogen was still an order of magnitude higher than production. This seems to indicate that it is difficult to have enough generation in a distributed energy setting to justify running electrolysis.

All energy trading in this work was carried out on a day-ahead basis. In reality, trading would need to continue throughout the day, to balance imperfections in forecasting. The extension of the model to include such real-time trading should be relatively straightforward. Also, the information technology aspect of the continuous double auction market has not been considered here in detail, and future work could explore this in conjunction with data privacy aspects. Voltage constraints have not been considered in this work (nor the analogous temperature constraints in the heat network); previous work such as [36] has explored such issues. Whilst heat pump COP in this work varied with conditions, it did not vary between devices, and introducing this variation in future

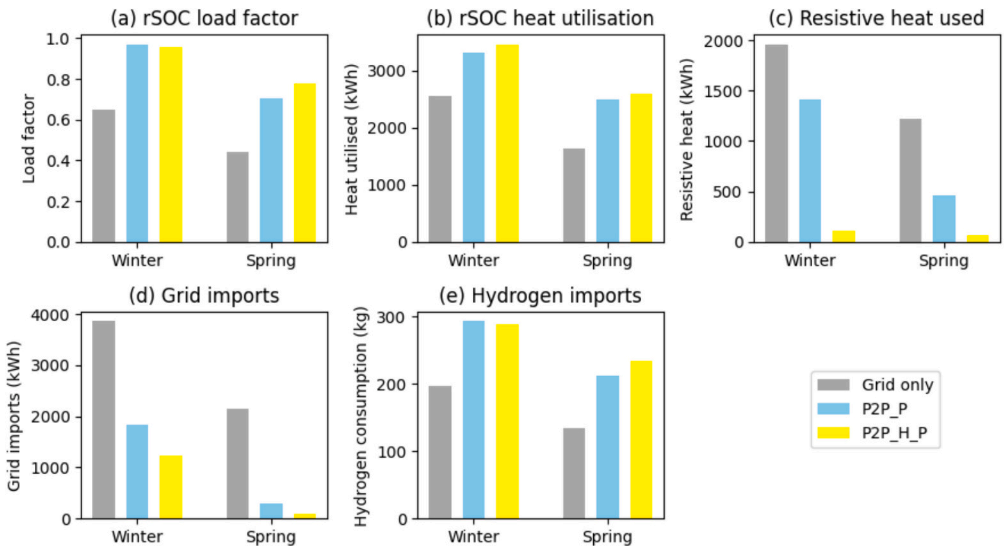

Fig. 12. Impact of P2P trading on various metrics: (a) Average load factor for SOFC mode over one week. (b) rSOC heat utilisation. (c) Resistive heat. (d) Grid imports. (e) Hydrogen imports.

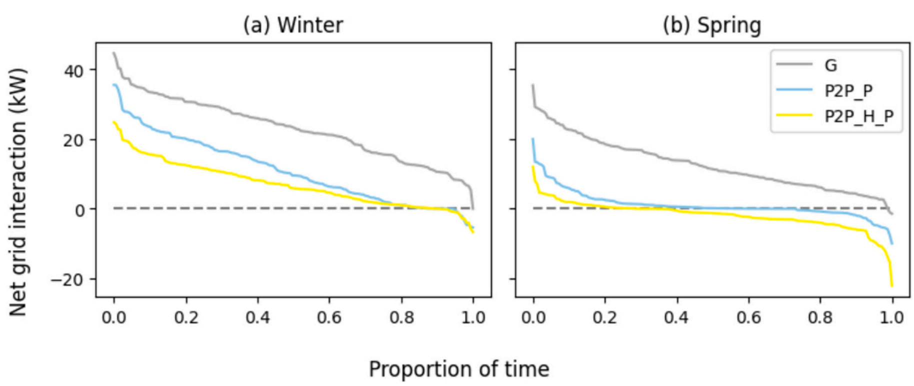

Fig. 13. Load duration curves for the grid connection in (a) winter and (b) spring, for the three trading setups.

work could enhance the motivation to trade [10].

The possibility for local storage of hydrogen was not modelled in this work, nor the possible fluctuations in hydrogen price over time. This is a topic worthy of interest. The fluctuating availability / price of hydrogen could provide additional incentives for P2P trading, as the relative desirability of procuring heat from ASHP and SOFC would see additional variation.

6. Conclusions

This work presented a continuous double auction peer-to-peer (P2P) market for trading of power and heat in the day ahead, simulated via an agent-based approach. Unlike in most existing literature, the proposed CDA model allows for forward trading across multiple future timeslots, and hence strategies were developed to address the interdependence of bidding both across timeslots and across energy types. Simulated over two week-long periods for a P2P scheme with 25 houses, both forms of market (with and without heat trading) were successful in reducing reliance on grid electricity, and significant household savings were observed of the order of £10 / week; however participants in the auction also occasionally incurred losses relative to the baseline with no P2P, indicating the potential for further strategy refinement and better price prediction to reduce this risk. Additionally, the availability of heat trading did not always provide an advantage over trading purely in power. Reversible solid oxide fuel cells (rSOCs) were particularly advantaged by the P2P energy markets: whilst the ‘reversible’ aspect proved relatively unimportant, with little hydrogen manufactured in the simulated case study, it is clear that regarding the combined heat and power (CHP) application, the P2P trading could help to incentivise the take-up of such devices.

CRediT authorship contribution statement

Timothy D. Hutty: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Solomon Brown:** Writing – review & editing, Supervision, Project administration, Conceptualization.

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 A. - MILP models for devices.

In this section details of the constraints that describe particular devices are given. Recall that H_{gen}, E_{gen}, H_{cons} and E_{cons} are the main variables interfacing the rest of the model.

ASHP.

Decision variables for the ASHP are the electrical energy consumed and heat energy produced for each time step, as related by COP. COP is assumed dependent only on the outdoor temperature, with no dependence on the load point. For simplicity, full modulation to arbitrary partial load is assumed to be possible.

$$H_{gen,ashp,t} = COP_t \bullet E_{cons,ashp,t} \quad \text{(n. 16)}$$

$$0 \leq E_{cons,ashp,t} \leq \Delta t \bullet P^{max}_{ashp} \quad \text{(n. 17)}$$

A.1. EV battery.

Optimisation of the EV battery includes two important time series inputs: the energy required for driving $E_{drive,t}$ and the availability α_t which takes a value in $[0, 1]$ for every timeslot. Decision variables are the AC power consumed by the battery $E_{cons,EV,t}$, AC power generated $E_{gen,EV,t}$, and power consumed from rapid charging while away from the house, $E_{rapid,t}$. Penalty terms include the cost of rapid charging and the assumed cost for discharging the battery V2X. Generally V2X discharge will not happen except when $p_{power,exp,t} > c_{V2X}/\eta_{inv}$.

$$E_{stored,t+1} = E_{stored,t} + \eta_{inv} \bullet \eta_{st} \bullet E_{cons,EV,t} + \eta_{st} \bullet E_{rapid,t} - \frac{1}{\eta_{inv}} \bullet E_{gen,EV,t} - E_{drive,t} \quad \text{(n. 18)}$$

$$0 \leq E_{stored,t+1} \leq C_{EV} \quad \text{(n. 19)}$$

$$E_{stored,t_{last}} \geq E_{min\_final} \quad \text{(n. 20)}$$

$$E_{rapid,t} \leq 50 \bullet (1 - \alpha_t) \quad \text{(n. 21)}$$

$$PEN_{EV,t} = c_{rapid} \bullet E_{rapid,t} + c_{V2X} \bullet E_{gen,EV,t} \quad \text{(n. 22)}$$

A.2. rSOC.

The rSOC may operate in either SOFC or SOEC mode. Operation is described principally by decision variables $E_{gen,rSOC,t}$, $E_{cons,rSOC,t}$ and $H_{gen,rSOC,t}$ with hydrogen consumption / production derived from these. Binary variables b_{SOFC} and b_{SOEC} describe the mode of the rSOC, and enable minimum partial loads to be imposed. Switching between modes incurs a penalty described by $PEN_{rSOC,t}$. The cost c_{switch} of switching modes is taken as £0.50 in the case study here. It is assumed that 'hot idle' operation corresponds to the lowest possible partial load for SOFC mode or SOEC mode; full cycling of the rSOC to a cold, fully off state is not considered in the context of the MILP formulation. Note that the rSOC is assumed to be able to reject heat to the environment if necessary.

$$\Delta t \bullet P^{min}_{SOFC} \bullet b_{SOFC,t} \leq E_{gen,rSOC,t} \leq \Delta t \bullet P^{max}_{SOFC} \bullet b_{SOFC,t} \quad \text{(n. 23)}$$

$$\Delta t \bullet P^{min}_{SOEC} \bullet b_{SOEC,t} \leq E_{cons,rSOC,t} \leq \Delta t \bullet P^{max}_{SOEC} \bullet b_{SOEC,t} \quad \text{(n. 24)}$$

$$b_{SOFC,t} + b_{SOEC,t} = 1 \quad \text{(n. 25)}$$

$$0 \leq H_{gen,rSOC,t} \leq \frac{\eta_{SOFCth}}{\eta_{SOFC}} E_{gen,rSOC,t} \quad \text{(n. 26)}$$

$$H2_{gen,rSOC,t} = E_{cons,rSOC,t}/\eta_{SOEC} \quad \text{(n. 27)}$$

$$H2_{cons,rSOC,t} = E_{gen,rSOC,t}/\eta_{SOFC} \quad \text{(n. 28)}$$

$$PEN_{rSOC,t+1} \geq c_{switch} \bullet (b_{SOFC,t+1} - b_{SOFC,t}) \quad \text{(n. 29)}$$

$$PEN_{rSOC,t+1} \geq c_{switch} \bullet (b_{SOEC,t+1} - b_{SOEC,t}) \quad \text{(n. 30)}$$

A.3. Space heating.

Buildings consist of two thermal masses, representing the building interior and building walls. Building archetypes consist of the thermal masses of these C_i and C_w, and heat transfer coefficients $K_{i\leftrightarrow w}$, $K_{i\leftrightarrow e}$, $K_{w\leftrightarrow e}$, between the thermal masses and the environment. Heat $H_{sh,t}$ representing space heating output is added to the building interior. A trapezoidal method is used to discretize the resulting system of ODEs. The demand temperature is given by $T_{dem,t}$ while $T_{max,t}$ gives an upper temperature limit. Penalty terms $PEN_{sh,t}$ are defined for infringing these limits, with c_{sh} representing the cost per degree-hour of temperature infringement. c_{sh} in this work was set to £1 per degree-hour. A penalty that rises more than linearly with the amount of temperature infringement could be of interest in future work. All temperatures and heat flows are technically decision variables, although they are ultimately dictated by the heat import / export and space heating output.

$$H_{i\leftrightarrow w,t} = 0.5 \bullet \Delta t \bullet K_{i\leftrightarrow w}\left(T_{i,t} + T_{i,t+1} - T_{w,t} - T_{w,t+1}\right) \tag{n. 31}$$

$$H_{i\leftrightarrow e,t} = 0.5 \bullet \Delta t \bullet K_{i\leftrightarrow e}\left(T_{i,t} + T_{i,t+1} - T_{e,t} - T_{e,t+1}\right) \tag{n. 32}$$

$$H_{w\leftrightarrow e,t} = 0.5 \bullet \Delta t \bullet K_{w\leftrightarrow e}\left(T_{w,t} + T_{w,t+1} - T_{e,t} - T_{e,t+1}\right) \tag{n. 33}$$

$$T_{i,t+1} = T_{i,t} + \left(H_{sh,t} + H_{gain,t} - H_{i\leftrightarrow w,t} - H_{i\leftrightarrow e,t}\right)/C_i \tag{n. 34}$$

$$T_{w,t+1} = T_{w,t} + \left(H_{i\leftrightarrow w,t} - H_{w\leftrightarrow e,t}\right)/C_w \tag{n. 35}$$

$$PEN_{sh,t} \geq 0 \tag{n. 36}$$

$$PEN_{sh,t} \geq \Delta t \bullet c_{sh} \bullet \left(T_{dem,t} - T_{i,t}\right) \tag{n. 37}$$

$$PEN_{sh,t} \geq \Delta t \bullet c_{sh} \bullet \left(T_{i,t} - T_{max,t}\right) \tag{n. 38}$$

A.4. TES

Sensible thermal storage with hot water is modelled as a single thermal mass. This is described by decision variables $T_{tes,t}$, $H_{cons,tes,t}$ and $H_{gen,tes,t}$. Losses $H_{loss,tes,t}$ are assumed proportional to the difference in temperature $T_{tes} - T_i$ between the storage and the house interior. These losses are added to the gains term $H_{gain,t}$ of the space heating model. C_{tes} gives the constant heat capacity of the storage in kWh/°C. Using a trapezoidal method to account for any variation in T_i over a timestep, the temperature of the storage evolves as specified in Eq. 40. Imposing a minimum usable temperature T_{tes}^{usable} requires the introduction of binary variables $b_{gen,tes,t}$ and $b_{cons,tes,t}$ together with the constraints given in Eqs. 42,43,44 and 46.

$$\Lambda := exp\left(-\frac{\Delta t \bullet K_{tes\leftrightarrow i}}{C_{tes}}\right) \tag{n. 39}$$

$$T_{tes,t+1} = \Lambda \bullet T_{tes,t} + (1-\Lambda) \bullet \left(\frac{H_{cons,tes,t} - H_{gen,tes,t}}{\Delta t \bullet K_{tes\leftrightarrow i}} + 0.5 \bullet T_{i,t} + 0.5 \bullet T_{i,t+1}\right) \tag{n. 40}$$

$$H_{loss,tes,t} = C_{tes} \bullet \left(T_{tes,t} - T_{tes,t+1}\right) - H_{gen,tes,t} + H_{cons,tes,t} \tag{n. 41}$$

$$b_{gen,tes,t} + b_{cons,tes,t} \leq 1 \tag{n. 42}$$

$$H_{cons,tes,t} \leq b_{cons,tes,t} \bullet \Delta t \bullet P_{tes}^{max} \tag{n. 43}$$

$$H_{gen,tes,t} \leq b_{gen,tes,t} \bullet \Delta t \bullet P_{tes}^{max} \tag{n. 44}$$

$$T_{tes}^{min} \leq T_{tes,t} \leq T_{tes}^{max} \tag{n. 45}$$

$$T_{tes,t+1} \geq b_{gen,tes,t} \bullet T_{tes}^{usable} \tag{n. 46}$$

A.5. Resistive heater.

A resistive heater in the model converts electrical power to heat with 100% efficiency. Decision variables are the consumption of electricity at each time step (also equal to the heat production).

$$H_{cons,rh,t} = E_{cons,rh,t} \tag{n. 47}$$

$$0 \leq E_{cons,rh,t} \leq \Delta t \bullet P_{rh}^{max} \tag{n. 48}$$

References

[1] Department for Business Energy & Industrial Strategy. Feed-in Tariff statistics *gov.uk*. https://www.gov.uk/government/collections/feed-in-tariff-statistics; 2021 [accessed Apr. 15, 2021].

[2] Jolly J. UK electric car sales surge despite Covid lockdown *theguardian.com*. https://www.theguardian.com/business/2021/apr/06/uk-electric-car-sales-covid-lockdown; 2021 [accessed Apr. 15, 2021].

[3] Zhou Y, Wu J, Long C. Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework. Appl Energy 2018;222:993–1022. https://doi.org/10.1016/j.apenergy.2018.02.089. no. November 2017.

[4] T. D. Hutty, A. Pena-Bello, S. Dong, D. Parra, R. Rothman, and S. Brown, Peer-to-peer electricity trading as an enabler of increased PV and EV ownership, Energ Conver Manage, vol. 245, p. 114634, Oct. 2021, doi: https://doi.org/10.1016/j.enconman.2021.114634.

[5] Centrica. Centrica joins community energy blockchain trial *centrica.com*. https://www.centrica.com/media-centre/news/2018/centrica-joins-community-energy-blockchain-trial; 2018 [accessed Feb. 20, 2021].

[6] Gordon P. EDF launches blockchain-enabled renewables trading pilot *smart-energy.com*. https://www.smart-energy.com/industry-sectors/distributed-generation/edf-launches-blockchain-p2p-solar-and-storage-trading-pilot/. [Accessed 20 February 2021].

[7] M. Davoudi and M. Moeini-Aghtaie, Local energy markets design for integrated distribution energy systems based on the concept of transactive peer-to-peer market, IET Gener Transm Distrib, vol. 16, no. 1, pp. 41–56, Jan. 2022, doi: https://doi.org/10.1049/gtd2.12274.

[8] El-Baz W, Tzscheutschler P, Wagner U. Integration of energy markets in microgrids: A double-sided auction with device-oriented bidding strategies. Appl Energy 2019;241:625–39. https://doi.org/10.1016/j.apenergy.2019.02.049. no. November 2018.

[9] D. Zhu *et al.*, Energy trading in microgrids for synergies among electricity, hydrogen and heat networks, Appl Energy, vol. 272, p. 115225, Aug. 2020, doi: https://doi.org/10.1016/j.apenergy.2020.115225.

[10] N. Wang, Z. Liu, P. Heijnen, and M. Warnier, A peer-to-peer market mechanism incorporating multi-energy coupling and cooperative behaviors, Appl Energy, vol. 311, p. 118572, Apr. 2022, doi: https://doi.org/10.1016/j.apenergy.2022.118572.

[11] Energy Saving Trust, Micro combined heat and power *energysavingtrust.org.uk*, 2022. https://energysavingtrust.org.uk/advice/micro-combined-heat-and-power/.

[12] W. Tushar, T. K. Saha, C. Yuen, D. Smith, and H. V. Poor, Peer-to-peer trading in electricity networks: an overview, IEEE Trans Smart Grid, vol. 11, no. 4, pp. 3185–3200, Jul. 2020, doi: https://doi.org/10.1109/TSG.2020.2969657.

[13] Li Z, Ma T. Peer-to-peer electricity trading in grid-connected residential communities with household distributed photovoltaic. Appl Energy 2020;278:115670. https://doi.org/10.1016/j.apenergy.2020.115670. no. July.

[14] Liu Y, Zuo K, Liu X (Amy), Liu J, Kennedy JM. Dynamic pricing for decentralized energy trading in micro-grids. Appl Energy 2018;228:689–99. https://doi.org/10.1016/j.apenergy.2018.06.124. no. June.

[15] Mengelkamp E, Gärttner J, Rock K, Kessler S, Orsini L, Weinhardt C. Designing microgrid energy markets: a case study: the Brooklyn microgrid. Appl Energy 2018;210:870–80. https://doi.org/10.1016/j.apenergy.2017.06.054.

[16] Farmer M. What recent trials teach us about peer-to-peer power trading *power-technology.com*. https://www.power-technology.com/features/peer-to-peer-energy-trading-p2p-irena-malaysia-seda-power-ledger-blockchain-automation; 2023.

[17] R. Alvaro-Hermana, J. Fraile-Ardanuy, P. J. Zufiria, L. Knapen, and D. Janssens, "Peer to peer Energy trading with electric vehicles," IEEE Intell Transp Syst Mag, vol. 8, no. 3, pp. 33–44, Sep. 2016, doi: https://doi.org/10.1109/MITS.2016.2573178.

[18] Guo Z, Pinson P, Chen S, Yang Q, Yang Z. Chance-constrained peer-to-peer joint Energy and reserve market considering renewable generation uncertainty. IEEE Trans Smart Grid 2021;12(1):798–809. https://doi.org/10.1109/TSG.2020.3019603.

[19] Li J, Zhang C, Xu Z, Wang J, Zhao J, Zhang YJA. Distributed transactive energy trading framework in distribution networks. IEEE Trans Power Syst 2018;33(6):7215–27. https://doi.org/10.1109/TPWRS.2018.2854649.

[20] D. H. Nguyen and T. Ishihara, "Distributed peer-to-peer energy trading for residential fuel cell combined heat and power systems," Int J Electr Power Energy Syst, vol. 125, p. 106533, Feb. 2021, doi: https://doi.org/10.1016/j.ijepes.2020.106533.

[21] Zhang C, Wu J, Cheng M, Zhou Y, Long C. A bidding system for peer-to-peer Energy trading in a grid-connected microgrid. Energy Procedia 2016;103:147–52. https://doi.org/10.1016/j.egypro.2016.11.264. no. April.

[22] Marzband M, Javadi M, Pourmousavi SA, Lightbody G. An advanced retail electricity market for active distribution systems and home microgrid interoperability based on game theory. Electr Pow Syst Res 2018;157:187–99. https://doi.org/10.1016/j.epsr.2017.12.024.

[23] M. Sabounchi and J. Wei, A decentralized real-time electricity market mechanism for autonomous microgrids, in *2017 IEEE Power & Energy Society General Meeting*, Jul. 2017, pp. 1–5, doi: https://doi.org/10.1109/PESGM.2017.8273727.

[24] Tushar W, et al. A coalition formation game framework for peer-to-peer energy trading. Appl Energy 2020;261:114436. https://doi.org/10.1016/j.apenergy.2019.114436. no. January.

[25] B. Kim, Y. Zhang, M. van der Schaar, and J. Lee, "Dynamic pricing and Energy consumption scheduling with reinforcement learning," IEEE Trans Smart Grid, vol. 7, no. 5, pp. 2187–2198, Sep. 2016, doi: https://doi.org/10.1109/TSG.2015.2495145.

[26] Liu N, Yu X, Wang C, Li C, Ma L, Lei J. Energy-sharing model with Price-based demand response for microgrids of peer-to-peer prosumers. IEEE Trans Power Syst 2017;32(5):3569–83. https://doi.org/10.1109/TPWRS.2017.2649558.

[27] Kim BG, Ren S, Van Der Schaar M, Lee JW. Bidirectional energy trading and residential load scheduling with electric vehicles in the smart grid. IEEE J Sel Areas Commun 2013;31(7):1219–34. https://doi.org/10.1109/JSAC.2013.130706.

[28] NEMO Committee, "EUPHEMIA Public Description", 2019. [Online]. Available: https://www.nordpoolgroup.com/globalassets/download-center/single-day-ahead-coupling/euphemia-public-description.pdf.

[29] P. Vytelingum, D. Cliff, and N. R. Jennings, "Strategic bidding in continuous double auctions," Artif Intell, vol. 172, no. 14, pp. 1700–1729, Sep. 2008, doi: https://doi.org/10.1016/j.artint.2008.06.001.

[30] Wang J, Wang Q, Zhou N, Chi Y. A novel electricity transaction mode of microgrids based on blockchain and continuous double auction. Energies 2017;10(12):1–22. https://doi.org/10.3390/en10121971.

[31] C. Zhang, T. Yang, and Y. Wang, "Peer-to-peer energy trading in a microgrid based on iterative double auction and blockchain," Sustain Energy, Grids Networks, vol. 27, p. 100524, Sep. 2021, doi: https://doi.org/10.1016/j.segan.2021.100524.

[32] Glismann S. Ancillary services acquisition model: Heuristic agent strategies. Europa-Universitat Flensburg; 2021.

[33] Marufu AMC, Kayem AVDM, Wolthusen SD. A distributed continuous double auction framework for resource constrained microgrids. Lect Notes Comput Sci (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 2016;9578:183–96. https://doi.org/10.1007/978-3-319-33331-1_15.

[34] K. Chen, J. Lin, and Y. Song, "Trading strategy optimization for a prosumer in continuous double auction-based peer-to-peer market: a prediction-integration model," Appl Energy, vol. 242, pp. 1121–1133, May 2019, doi: https://doi.org/10.1016/j.apenergy.2019.03.094.

[35] S. Thakur, B. P. Hayes, and J. G. Breslin, "Distributed Double Auction for Peer to Peer Energy Trade using Blockchains", in *2018 5th International Symposium on Environment-Friendly Energies and Applications (EFEA)*, Sep. 2018, pp. 1–8, doi: https://doi.org/10.1109/EFEA.2018.8617061.

[36] H. Haggi and W. Sun, "Multi-round double auction-enabled peer-to-peer Energy exchange in active distribution networks," IEEE Trans Smart Grid, vol. 12, no. 5, pp. 4403–4414, Sep. 2021, doi: https://doi.org/10.1109/TSG.2021.3088309.

[37] Zhang Z, Li R, Li F. A novel peer-to-peer local electricity market for joint trading of Energy and uncertainty. IEEE Trans Smart Grid 2020;11(2):1205–15. https://doi.org/10.1109/TSG.2019.2933574.

[38] Zhang C, Wu J, Zhou Y, Cheng M, Long C. Peer-to-Peer energy trading in a Microgrid. Appl Energy 2018;220:1–12. https://doi.org/10.1016/j.apenergy.2018.03.010. no. December 2017.

[39] W. Gan, M. Yan, W. Yao, and J. Wen, "Peer to peer transactive energy for multiple energy hub with the penetration of high-level renewable energy," Appl Energy, vol. 295, p. 117027, Aug. 2021, doi: https://doi.org/10.1016/j.apenergy.2021.117027.

[40] A. S. Faria, T. Soares, J. M. Cunha, and Z. Mourão, "Liberalized market designs for district heating networks under the EMB3Rs platform," Sustain Energy, Grids Networks, vol. 29, p. 100588, Mar. 2022, doi: https://doi.org/10.1016/j.segan.2021.100588.

[41] Odgaard O, Djørup S. Review of price regulation regimes for district heating. Int J Sustain Energy Plan Manag 2020;29. https://doi.org/10.5278/ijsepm.3824.

[42] H. Lund *et al.*, "4th Generation District heating (4GDH)," Energy, vol. 68, pp. 1–11, Apr. 2014, doi: https://doi.org/10.1016/j.energy.2014.02.089.

[43] Shi M, Wang H, Xie P, Lyu C, Jia Y. Distributed Energy scheduling for integrated Energy system clusters with peer-to-peer Energy transaction. IEEE Trans. Smart Grid 2022:1. https://doi.org/10.1109/TSG.2022.3197435.

[44] R. Jing, M. N. Xie, F. X. Wang, and L. X. Chen, "Fair P2P energy trading between residential and commercial multi-energy systems enabling integrated demand-side management," Appl Energy, vol. 262, p. 114551, Mar. 2020, doi: https://doi.org/10.1016/j.apenergy.2020.114551.

[45] A. G. Daryan, A. Sheikhi, and A. A. Zadeh, "Peer-to-peer Energy sharing among smart Energy hubs in an integrated heat-electricity network," Electr Pow Syst Res, vol. 206, p. 107726, May 2022, doi: https://doi.org/10.1016/j.epsr.2021.107726.

[46] Block C, Neumann D, Weinhardt C. A market mechanism for energy allocation in micro-CHP grids. Proc Annu Hawaii Int Conf Syst Sci 2008:1–11. https://doi.org/10.1109/HICSS.2008.27. no. May 2006.

[47] C. Schimeczek *et al.*, "AMIRIS: agent-based market model for the investigation of renewable and integrated energy systems," J Open Source Softw, vol. 8, no. 84, p. 5041, Apr. 2023, doi: 10.21105/joss.05041.

[48] Hart WE, et al. Pyomo — Optimization modeling in Pythonvol. 67. Cham: Springer International Publishing; 2017.

[49] Makhorin A. GLPK (GNU linear programming kit). https://www.gnu.org/software/glpk/. [Accessed 6 April 2021].

[50] The AnyLogic Company. AnyLogic. https://www.anylogic.com/; 2019.

[51] Preist C, van Tol M. Adaptive agents in a persistent shout double auction. In: Proceedings of the first international conference on Information and computation economies - ICE '98; 1998. p. 11–8. https://doi.org/10.1145/288994.288998.

[52] S. Rennie and J. Adamson, "UK environmental change network (ECN) meteorology data: 1991-2015," Centre Ecol Hydrol (Nat Environ Res Council), 2017. https://doi.org/https://doi.org/10.5285/fc9bcd1c-e3fc-4c5a-b569-2fe62d40f2f5.

[53] UK Power Networks. SmartMeter Energy Consumption Data in London Households. 2015.

[54] T. D. Hutty, S. Dong, and S. Brown, "Suitability of energy storage with reversible solid oxide cells for microgrid applications," Energ Conver Manage, vol. 226, p. 113499, Dec. 2020, doi: https://doi.org/10.1016/j.enconman.2020.113499.

[55] UK Government, "National Travel Survey", Jul. 2020. .

[56] E. McKenna and M. Thomson, "High-resolution stochastic integrated thermal–electrical domestic demand model," Appl Energy, vol. 165, pp. 445–461, Mar. 2016, doi: https://doi.org/10.1016/j.apenergy.2015.12.089.
[57] M. Brunner, S. Tenbohlen, and M. Braun, "Heat pumps as important contributors to local demand-side management", in *2013 IEEE Grenoble Conference*, Jun. 2013, pp. 1–7, doi: https://doi.org/10.1109/PTC.2013.6652381.
[58] Ofgem. Check if the energy price cap affects you *ofgem.gov.uk*. https://www.ofgem.gov.uk/check-if-energy-price-cap-affects-you; 2022.
[59] Solar Energy UK. Smart export guarantee league table *solarenergyuk.org*. https://solarenergyuk.org/resource/smart-export-guarantee/; 2022.
[60] RAC. Cost to rapid charge an electric car rises by a fifth in eight months *rac.co.uk*. https://www.rac.co.uk/drive/news/rac-news/cost-to-rapid-charge-an-electric-car-rises-by-a-fifth-in-eight-months/; 2022.
[61] Pod Point. Cost of charging an electric car *pod-point.com*. https://pod-point.com/guides/driver/cost-of-charging-electric-car. [Accessed 4 June 2021].
[62] KPMG. The hydrogen trajectory *KPMG*. 2022. https://home.kpmg/xx/en/home/insights/2020/11/the-hydrogen-trajectory.html#:~:text=Cost of green hydrogen from,-6 USD%2Fkg H2.
[63] Collins L. Green hydrogen to become cheaper than grey *rechargenews.com*. https://www.rechargenews.com/energy-transition/violent-shakedown-green-hydrogen-to-become-cheaper-than-grey-within-two-years-says-analyst/2-1-1147440; 2022.
[64] BEIS. Green book supplementary guidance: valuation of energy use and greenhouse gas emissions for appraisal *gov.uk*. https://www.gov.uk/government/publications/valuation-of-energy-use-and-greenhouse-gas-emissions-for-appraisal; 2021.