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Peer-to-peer electricity trading as an enabler of increased PV and EV ownership

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Abstract

Peer-to-peer (P2P) energy trading enables households to trade electricity with one another, rather than just with their supplier. This can help to incentivise the shifting of electrical loads to align with local renewable generation, which leads to decreased dependence on grid electricity and can bring financial savings for households. P2P is expected to be particularly suitable to complement embedded PV generation and electrical vehicles (EVs), two key technologies for grid decarbonisation. In this work we simulate P2P energy sharing for a local microgrid of 50 households with PV and EV ownership at various penetrations. In particular, we consider the merits of P2P in combination with uni-directional EV chargers ('V1G), and with chargers that can discharge EV battery energy to the home ('V2H') or the grid ('V2G'); we also consider the use of community energy storage ('CES') as an alternative to storage of energy in EV batteries. We simulate the interactions of the households with the P2P energy market over one week, for each of three seasons, and evaluate the microgrid's energy independence and the financial savings for households. Results suggest that P2P trading with V1G can effect an increase in shared energy, modest improvements to microgrid self-sufficiency, and improvements to household bills. However, the combination of P2P with V2H brings advantages substantially greater than either innovation individually. The typical household can save approaching £100/a (compared to an average bill of ca. £540 with no P2P), with savings exceeding £200/a in some situations. Importantly, we find that the P2P can achieve savings regardless of technology penetration, and furthermore, all types of household can benefit, including households that own both PV and EV. Under the market mechanism considered, we find only negligible impact for allowing V2G in addition to V2H.

Keywords: Peer-to-peer electricity trading; vehicle-to-house V2H; vehicle-to-X V2X; solar PV; microgrid; community energy storage

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1. Introduction

1.1 Outline and key definitions

Two significant aspects of energy decarbonisation that impact the electricity grid at a local level are the proliferation of embedded renewable generation (especially PV) and the electrification of transport. In the UK there are currently almost a million small scale solar PV installations, still leaving immense scope for growth [1]; and whilst electric vehicles (EVs) currently account for around 1% of vehicles on UK roads, the government plans to impose a ban on combustion vehicles by 2030 [2], [3] and it has been suggested that the UK fleet will need to be 55% electric by that date [3]. These technologies come with challenges and opportunities. High take-up of EVs will require considerable extra electrical energy for charging, and existing distribution grid infrastructure may struggle to meet peak charging demand [4]. Meanwhile, solar PV is a fluctuating, non-dispatchable resource, and generation is not guaranteed to align well with electrical demand (self-consumption for a UK household is typically below 50% annually [5]). Exports of solar power from multiple houses simultaneously pose a threat to distribution grids, potentially giving rise to voltage violations and line overload [6].

Clearly, PV and EVs offer a potential synergy, with EV batteries absorbing surplus power from nearby PV installations. However, the conventional energy system, wherein households can only trade power with their electricity supplier, provides no incentive for this (unless PV and EV are behind the same meter) [7]–[9]. The formation of local energy communities, with energy traded between households (as for instance in [7], [10]) could help to address this. An EV using a neighbour's surplus energy to charge would need to pay a price above the supplier's feed-in tariff but below the retail electricity price; both parties to the transaction would then benefit. We term such an exchange of energy a peer-to-peer (P2P) trade. As well as bringing financial savings, communities with P2P trading can achieve environmental benefits and reduce stress on the distribution grid [7], [11].

‘Smart’ scheduling of EV charging (for instance, to absorb renewable generation as described above) is generally termed V1G, denoting a one-way flow of power from grid to vehicle [12]. If a two-way charger is available, the vehicle can also discharge power to supply its own household (vehicle-to-home, V2H) or to export (vehicle-to-grid, V2G); the EV thereby becomes an energy storage device, shifting renewable energy to the time when it is required [12].

This work considers the benefits of P2P in combination with PV and V1G/V2H/V2G, in a local community of residential households. We will refer to this community as a ‘microgrid’, the term commonly applied to a local group of electrical loads and generation capable of a degree of autonomy from the main grid. We combine a realistic model for EV usage with a simulation of an iteratively settled P2P market. We compare the relative merits of V1G, V2H and V2G, evaluating performance in terms of the savings achieved by households, as well as the increased energy autonomy of the microgrid as a whole. Additionally, we consider the combination of the P2P market with community energy storage (CES) as an alternative to the use of EV batteries for energy storage.

The remainder of this section will discuss existing work on P2P energy trading, and V2H/V2G.

1.2 P2P energy markets

In traditional energy systems, households are purely consumers of energy, which is bought exclusively from a large-scale supplier; thus P2P energy trading represents a disruptive shake-up of this paradigm. Whilst in its strictest sense, P2P refers to trades of energy that are negotiated bilaterally between parties, here we use the term in its broader sense to denote any energy tariff or market that can incentivise and remunerate the sharing of electricity between households, a definition consistent with [7], [10]. Interest in P2P is growing, with companies including Centrica and EDF carrying out pilot schemes in recent years [13], [14]; a number of platforms for the P2P exchange of energy have also been designed, including among others Piclo and Vandebron [15].

In terms of the actual market mechanism through which P2P exchange of power is agreed and paid for, the literature covers a number of different possibilities. These include **centralised control**; **centrally issued price signals**; **auctions** and **iterative markets** – where these categories are not exhaustive and may also overlap. Under **centralised control**, optimisation is carried out centrally to determine which microgrid participants should trade energy, and how all the microgrid’s flexible devices are to be scheduled. For instance, in [16] central optimisation is used to determine P2P energy trades between EVs. Centralised control raises concerns about participants’ privacy and autonomy, and may also be computationally intensive unless the number of devices is small. Several researchers [17]–[20] pose a centralised optimisation problem, before going on to discuss distributed optimisation methods whereby participants need not surrender as much control or data. Another approach is for microgrid participants to retain full autonomy and plan their behaviour in response to **centrally issued price signals**. The problem then is for the operator to set the best prices to incentivise desirable behaviour; this problem may be interpreted as a Stackelberg game as in [21], [22], whilst in [23] a reinforcement learning approach is used. A natural approach to P2P markets is through the use of **auctions** – which may be designed to emulate traditional energy markets, as in [24]. Double auctions, wherein buyers of energy submit ‘ask’ prices and sellers submit ‘bid’ prices are typically of most interest. In an auction market the chief problem is for individual participants to set their strategies intelligently; the literature includes approaches such as adaptive learning [25], the adaptive aggressive strategy [26], ‘eyes on best price’ [27] and ‘zero intelligence’ [27]. Literature covering P2P electricity auctions with flexible loads includes [11], [28]. In **iteratively settled markets**, feedback from each round of bidding is used by participants to update their new bids, and the market is settled if and when it converges, otherwise requiring an exit mechanism of some kind. Iterative market mechanisms of various kinds are employed in [7], [10], [17], [27], [29].

Liu et al [10] contrived an iterative pricing mechanism for an energy-sharing zone consisting of buildings with PV generation and some adjustable loads. The internal tariffs for import and export of power were functions of the supply-demand ratio (SDR), i.e. the total of all exported power over all buildings, divided by the total of imported power. As such, this pricing mechanism will henceforth be referred to as the SDR tariff; it is the mechanism adopted in the present work. When SDR > 1, prices are low (equal to the grid feed-in tariff), incentivising demand to be increased or supply reduced. For SDR < 1, prices increase towards the cost of grid power, incentivising demand to be reduced or supply increased. Prices are designed so that the operator operates a balanced budget – i.e. all payments effectively flow between households and the utility grid, or between different households, with the operator not profiting. The final prices and load schedules are decided iteratively; in each round, participants optimise their load schedule relative to the most recently issued internal prices. The process repeats until convergence is achieved: viz. prices do not significantly change between iterations. In [10], this market mechanism was implemented in a case study with a number of residential and commercial/office buildings, and was found to achieve modest technical and economic benefits. Zhou et al [7] also consider the SDR tariff. This work was focused on (i) possible approaches to improving the convergence of the iterative market mechanism; and (ii) the comparison of the SDR tariff to alternatives (mid-market rate and bill-sharing). Simulations involved 20 households equipped with PV and flexible loads, with one day simulated at a time. Flexible loads considered were water heaters and washing / drying machines in addition to EVs. The methods to improve convergence were found to be effective, and the SDR pricing tariff was considered to outperform the alternative pricing formulas.

In this work the SDR tariff with iterative bidding is adopted. Reasoning for this choice is as follows:

(i) The approach is amenable to use with energy storage. By contrast, strategies for energy storage in auction markets can be complex, and the auctioneer may need to process complex bids (as also in large scale power markets [30]).
(ii) Fairness: all households are offered the same prices at each timeslot.
(iii) Autonomy: except for the constraints imposed by the convergence aids, houses are free to optimise their schedules in their own interests.
(iv) Confidentiality: only the planned net power of a household needs to be shared with the market, and no other details.

1.3 EVs in P2P power markets

Existing studies on P2P markets are often preoccupied with demonstrating the feasibility of a particular market mechanism; they tend to confine themselves to small scale, 'proof-of-concept' case studies. These may involve various different technologies, as shown in Table 1. The use of flexible load (either in the abstract, or pertaining to appliances like washers/dryers) in case studies is more common than either EVs or energy storage. Kim et al [29] performed a case study with eight households, with a mixture of EVs of three types – capable of V2H, V2G, or V1G only. PV generation was not included. El-Baz et al [11] carried out a case study for their double auction model, wherein ten households all possess PV, an EV and a heat pump; household savings up to 23% were achieved. Zhang et al [28] carried out a study where 10 PV systems were matched with 100 flexible loads including EVs. The emphasis of this work was the use of flexibility to address inaccuracy in PV forecasting; it was found that 78% of forecasting error was able to be absorbed locally in the case study. V2H/V2G were not considered. Alvaro-Hermana et al [16] considered the P2P exchange of power between EVs in Belgium, employing a detailed data-driven model for EV power consumption and availability. For those EVs requiring charging during the daily travel schedule, costs were reduced by 71%. Renewable generation was not modelled: the motivation to trade relied on a time-variable grid tariff. Finally, Zhou et al [7], as already noted, include EVs in their work comparing the SDR tariff to alternatives. This work is more far-reaching in its consideration of EVs than previous references; in particular, it includes sensitivity analysis of EV and PV technology penetration in the community of 20 households. This work does not, however, discuss possible household savings in absolute terms. Also, although V2H/V2G are available to the EVs in the model, the paper does not discuss the value of these options versus V1G.

Table 1. Aspects included in P2P studies from the literature. N.B. This signifies whether such aspects have been used in an actual case study, not whether the P2P system could theoretically accommodate them.

Reference(s)	Aspects modelled					
	P2P / local energy market	Flexible load	PV	Stationary energy storage	EV	V2H/V2G
[17], [21]–[23]	✓	✓	-	-	-	-
[25]	✓	-	-	✓	-	-
[16]	✓	-	-	-	✓	✓
[29]	✓	✓	-	-	✓	✓
[31]	✓	✓	✓	✓	-	-
[32], [33]	✓	-	✓	✓	-	-
[18], [34]	✓	✓	✓	-	-	-

[27]	✓	-	✓	-	-	-
[28]	✓	✓	✓	-	✓	-
[11]	✓	✓	✓	✓	✓	-
[7]	✓	✓	✓	-	✓	✓

1.4 Contribution of this work

The aim of this work is specifically to consider the possible advantages of a P2P energy market to complement PV generation and EVs, in the setting of a community of households forming a grid-connected microgrid. For this purpose, we adopt the SDR tariff introduced in [10]. We are interested in quantifying the possible real-world financial benefits for households, as well as the impact on the microgrid's overall energy autonomy. Additionally, since community energy storage (CES) has been proposed in the literature as an interesting alternative to household level energy storage [35], [36], we introduce shared CES as an alternative / complementary technology, and compare this to the use of the EV batteries for energy storage.

This paper's contributions can be summarised as follows:

- Comparison of the impact of V1G, V2H and V2G operating within a P2P energy sharing market, which to the authors' knowledge has not been addressed before.
- Estimation of annual savings for households (rarely covered by existing work), and comparison between households of different categories.
- Adaption of the SDR market mechanism to work in tandem with community energy storage (CES); comparison of CES to V2H / V2G.

2. Method

2.1 Model overview

In this work we model an energy community consisting of a number of households. These are assumed to be proximately located and to share the same distribution transformer, so as to form a grid-connected microgrid. The houses may each own an EV and / or a PV system. We consider different combinations of a P2P tariff with the options of V1G, V2H and V2G, and compare these to a baseline with the standard grid tariff. We also consider the use of the P2P tariff in tandem with CES. This forms an interesting comparison with the use of EV batteries for energy storage: the latter are dispersed, sometimes unavailable, and under the direct control of a subset of individual households; whereas the former is always available, and interacts with all the households via the market. Figure 1 gives a high-level schematic of the model.

The various sub-models will now be discussed.

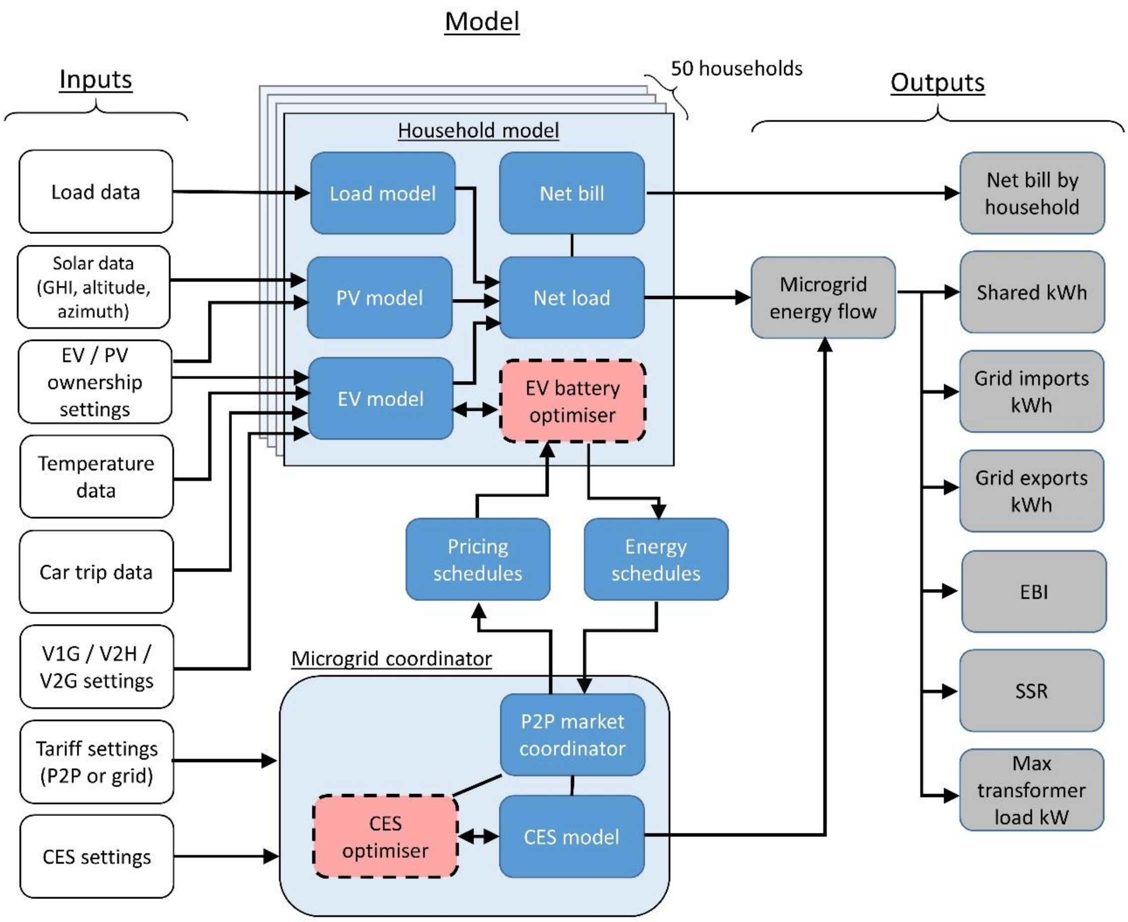


Figure 1. Overall schematic of model. All model aspects are implemented in AnyLogic [48], except optimisers which use Pyomo [37], [38] with the GLPK solver [39]. Key to note is the exchange of information between the coordinator and the households: the coordinator sends prices and receives energy schedules back.

Solar model

The solar model utilised here is reported in [40], and uses measured data for global horizontal irradiance to predict the radiation incident on an inclined plane. A constant efficiency of 15.4% is then applied to calculate generation; this efficiency is calibrated so that a south-facing system with 40° tilt, located in the London area, would have capacity factor of 11.8% [41].

EV model

EVs in the model follow week-long travel schedules recorded in the UK National Travel Survey, 2017 – 2019 [42]. The survey includes 27,516 vehicles for these years. Here, we restrict to cars belonging to single-car households in an urban location, of which there are 8,948. Further, we restrict to vehicle schedules that can be completed by EVs with a 30 kWh battery and 7.2 kW charger, assuming a constant fuel economy of 3.75 miles/kWh: this is 7,769 vehicles. The final sample of vehicles is then taken as a stratified sample by number of trips in the week (vehicles with data inconsistencies are excluded). It is worth noting that around 18% of vehicles make no trips at all over the course of a week.

Table 2. Details of vehicle sample.

Sample	Number of vehicles	Distance driven (miles)		Trips taken	
		Mean	Median	Mean	Median
Urban cars	21,189	99.7	63.7	12.4	12
Urban cars, one car household	8,948	94.7	61.5	13.3	12
Urban cars; one car household; viable for 30 kWh EV battery	7,769	84.0	54	12.2	11
Final sample	50	78.1	53.3	12.4	12

The 30 kWh Nissan Leaf is taken as the template for the modelled EVs. It is assumed that actual available battery capacity is 28.5 kWh, and that average fuel economy is 3.75 miles / kWh [43], [44]. This fuel economy is then adjusted according to the temperature, as shown in Figure 2.

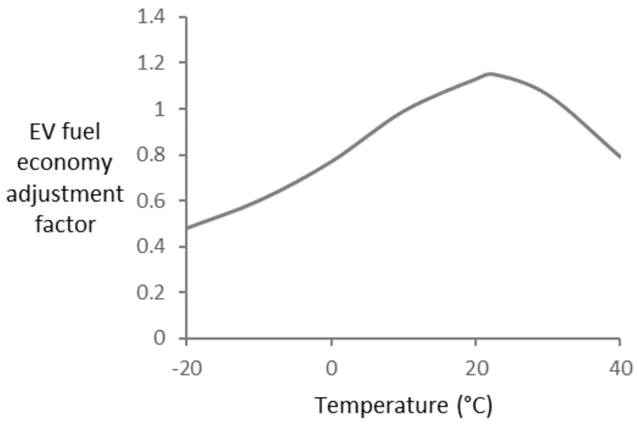


Figure 2. Adjustment to EV fuel economy according to outdoor temperature [43].

We use the same trip schedules regardless of the time of year, as the seasonal variation of weekly mileage / number of trips in the source data is negligible. The significant seasonal effect comes via the impact of temperature on fuel economy, rather than vehicle usage.

V2X efficiency

In this work we allow for energy losses of 5% for power conversion between AC and DC, and for 6% losses from the battery itself [45], [46]. Thus, the V2G storage efficiency is 84.9%. Although [47], [48] suggest that V2G round-trip efficiency may only be 50 – 70%, experimental work published more recently by Schram et al [49] suggests a range of 79.2 to 87% is realistic. Schram et al also found that the effects of SOC or temperature on charging efficiency are relatively small, so these are neglected here.

2.2 Microgrid internal pricing and iterative bidding process

For this work, we adapt the P2P mechanism laid out in Liu et al [10]. This is not a P2P mechanism in the strictest sense (trades that are negotiated bilaterally) but in the broader sense that it incentivises and remunerates power sharing between peers. Houses receive prices from the microgrid coordinator and plan their battery schedules accordingly. The new energy schedules are submitted to the microgrid operator, and new prices are calculated. The process iterates until convergence is achieved (or the maximum number of iterations is reached). The microgrid operator operates a balanced budget. Details of the process will now be given.

Pricing formula

The prices for household import and export of power are set according to the SDR formula [10]. Eqs. (1) – (5) give the details. If $E_{h,t}$ is the net energy flow for household *h* during time period *i*, then the total of all household energy surpluses is:

$$E_{surplus,i} = \sum_{h \epsilon H} max(0, E_{h,i}) \quad (1)$$

whereas the total of energy deficits is:

$$E_{deficit,i} = \sum_{h \epsilon H} max(0, -E_{h,i}) \quad (2)$$

The supply demand ratio may then be defined:

$$SDR_i = \frac{E_{surplus,i}}{E_{deficit,i}} \quad (3)$$

The prices that will be applied to the households' bills are then calculated in terms of the SDR, and fixed costs π_{high} and π_{low} in £/kWh [10]:

$$\pi_{export}(SDR_i) = \begin{cases} \frac{\pi_{high} \cdot \pi_{low}}{(\pi_{high} - \pi_{low}) \cdot SDR + \pi_{low}} & , SDR < 1 \\ \pi_{low} , & SDR \geq 1 \end{cases} \quad (4)$$

$$\pi_{import}(SDR_i) = \begin{cases} SDR \cdot \pi_{export} + (1 - SDR) \cdot \pi_{high} & , SDR < 1 \\ \pi_{low} & SDR \geq 1 \end{cases} \quad (5)$$

In general, π_{high} and π_{low} are respectively equal to the retail price and the feed-in tariff, that is, $\pi_{grid,imp}$ and $\pi_{grid,exp}$; however, they may take different values when CES is used, as detailed below. Note that, as SDR rises to 1, import and export prices fall towards π_{low}, whereas they rise towards π_{high} when SDR approaches 0.

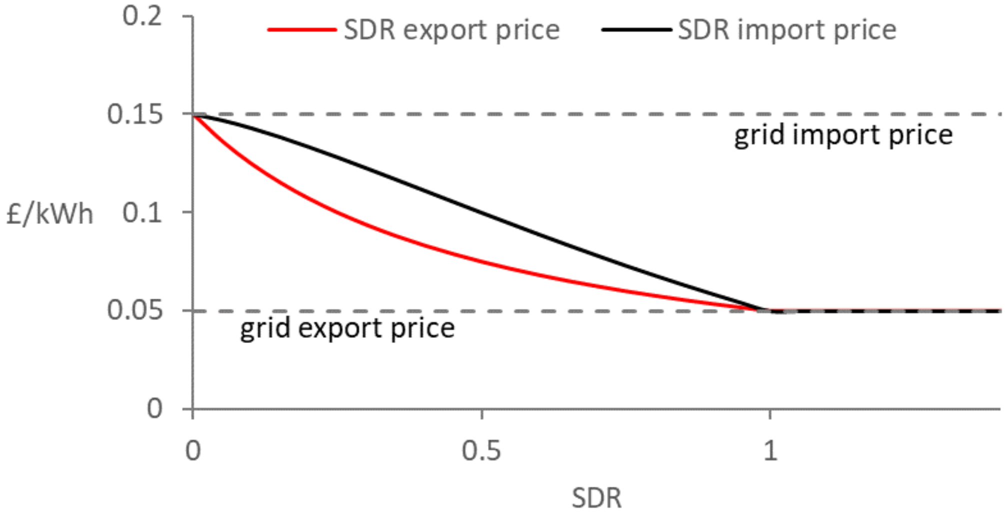


Figure 3. Internal microgrid prices as a function of SDR.

Iterative bidding process

The P2P market in this work is for periods of one day at half hour resolution. Days run from 5.30am, since very few cars have trips earlier than this; this time can be regarded as the 'beginning of the EV day'. *k* is used to index the iterations of the bidding process, whereas *i* is used to index the day's 48 time periods. Thus, $E_{h,i}^{k}$ is the signed net energy production of house *h* for time interval *i*, as scheduled at iteration *k* of the market mechanism (where a positive sign indicates power export).

$SDR_{PRE,i}^{k}$ is the SDR corresponding to the prices issued to households for bidding round *k*. $SDR_{POST,i}^{k}$ is the SDR resulting from the re-optimisation of household schedules at round *k*.

For each household, $E_{h,i}^{0}$ is initialised according to the inelastic demand $E_{load,i}$ and generation $E_{PV,i}$, i.e.

$$E_{h,i}^{0} = \eta_{inv} \cdot E_{PV,i} - E_{load,i} \tag{6}$$

(η_{inv} represents the efficiency of the household's inverter.) From this, $SDR_{PRE,i}^{1}$ can be calculated, and hence prices $\pi_{import,i}^{1}, \pi_{export,i}^{1}$. For each subsequent iteration, $k \geq 1$, each household with an EV optimises its EV battery schedule in response to the latest prices $\{\pi_{export,i}^{k}, \pi_{import,i}^{k}\}$. The optimisation model employed by households uses MILP and is detailed in Section 2.5. The new values of $E_{h,i}^{k}$ are then used to calculate the resulting supply demand ratio $SDR_{POST,i}^{k}$.

For the next round, $SDR_{PRE,i}^{k+1}$ is calculated as

$$SDR_{PRE,i}^{k+1} = 0.5 \cdot SDR_{PRE,i}^{k} + 0.5 \cdot SDR_{POST,i}^{k} \qquad (\forall k \geq 1) \tag{7}$$

An alternative would be to set $SDR_{PRE,i}^{k+1} = SDR_{POST,i}^{k}$ as in [10] but we find that the approach given in Eq. (7) can achieve better convergence. New prices are then calculated according to the SDR and the iteration continues. To improve convergence, we impose a maximum adjustment ΔE_{max} to the net household energy flow at each time interval; this applies from the second iteration onward, and the value of ΔE_{max} is reduced in subsequent rounds:

$$\left|E_{h,i}^{k} - E_{h,i}^{k-1}\right| \leq \Delta E_{max,k} := \begin{cases} 0.5 \text{ kWh} & , \quad 2 \leq k < 6 \\ 0.1 \text{ kWh} & , \quad 6 \leq k < 12 \\ 0.05 \text{ kWh} & , \quad 12 \leq k \end{cases} \tag{8}$$

Convergence criteria

Satisfactory convergence is considered to be achieved at round $\hat{k}$ if the following hold:

1. SDR has converged to a fixed point so that values before and after the round of optimisations are close:

$$\left|SDR_{PRE,i}^{\hat{k}} - SDR_{POST,i}^{\hat{k}}\right| < 0.02 \tag{9}$$

2. No household has incremented its energy flow by the maximum permitted amount, and in the same direction, for two consecutive steps. This can be expressed as:

$$\left(E_{h,i}^{\hat{k}} - E_{h,i}^{\hat{k}-1}\right)\left(E_{h,i}^{\hat{k}-1} - E_{h,i}^{\hat{k}-2}\right) < 0.05^2, \quad \forall h, i \tag{10}$$

When convergence is achieved, households are committed to the energy bids submitted at the last iteration. The final prices will be calculated according to $SDR_{POST,i}^{\hat{k}}$. If convergence has not been achieved after 25 iterations, the prices and schedules for the 25th iteration are implemented.

Adaption of process for community energy storage

When CES is present, it is scheduled by the microgrid operator to benefit the whole microgrid as a collective. The iterative bidding process is adapted to incorporate CES as follows. At each iteration, dispatch of the CES is optimized immediately after households submit their own newly optimised schedules. The objective function for minimisation is the total cost of energy exchanged with the grid, plus a penalty term to encourage peak shaving:

$$\sum_i \left\{-\pi_{grid,exp} \cdot max\left(E_{CES,i} + \sum_h E_{h,i}, 0\right) + \pi_{grid,imp} \cdot max\left(-E_{CES,i} - \sum_h E_{h,i}, 0\right)\right\} + \pi_{capacity} \cdot max_i\left(2\left|E_{CES,i} + \sum_h E_{h,i}\right|\right) \tag{11}$$

where $E_{CES,i}$ is the net energy from the CES at time interval i (with positive sign corresponding to energy generation) and $\pi_{capacity}$ is a nominal cost per kW for the peak usage of the grid connection (N.B. this does not actually form part of the retail tariff).

The contribution of CES is excluded from the calculation of SDR as specified in Eq. (3). The discharge of CES does not make energy cheaper to buy for households at the specific time it occurs (conversely, when the CES charges, the households do not get an increased export tariff at that specific time). Instead, the value gained by use of the CES is distributed to households throughout the day, by adjusting the value of π_{high} and π_{low} in Eqs. (4) and (5):

$$\begin{aligned} \pi_{high} &= \pi_{grid,imp} - \lambda \\ \pi_{low} &= \pi_{grid,exp} + \lambda \end{aligned} \tag{12}$$

The value of λ is chosen to ensure that the microgrid operator has a balanced budget – i.e. net cash flow of zero for the day. Prices for the next bidding iteration are then calculated as per Eqs. (12), (4) and (5). This approach ensures that the dispatch of CES is not detrimental to the convergence of the bidding process.

2.3 Case study

We consider a grid-connected microgrid consisting of 50 households, notionally located in the south-east of England. The number of households is intentionally larger than in most previous literature; this is to help ensure that the model captures the diversity between demand profiles and vehicle schedules for different households, since such diversity is a motivating factor for P2P. These households are assumed to share a single distribution transformer, and may each have an EV, a 3 kW PV installation, or both. 3 kW is the average capacity for small-scale solar installations in the UK [1]. The houses' basic electrical load comes from half-hourly measured data recorded by UK Power Networks in 2013 [50]. Measured irradiance data used for the PV model was recorded at Rothamsted in 2013, by UK Environmental Change Network [51]. PV systems are assumed to be split roughly evenly between south-facing, east-facing and west-facing systems; tilt angle of 40° is assumed in each case. The retail price of electricity is assumed to be £0.15/kWh and the feed-in tariff £0.05/kWh. Sizes of CES considered are 100 kWh, corresponding to ca. five hours of storage with respect to the load, and 500 kWh, corresponding to roughly a day of storage.

Representative climate weeks

We simulate the microgrid over one week for each of three seasons, with low, medium and high irradiance. Thus, 21 days are simulated overall (more than in most extant work), enabling estimation of annual performance. Details of the representative weeks are given in Table 3. Estimation of annual household savings is done by assuming 52 weeks to a year, and giving double weighting to the Autumn week. This weighting corresponds to annual insolation of 982 kWh / m^2, which is reasonable given that insolation for Southern England is typically 950 – 1100 kWh / m^2 / a (equivalently, 108 - 126 W/m^2) [52].

Table 3. Representative weeks for three seasons.

Season	Dates	Average irradiance (W/m^2)	Load excluding EVs (kWh/house/day)	Weighting
Winter	23rd – 30th Nov 2013	26.3	13.7	0.25
Autumn	22nd – 29th Sept 2013	97.7	10.0	0.5
Summer	4th – 11th June 2013	226.7	10.0	0.25

Systems and scenarios

We compare seven different microgrid setups, or 'systems'; these are shown in Table 4. G_V1G is the baseline system, whereby households are billed according to the grid tariff. EVs cannot engage in V2H or V2G; however, households with an EV and PV can optimise EV charging against their own generation. Subsequent systems allow different combinations of tariff with V2H or V2G. Note that all EV households are assumed to have the same capability regarding V2H / V2G. In the final two systems, CES sized at respectively 100 kWh (ca. five hours of storage) and 500 kWh (ca. one day of storage) is used for energy storage, but there is no V2H or V2G.

Table 4. Microgrid systems.

System name	Description
G_V1G	Grid tariff; V1G.
G_V2H	Grid tariff; V2H.
P2P_V1G	P2P tariff; V1G.
P2P_V2H	P2P tariff; V2H.
P2P_V2G	P2P tariff; V2G.
P2P_CES_100	P2P tariff; V1G, community energy storage 100 kWh
P2P_CES_500	P2P tariff; V1G, community energy storage 500 kWh

We consider penetrations of EV and PV ownership of 10%, 20%, 40%, 60%, 80% and 90%, so that there are 36 penetration scenarios overall. We do not consider 0% or 100% penetration, since it is more interesting to observe the performance of households that are in a minority, rather than completely eliminate a type of household. For some of the analysis in Section 3, we also group aggregate scenarios into four quadrants Q1 – Q4; see Figure 4.

Penetration scenarios assume that EV and PV ownership are statistically independent. Thus, for instance, if EV and PV penetration are respectively 60% and 20%, then 12% of houses will have both technologies.

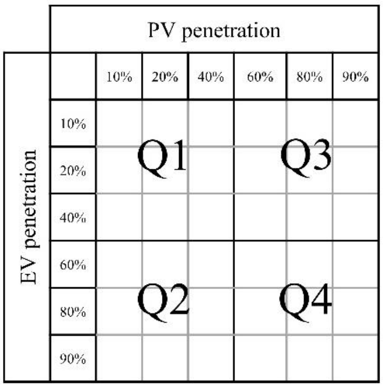


Figure 4. Shows the 36 technology penetration scenarios. These are also grouped into four quadrants Q1 – Q4.

2.4 Performance metrics

Self-sufficiency ratio (SSR) is defined as the proportion of load which is procured locally within the microgrid, i.e. not procured from grid imports. As such this provides a measure of the microgrid's energy independence, and a rough indication of emissions curtailment:

$$SSR = \frac{total\ energy\ consumed - total\ grid\ imports}{total\ energy\ consumed} \qquad (13)$$

Here, 'total energy consumed' includes energy charged to cars, as well as energy required for the basic household load.

Energy balance index (EBI) is a measure introduced in [7]. Like SSR, it is a measure of grid independence, but penalises exports to the grid as well as imports:

$$SSR = 1 - \frac{total\ grid\ imports + total\ grid\ exports}{total\ energy\ consumed + total\ energy\ generated} \qquad (14)$$

We also consider the total energy shared between households:

$$total\ shared\ energy = \sum_i min(E_{surplus,i}, E_{deficit,i}) \tag{15}$$

We also consider the maximum power flow through the transformer at the microgrid's grid coupling in either direction. The grid connection is assumed to balance the microgrid's net energy demand, whenever sharing energy / CES cannot wholly do so.

2.5 Optimisation of a household's EV dispatch

The optimisation model employed by households for scheduling of EV batteries is based on the 'BASOPRA' model reported in [53]. The model has been adapted to represent an EV battery by introducing parameters to represent battery availability and battery discharge to the EV. Unlike in [53], the battery may be permitted to export power to the grid. Additional constraints can also impose a minimum state-of-charge for the battery at the end of the optimisation time frame (one day), and a minimum state-of-charge at which V2X can take place. A variable is also introduced to allow rapid charge of EV batteries while the car is away from home. This energy is priced at £0.30/kWh [54], [55]. The availability of rapid charge ensures that individual optimisations are always feasible, although the high cost of this energy means that use of rapid charging will always be as minimal as possible. Optimisation is conducted using the GLPK solver.

Table 5. Nomenclature for EV battery optimisation

Description	Symbol	Unit	Set, or default value
Optimisation parameters			
Time parameters			
Time instant	t	-	$T = \{0,1,\dots 48\}$
Time step	i	-	$I = \{1,2,\dots 48\}$
Length of time step	dt	hours	0.5
Settings			
Permit EV battery discharge (V2X)	B_{V2X}	-	$\{0,1\}$
Permit household power export	B_{exp}	-	$\{0,1\}$
Valuation of final energy stored	π_{final}	£ / kWh	0.06
Price for rapid charge during trip	$\pi_{rapid,i}$	£ / kWh	0.30
Capacity tariff	$\pi_{capacity}$	£ / kW	0
Battery and inverter			
Battery nominal capacity	C_{batt}^{nom}	kWh	30
Battery DC efficiency	η_{batt}	-	0.94
Battery initial energy stored	E_{stored_init}	kWh	$[0,\infty)$
Minimum final energy stored	$E_{stored\_\min\_final}$	kWh	$[0,\infty)$
Minimum battery energy for V2X	$E_{stored\_\min\_V2X}$	kWh	$[0,\infty)$
Battery maximum charge power	$P_{max-char}$	kW	7.2
Battery maximum discharge power	$P_{max-disch}$	kW	7.2
Battery maximum state of charge	SOC_{max}	-	0.95
Batter minimum state of charge	SOC_{min}	-	0.05
Inverter efficiency	η_{inv}	-	0.95
Inverter power	P_{inv}	kW	10
Time series inputs			
Price for household power import	$\pi_{import,i}$	£ / kWh	$[0,\infty)^{\lvert I \rvert}$
Price for household power export	$\pi_{export,i}$	£ / kWh	$[0,\infty)^{\lvert I \rvert}$
Household load	$E_{load,i}$	kWh	$[0,\infty)^{\lvert I \rvert}$
PV generation	$E_{PV,i}$	kWh	$[0,\infty)^{\lvert I \rvert}$
Energy required for driving	$E_{drive,i}$	kWh	$[0,\infty)^{\lvert I \rvert}$
Availability of EV battery	α_i	-	$[0,1]^{\lvert I \rvert}$
Optimisation decision variables			
Energy stored in battery	$E_{stored,t}$	kWh	$[0,\infty)^{\lvert T \rvert}$

DC kWh for battery charge	$E_{char,i}$	kWh	$[0,\infty)^{\|I\|}$
DC kWh from battery discharge	$E_{disch,i}$	kWh	$[0,\infty)^{\|I\|}$
Binary variable for battery charge	$B_{char,i}$	-	$\{0,1\}^{\|I\|}$
Binary variable for battery discharge	$B_{dis,i}$	-	$\{0,1\}^{\|I\|}$
Net AC energy for inverter	$E_{inv\_net,i}$	kWh	$\mathbb{R}^{\|I\|}$
Net energy flow for household	$E_{house\_net,i}$	kWh	$\mathbb{R}^{\|I\|}$
Energy from rapid charger	$E_{rapid,i}$	kWh	$[0,\infty)^{\|I\|}$
Net cashflow	CF_i	£	$\mathbb{R}^{\|I\|}$
Max powerflow	$P_{house,max}$	kW	$[0,\infty)$

$B_{char,i}$ and $B_{dis,i}$ are initialised to random values before solving. This encourages households to find different solutions, aiding convergence of prices.

Optimisation Constraints

Constraints on EV battery

Eqs. (16) to (19), below, describe the stored energy in the EV battery $E_{stored,i}$, including the initial and final values.

$$E_{stored,0} = E_{stored\_init} \tag{16}$$

$$E_{stored,i} = E_{stored,i-1} + \eta_{batt} \cdot E_{char,i} - E_{disch,i} - E_{drive,i} + E_{rapid,i}, i > 0 \tag{17}$$

$$SOC_{min} \cdot C_{batt}^{nom} \leq E_{stored,i} \leq SOC_{max} \cdot C_{batt}^{nom} \tag{18}$$

$$E_{stored,48} \geq E_{stored\_\min\_final} \tag{19}$$

Eqs. (20) and (21) impose the availability of the EV battery, the maximum charge/discharge power; and the binary on/off state for charge/discharge. Eq. (22) ensures that charge and discharge are not simultaneous.

$$E_{char,i} \leq \alpha_i \cdot P_{max-char} \cdot B_{char,i} \cdot dt \tag{20}$$

$$E_{disch,i} \leq \alpha_i \cdot P_{max-disch} \cdot B_{disch,i} \cdot dt \tag{21}$$

$$B_{char,i} + B_{disch,i} \leq 1 \tag{22}$$

Eq. (23) prevents discharge of the battery if V2X is not permitted; Eq. (24) imposes the minimum battery state-of-charge for V2X. Eq. (25) ensures that rapid charging only occurs while the vehicle is away from home.

$$E_{disch,i} \leq B_{V2X} \cdot 10^6 \tag{23}$$

$$E_{disch,i} \leq E_{stored,i-1} - E_{stored\_\min\_V2X} \cdot B_{disch,i} \tag{24}$$

$$E_{rapid,i} \leq (1 - \alpha_i) \cdot 10^6 \tag{25}$$

Inverter constraints

Eqs. (26) and (27) constrain the net power on the AC side of the inverter; Eq. (26) covers the case of power export through the inverter, whilst Eq. (27) covers the case of power import. Eq. (28) imposes the inverter capacity. The inverter can curtail power if necessary.

$$E_{inv\_net,i} \leq \eta_{inv} \cdot \left(E_{disch,i} - E_{char,i} + E_{PV,i}\right) \quad (26)$$

$$E_{inv\_net,i} \leq \frac{1}{\eta_{inv}} \left(E_{disch,i} - E_{char,i} + E_{PV,i}\right) \quad (27)$$

$$-P_{inv} \cdot dt \leq E_{inv\_net,i} \leq \eta_{inv} \cdot P_{inv} \cdot dt \quad (28)$$

Household constraints

Eq. (29) gives the overall net load for the household; Eq. (30) controls whether export of power is allowed. Eqs. (31) and (32) control the net payments for export / import of energy.

$$E_{house\_net,i} = E_{inv\_net,i} - E_{load,i} \quad (29)$$

$$E_{house\_net,i} \leq B_{exp} \cdot 10^6 \quad (30)$$

$$CF_i \leq E_{house\_net,i} \cdot \pi_{export,i} \quad (31)$$

$$CF_i \leq E_{house\_net,i} \cdot \pi_{import,i} \quad (32)$$

Objective function

This consists of the nominal value assigned to final energy stored, the payment for rapid charging, and the net bill for import and export of power.

$$OBJ = \pi_{final} \cdot E_{stored,48} - \pi_{rapid} \cdot \sum_i E_{rapid,i} + \sum_i CF_i \quad (33)$$

3. Results

This section is organised as follows. We first present results for the operation of the microgrid over the summer week, and consider the overall performance in terms of the technical performance indicators, and household savings. We then assess the impact of season on the microgrid's performance, before focusing specifically on the annual savings for households, and how these are distributed to households of different classifications.

3.1 Results for summer

To illustrate the operation of the microgrid, Figure 5 shows simulation results for system P2P_V2G over the course of the summer week, for a scenario with 80% PV penetration and 40% EV penetration. Shown are energy production, energy consumption, self-consumed vs. shared power, and internal microgrid prices. By comparison of Figures 5 (a) and 5 (b), it will be seen that the charging of EVs tends to track the rise and fall of solar generation. Conversely, the discharging of EVs at night time tracks the standard (inflexible) electric load. As shown in Figure 5 (c), this flexibility is accomplished both by self-consumption within houses, and also to a significant extent by power sharing via the P2P market. The total shared energy over the week was 1681 kWh, compared to 619 kWh for the baseline system G_V1G at the same technology penetration levels. Grid imports across the week are reduced by 59%, from 1714 to 701 kWh; grid exports by 55% from 2012 kWh to 908 kWh; self-sufficiency increases from 55% to 86%. Consequently the average household is £3.19 better off across the week compared to the baseline system.

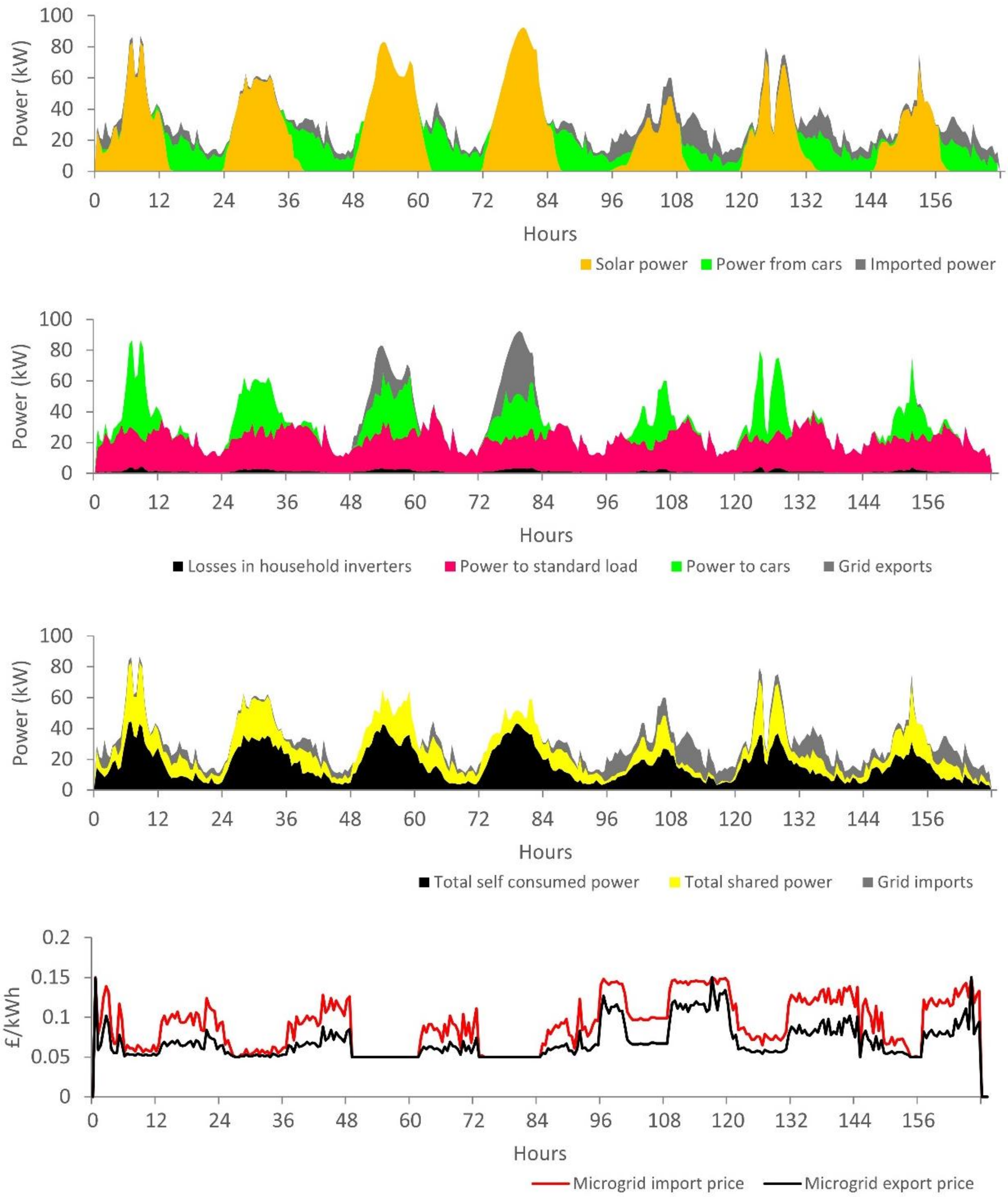


Figure 5. Operation of microgrid P2P_V2G over the simulated week, with 80% PV penetration and 40% EV penetration. (Hour zero is Monday 5.30am.)

(a) Power generation
(b) Power consumption
(c) Power self-consumed by households / shared between households / imported from grid
(d) Internal microgrid prices

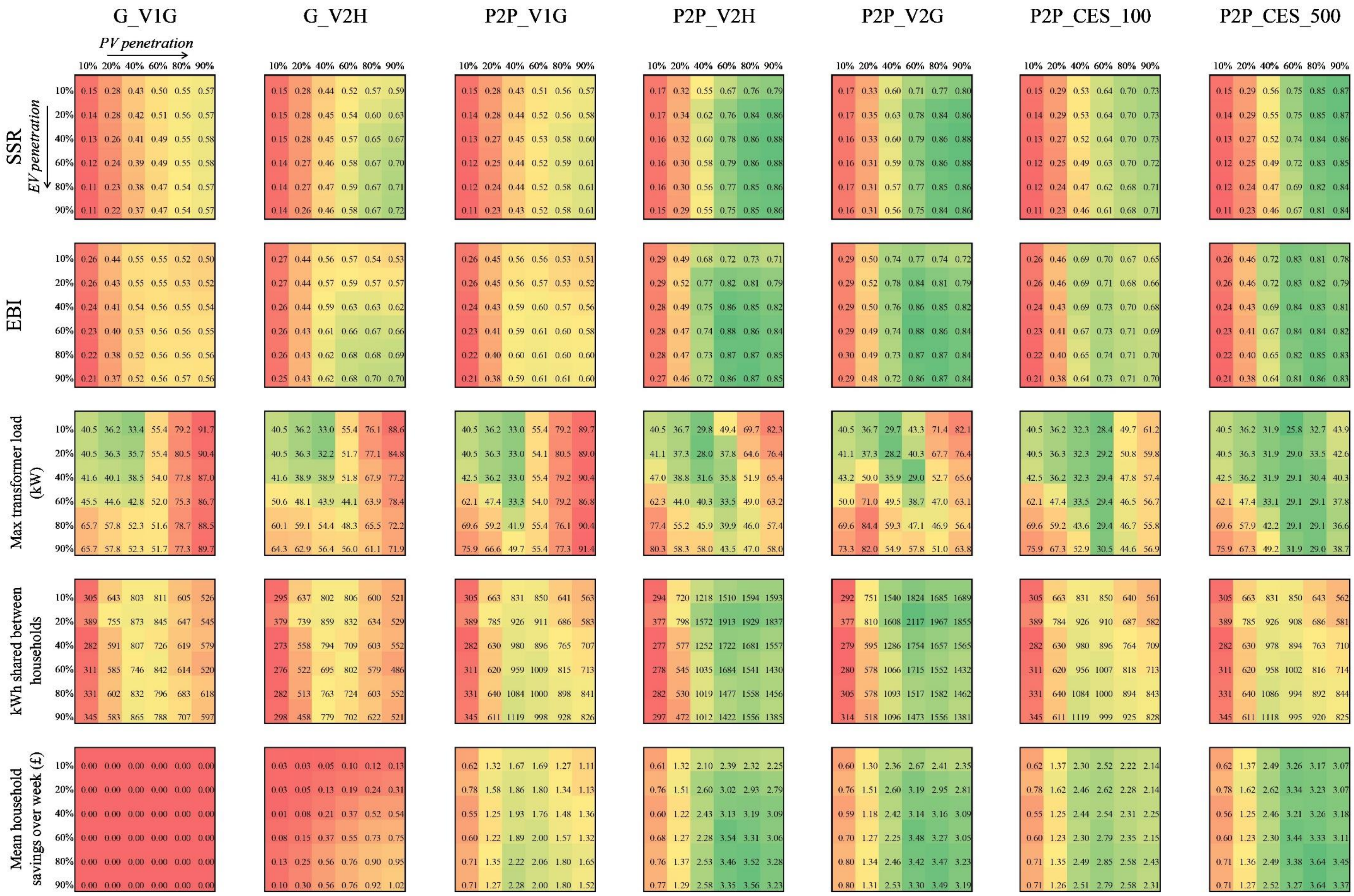


Figure 6. Performance indicators for the microgrid, for the various systems and scenarios, over the summer week. In each block, PV penetration increases from left to right, and EV penetration increases from top to bottom. Shading has highest values coloured green and lowest values red, except for 'Max transformer load' where this colour scheme is reversed.

Figure 6 summarises the performance of the microgrid over all systems and technology penetration levels for the summer week. Performance indicators shown are SSR, EBI, maximum transformer loading at the grid connection, shared kWh and average household savings (versus the baseline scenario, G_V1G). Certain broad observations can be made: the impact of PV penetration on these metrics is generally strong, whereas the impact of EV penetration tends to be more subtle, even when V2H / V2G are permitted. Whilst SSR naturally climbs with increasing PV penetration, shared energy and household savings (relative to the grid tariff) tend to peak at middling PV penetration. Peak transformer loading and EBI also achieve their best values for middling PV penetration.

In G_V1G (the baseline system) SSR for the week varies between 11% and 58%, EBI between 21% and 57%, and maximum transformer loading between 40.5 kW and 91.7 kW, according to the technology penetration. Power shared varies between 282 and 873 kWh (N.B. this is power which is physically shared, although not traded). SSR and EBI improve strongly as PV penetration increases. Increasing EV penetration tends to have a more modest, downward impact on these metrics. However, additional EVs can improve EBI if PV penetration is high, owing to the reduction in grid exports.

In G_V2H, EV households are permitted to discharge their batteries as V2H. Without a P2P trading system or time-of-use tariff, only the households in possession of EV and PV can profit by this. Thus the impact is negligible unless PV and EV penetration are high. With high enough penetration, we see moderate improvements in the microgrid's SSR and EBI, and decreased transformer loading; the highest SSR and EBI achieved are now 72% and 70%. Shared power decreases somewhat under G_V2H, since PV households can store surplus power for later use.

P2P_V1G introduces the P2P market mechanism (but does not allow V2H). There is now an incentive for households with EVs, but no PV, to schedule their charging to synchronise with peaks in solar generation. The effect is best demonstrated by observing the increase in energy shared between households, relative to the baseline G_V1G. This increase is typically at least 20%, representing up to 250 additional shared kWh across the week; across all technology penetration scenarios, the maximum shared energy is now 1,119 kWh (for 40% PV, 90% EV penetration). The increases in shared power correspond to modest improvements in SSR and EBI, although less than the improvements effected by G_V2H. No improvement is seen in the maximum transformer loading. The P2P tariff achieves household savings averaging up to £2.28 for the week; the best savings are seen when EV penetration is high and PV penetration is medium.

For most penetration scenarios, performance indicators for P2P_V2H are significantly improved versus G_V1G, G_V2H and P2P_V1G. Thus, the combination of V2H and a P2P tariff achieves much more than either innovation individually, a point we wish to emphasize. (However, for PV penetration below 20%, performance is similar to P2P_V1G, as there is insufficient surplus energy to store for V2H.) The increase in shared power versus the baseline is often several hundred kWh, with the largest increases of over 1 MWh additional shared power, occurring for PV penetration ≥ 60% and EV penetration 10 – 40%. Imported power is much reduced; for instance at 60% PV, 40% EV penetration, imports fall from 1,952 kWh baseline to 1,071 kWh under P2P_V2H (-45%). The reduced grid interaction is also reflected in improved SSR and EBI scores, with the best values now 88% and 87% respectively. Further, the maximum loading on the microgrid's transformer is also reduced; for instance, 90% penetration of both PV and EV can be accommodated with a peak loading of 58 kW, compared to 90 kW under G_V1G; a 36% reduction (although it should be remembered that this peak reduction is just over a one-week duration). The savings for households across the week can average up to £3.54.

P2P_V2G additionally allows all EV households to export power from EV batteries (V2G). In these results, the impact of allowing V2G is minimal to non-existent, so that P2P_V2G and P2P_V2H have very similar performance across all performance indicators. At middling PV penetration, V2G does result in an increase in shared power, but this increase is small. A possible explanation would be that households prefer to expend all energy stored in the EV battery on offsetting their own local electrical load. However, the average daily load for a household is only ca. 10 kWh, compared to 15 kWh of EV battery storage made available for V2X. Thus, the average household carrying out V2X should have enough battery capacity for V2G as well as V2H. The other explanation is simply that the iterative market mechanism is not good at incentivising V2G. Specifically, the SDR approach cannot allow a large proportion of supply to be exported from EV batteries, as the price paid for household export inevitably falls as the power exported from EVs increases. To incentivise V2G, some form of double auction is preferable, since this allows owners of EV batteries (or other flexible generation / storage) to make energy bids contingent on securing a given price. This power to dictate prices is absent from the market mechanism used here.

The final two systems introduce stationary CES (respectively 100, 500 kWh) but do not allow V2H or V2G. The energy independence measures, SSR and EBI, are improved substantially versus the baseline, reaching SSR = 73%, EBI = 74% for P2P_CES_100; and SSR = 87%, EBI = 86% for P2P_CES_500. The 500 kWh CES outperforms the 100 kWh CES only when PV penetration exceeds 60%; this is reflected in the scores for SSR, EBI and transformer loading, as well as the household savings. Thus it seems that for the lower PV penetration, 100 kWh of community storage is adequate. Broadly speaking, P2P_CES_500 achieves similar levels of energy independence to P2P_V2H across most technology penetration scenarios. On the other hand, the CES is significantly more successful at reducing peak transformer load. For example, P2P_CES_500 can accommodate 90% penetration of both EV and PV ownership, with a peak load of 39 kW – compared to 58 kW under P2P_V2H and 90 kW under G_V1G. This is expected since the CES is controlled with peak shaving as an explicit objective, whereas for previous systems, any peak shaving is an incidental consequence of households pursuing their self-interest.

Besides the clear advantages of combining P2P with V2H, a further point to emphasize is that doing so can achieve benefits regardless of EV and PV penetration. This contradicts a result of Zhou et al [7] who suggested that P2P becomes redundant when PV and EV penetrations are both high, as households can charge their own EV with their own generation. In our results, the average household saves £3.23 when EV and PV penetration are at 90% thanks to the P2P system.

Seasonal variation

The results up to this point have been for the typical summer week; we now introduce the impact of seasons. Figure 7 shows SSR and mean household savings for the various microgrid systems, across three seasons, with the penetration scenarios averaged into four quadrants (see Section 2.3). Season has a pronounced effect on both measures. In autumn, the P2P systems can still achieve notable improvements to SSR and to bills, although the improvements are reduced in magnitude. Generally, the relative performance of the different systems in summer and autumn is very similar; in particular, P2P_V2H still clearly outperforms G_V2H and P2P_V1G in autumn. For winter, savings and SSR are around an order of magnitude less than in summer, and the P2P systems can make only negligible impact. In the next section, we discuss the annual savings for households, which are estimated as a weighted combination of weekly savings in summer, autumn and winter.

(a)

(b)

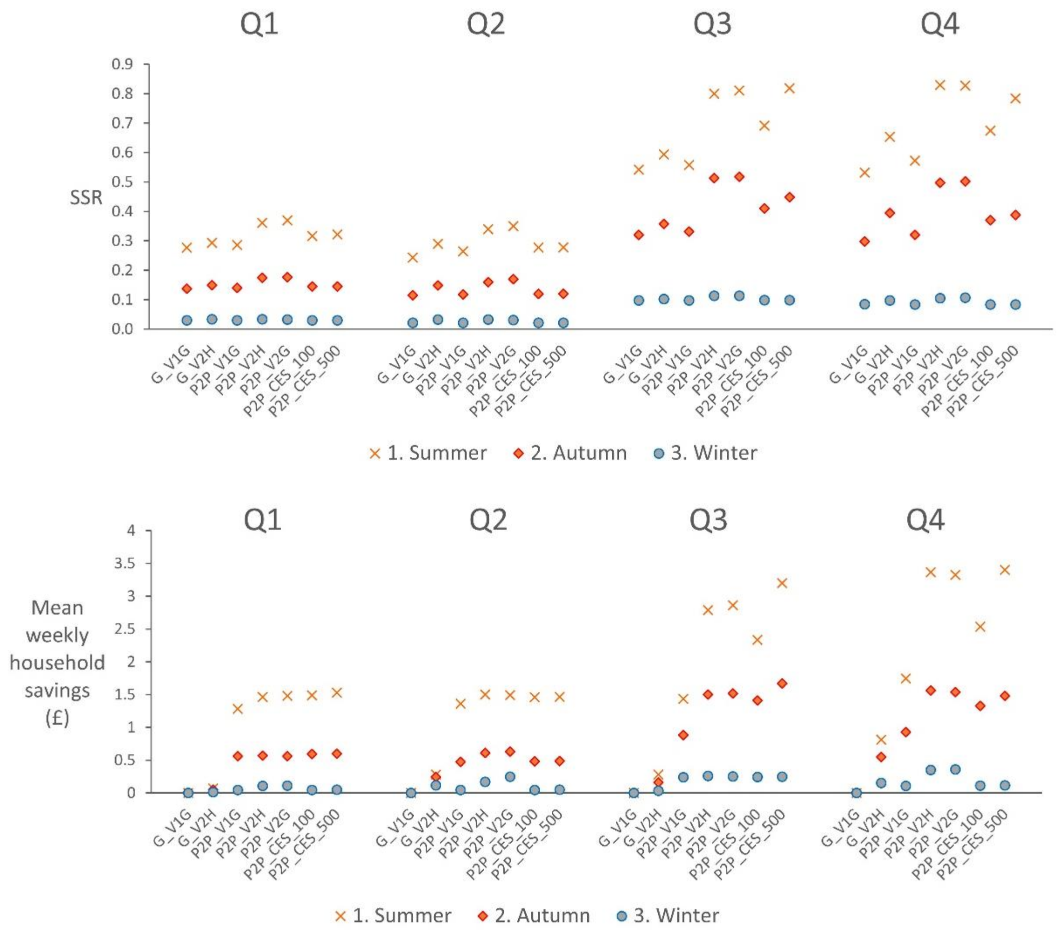


Figure 7. Impact of season on (a) SSR and (b) weekly household savings, for each of the seven microgrid systems. Household savings are relative to the baseline system with no P2P (G_V1G). Quadrants Q1 – Q4 are used for technology penetration (see Section 2.3).

3.2 Household savings and distribution of benefits

In this section we discuss the possible annual savings for households participating in the microgrid's market. Under G_V1G the average annual bill is £590 for a household with no EV or PV, £770 for a household with an EV; £380 for a household with PV; £440 for a household with both technologies. Figure 8 shows estimated annual savings across all microgrid systems and penetration scenarios, with households classified according to ownership of PV / EV. Figure 9 uses additional classifications of households (commuter / non-commuter; PV orientation), and shows results for P2P_V1G, P2P_V2H and P2P_CES_500.

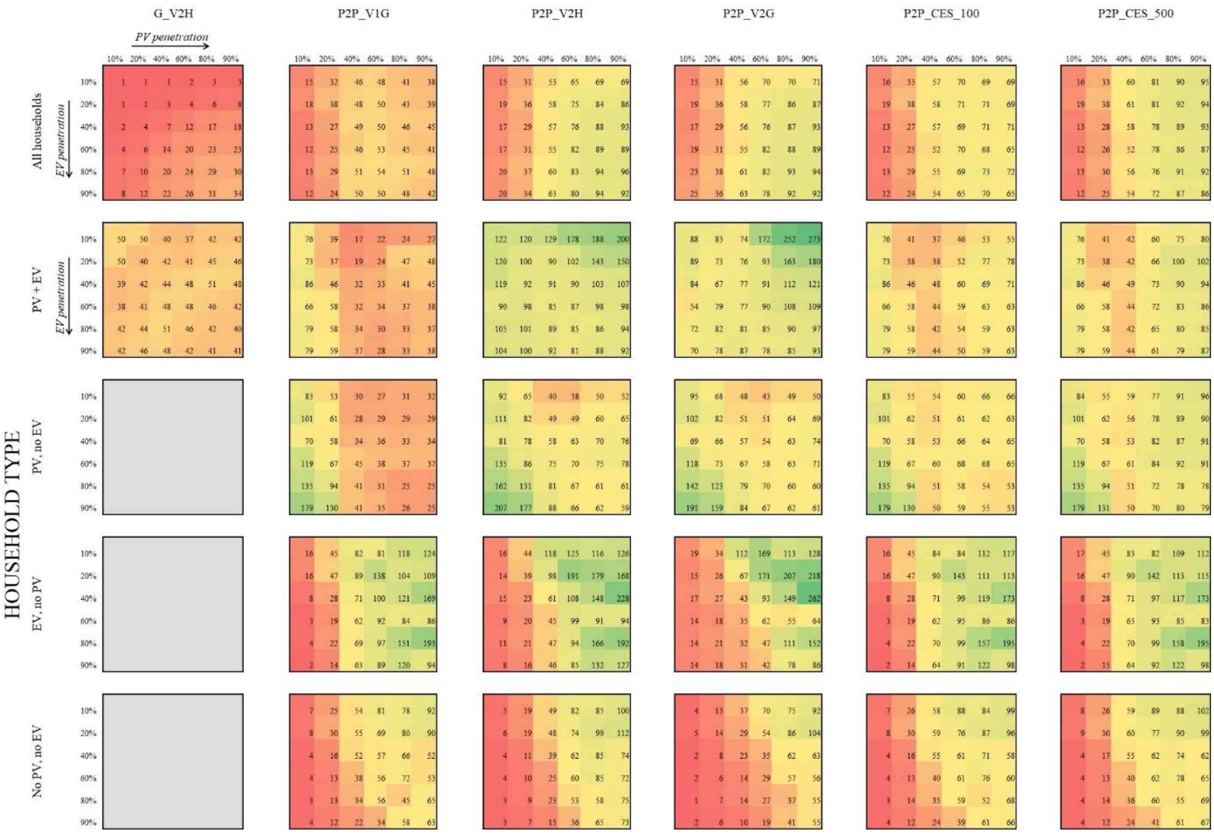


Figure 8. Average improvement in annual household bill, relative to G_V1G, for different household types and scenarios. In each block, PV penetration increases from left to right, and EV penetration increases from top to bottom. Blocks with no possibility of households making a saving are left blank. Unit is GBP.

Annual bill savings enabled by the various P2P systems tend to average up to £100, but can be over £200 for some household types in some scenarios. It is important to note that *all* types of households can benefit from the P2P. For instance, even for households with both PV and EV, P2P_V2H achieves markedly higher savings than G_V2H. Thus, these households evidently benefit from the ability to trade energy with neighbours, despite possessing their own generation and energy storage. This even remains true even at 90% penetration of the technologies. Households with neither PV nor EV can also benefit, although usually to a lesser extent than households with EV/PV. The largest savings (>£200/a) from P2P are enjoyed by households with an EV but no PV of their own, in scenarios with high PV penetration creating a buyer's market. Conversely, large benefits can also be felt by households with PV but no EV, especially when low PV penetration and high EV penetration create a seller's market.

Under G_V2H (given that the grid tariff is assumed constant) households must have both PV and EV in order to benefit economically; for these households, the benefits to the annual bill average ca. £44. Under P2P_V1G, household savings average £38/a across all household types and technology penetrations; savings are greatest at middling PV penetration, reaching a maximum of £54/a. Middling PV penetration allows that different households can simultaneously be in deficit or surplus, so that the P2P is most beneficial.

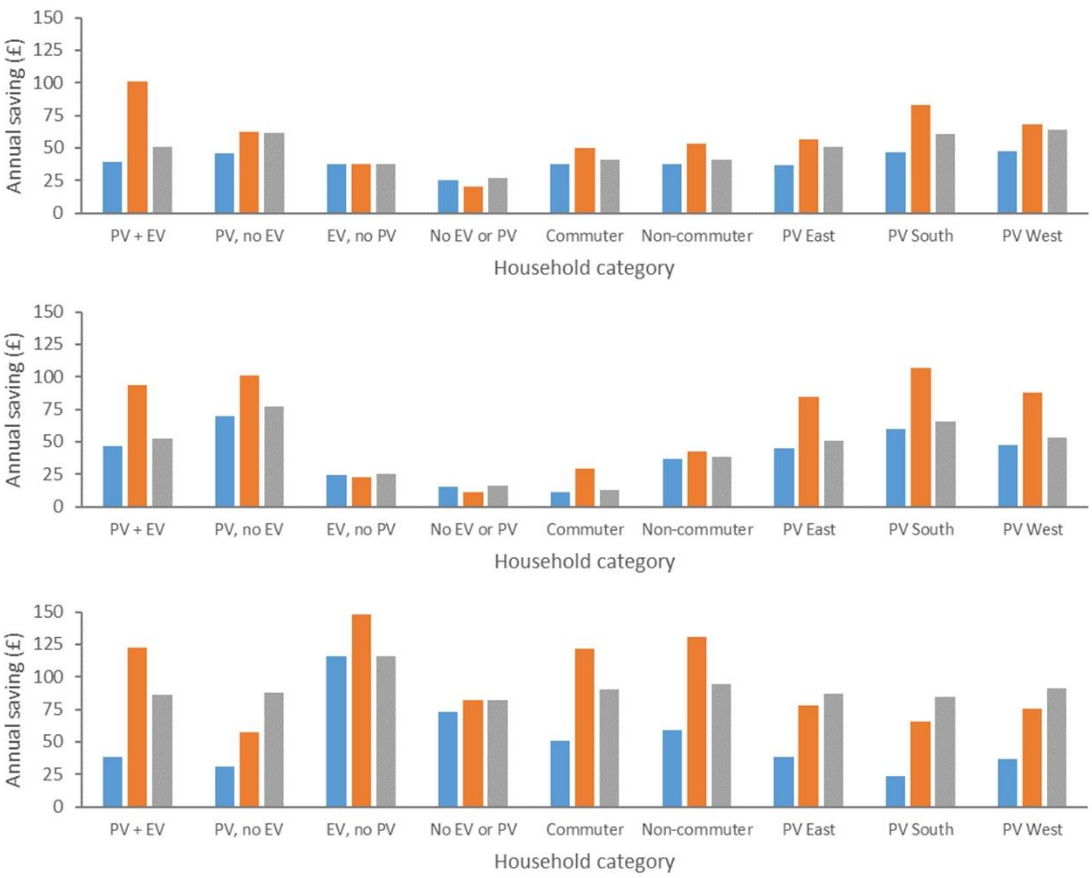
As with the technical performance measures, P2P_V2H achieves notably greater household savings than either G_V2H or P2P_V1G; the average across all household types and scenarios is £60/a. The savings are most significant at middling to high PV penetration, which allows households to charge cheap power to their vehicles during the day for use after sunset. Unlike P2P_V1G, savings do not peak at mid-range PV penetration, suggesting that more generation can always be put to use; savings reach ca. £90/a when PV penetration is high. Again, the biggest savings versus G_V1G (sometimes >£200) are made by households with EVs but no PV. Interestingly though, the jump in savings from P2P_V1G to P2P_V2H is actually less for the EV owners than the PV owners, who evidently benefit from the competition to buy power for V2H.

As already discussed, the market mechanism is not well-designed to incentivise V2G. Thus savings under P2P_V2G are very similar to P2P_V2H, with the average benefit again being £60/a across all tech penetration levels. Household savings for P2P_CES_100 and P2P_CES_500 average respectively £51 and £60. Because the CES enables microgrid prices to be smoother throughout the day, avoiding extreme values, distribution of benefits to different classes of households is somewhat more even than under P2P_V2H (see also Figure 9). The magnitude of household savings is broadly comparable for systems P2P_V2H and P2P_CES_500.

EV usage and PV orientation

For an EV owner, pay-off from the P2P systems comes from charging the vehicle when power is cheap, i.e. when PV generation is high. Thus it would be expected that commuter vehicles, that are often away at work during the daytime, will benefit less. This does indeed prove to be the case in our results (wherein we define a commuter household to be any household with four or more trips to work in the morning, over the week-long travel schedule). For instance, under P2P_V1G, average annual benefits for commuter EV households are £29, but £47 for non-commuters; under P2P_V2H the discrepancy is £60 to £77. Figure 9 shows that the discrepancy in earnings between commuters and non-commuters is greater when EV penetration is higher (3.5 (b) and (d)); whereas higher PV penetration is beneficial to both groups of EV drivers (3.5 (c) and (d)).

Additionally, we consider the orientation of PV systems (east, west, or south). Overall the benefits of the P2P mechanisms for each orientation appear very similar (see Figure 9). There is some indication that high PV penetration in the microgrid is more detrimental to the households with south-facing PV (see particularly Figure 9 (c)). However, it's important to note that the bills for households with south-facing systems are already lower in absolute terms (average £362/a for south-facing PV, versus £431/a for the other orientations, under G_V1G).



(a) Q1

(b) Q2

(c) Q3

(d) Q4

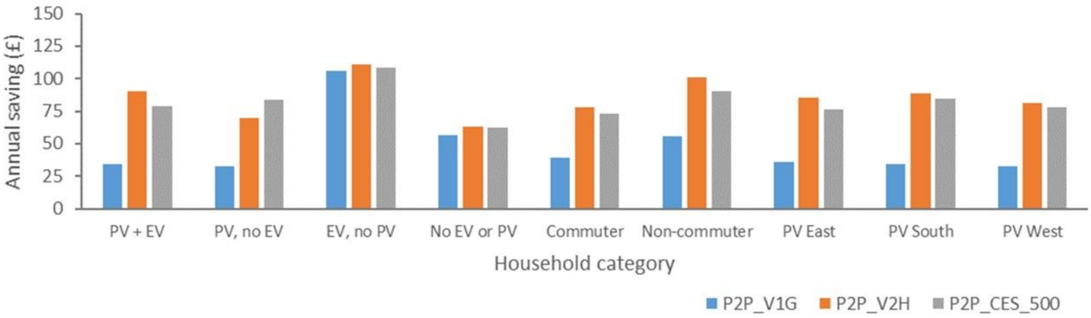


Figure 9. Average improvement in household net daily bill relative to G_V1G, for different household categories and microgrid systems. Estimated for one full year. Systems shown are P2P_V1G, P2P_V2H and P2P_CES_500.

4. Discussion

This work has developed a simulation model to investigate a P2P market mechanism based on iterative bidding, in combination with realistic models for EV usage and PV generation. We have confirmed that P2P trading can achieve significant benefits, both technical and economic. These are particularly interesting when the P2P market is combined with V2H technology. For instance, at 40% penetration for EV and PV ownership, average bills over a summer week improve by £2.42 (around 33% of the average summer weekly bill) and SSR increases from 41 to 60%. The benefits of V2H and P2P in tandem exceed the benefits of either in isolation. Perhaps counter-intuitively, this is still true when PV penetration and EV penetration are both high, so that most households possess both: for 90% penetration of each, V2H alone achieves average weekly savings of £1.02; P2P achieves £1.52; but the two in combination save households an average of £3.23. That P2P trading is profitable even when most households have PV and EV makes sense when considering two factors (i) EVs are not always available and (ii) they can charge at higher power than the output of typical rooftop solar (respectively 7.2 kW and 3 kW in this work). Thus, an available vehicle can utilise all the surplus PV from its own household, and still benefit from buying additional power from a neighbour whose car is unavailable.

We find some indication that the benefits of the P2P market for commuters, whose cars are likely to be unavailable during the day, may be less than for non-commuters. For the system with V2H and P2P, the annual benefits for non-commuters are 28% greater, averaged over all scenarios. We also compared the usage of EVs for energy storage with shared, stationary CES. This was controlled to minimise the microgrid's aggregate net bill, whilst also peak shaving for the grid connection. Because the CES schedule is controlled directly – whereas the schedules of EV batteries can only be influenced by market conditions – CES proved more successful at reducing peak loads than V2H; whereas household cost savings and improvements in energy autonomy were similar for V2H / CES.

The iterative bidding market mechanism used for this study has various strengths and weaknesses. Optimisation of household schedules in response to published prices is a simple and intuitive problem. Unlike in other market mechanisms, energy bids are never declined – rather, adjustments are encouraged by the price changes for the next iteration. Thus, there are no 'lucky' or 'unlucky' participants in the daily market. On the other hand, the need for constraints to encourage convergence of prices means that a level of central control is still present – the households are not fully free in their decision making. Pricing can tend to favour consumers more than generators. In particular, this market mechanism would need adapting in order to incorporate generation with non-zero marginal cost (V2G, CHP) as the mechanism currently assumes prices must be low whenever most supply is procured internally. Thus in this work, making V2G available achieved negligible benefits versus V2H – but there is no reason why this has to be true in general. Future work could compare this iterative market mechanism with other mechanisms: for instance, full central control; one-shot double auction; continuous double auction.

It is worth noting that passive participants in the microgrid (who have neither an EV or a PV) still benefit from the P2P market, especially in a buyer's market scenario (see Figures 8, 9). These benefits are always less than households with flexible load, but can sometimes be greater than the benefits to PV households. This is not necessarily reasonable, as these households are essentially profiting at the energy supplier's expense whilst taking no actions to benefit the community. The rationale for allowing these households to participate is that the market mechanism should not necessarily be aware of, or care about, what is 'behind' a household's meter. However, it might be worthwhile to consider market designs that more explicitly reward flexibility in demand. One possibility could be to reward load adjustments which are made to alleviate forecasting uncertainty or unforeseen fluctuations – see for instance [28]. Another possibility might be to impose a fee to join the P2P market, and thus recoup the average benefit of passive participants. It's also worth noting that participants without EV or PV could still contribute to the microgrid through control of smaller flexible loads (e.g. dishwashers, fridges) although these have not been modelled here.

5. Conclusions and future work

The authors believe that this work has demonstrated P2P to be a very interesting innovation that could greatly assist the integration of a high penetration of PV and EVs in the built environment. It can enable significant gains in energy independence (which should correspond to a reduction in emissions) and significant reduction of household bills, especially when PV penetration is high (see Figure 7). In particular, the coupling of P2P with V2H chargers is of interest, bringing greater benefits than either innovation individually.

Suggested topics for future work include:

- P2P market mechanisms that can take account of forecasting uncertainty. Uncertainty in forecasting generation / demand has received some attention; in contrast, forecasting of EV usage / availability has received little if any.
- Simulation of P2P mechanisms at higher time resolution. Existing work, including the present work, tends to use hourly or half-hourly resolution. Real life management of a microgrid demands attention to shorter term fluctuations.
- Coupling of markets for heat and power. Some proposals have been made for this (e.g. [31]) but such work is rare.

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