

Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework^{☆, ☆ ☆}

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HIGHLIGHTS

- A multiagent framework was established to simulate P2P energy sharing.
- Indexes were proposed to evaluate P2P energy sharing mechanisms.
- Heuristic techniques were devised to facilitate convergence of simulation.
- Three existing P2P mechanisms were evaluated in Great Britain context.

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ABSTRACT

Peer-to-peer (P2P) energy sharing involves novel technologies and business models at the demand-side of power systems, which is able to manage the increasing connection of distributed energy resources (DERs). In P2P energy sharing, prosumers directly trade energy with each other to achieve a win-win outcome. From the perspectives of power systems, P2P energy sharing has the potential to facilitate local energy balance and self-sufficiency. A systematic index system was developed to evaluate the performance of various P2P energy sharing mechanisms based on a multiagent-based simulation framework. The simulation framework is composed of three types of agents and three corresponding models. Two techniques, i.e. step length control and learning process involvement, and a last-defence mechanism were proposed to facilitate the convergence of simulation and deal with the divergence. The evaluation indexes include three economic indexes, i.e. value tapping, participation willing and equality, and three technical indexes, i.e. energy balance, power flatness and self-sufficiency. They are normalised and further synthesized to reflect the overall performance. The proposed methods were applied to simulate and evaluate three existing P2P energy sharing mechanisms, i.e. the supply and demand ratio (SDR), mid-market rate (MMR) and bill sharing (BS), for residential customers in current and future scenarios of Great Britain. Simulation results showed that both of the step length control and learning process involvement techniques improve the performance of P2P energy sharing mechanisms with moderate ramping/learning rates. The results also showed that P2P energy sharing has the potential to bring both economic and technical benefits for Great Britain. In terms of the overall performance, the SDR mechanism outperforms all the other mechanisms, and the MMR mechanism has good performance when with moderate PV penetration levels. The BS mechanism performs at the similar level as the conventional paradigm. The conclusion on the mechanism performance is not sensitive to season factors, day types and retail price schemes.

1. Introduction

In recent years, there have been an increasing number of distributed energy resources (DERs) connected to the demand side of power systems. DERs include distributed generators, energy storage systems and

flexible demands, and are usually connected to individual houses, buildings, microgrids or distribution networks [1]. The proliferation of DERs pose many challenges, such as reverse power flow and over-voltage issues due to distributed generation, but also bring increasing flexibility contained in energy storage systems and flexible demands

[☆] The short version of the paper was presented at WES-CUE2017, Jul 19–21, Singapore. This paper is a substantial extension of the short version of the conference paper.

^{☆☆} Information on the data underpinning the results presented here, including how to access them, can be found in the Cardiff University data catalogue at <http://doi.org/10.17035/d.2018.0046405003>.

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[2]. Therefore, there have been increasing interests in investigating how to manage DERs in an optimal way, with a large number of academic literature published and industrial technologies developed.

In the management of DERs, there are mainly two types of entities, i.e. operators and prosumers. The operators refer to either market operators that organise the energy trading between DERs, as well as the related consumers and retailers; or network operators (e.g. distribution network operators, microgrid operators, etc.) that deal with network planning and operation [3]. Prosumers refer to the owners of various DERs, and they are able to generate electricity as well as consume electricity [4]. The research on the management of DERs is categorised into two main streams according to the relationship between operators and prosumers.

In the first category, the operators coordinate all the DERs in a centralized or distributed way to maximise the overall economic benefits or to provide specific types of ancillary services, such as frequency response and voltage support, for power systems [5]. For centralized coordination, direct control is extensively studied and applied to control demand-side resources such as residential and commercial thermostatically controlled loads (TCLs) [6,7], energy storage systems [8] and electric vehicles (EVs) [9]. For distributed coordination, many techniques, such as stochastic pricing [10], Lagrange relaxation (LR) [11] and alternating direction method of multipliers (ADMM)-based optimization [12], are used to obtain a desirable outcome by achieving a convergence (e.g. Nash equilibrium) after an iterative procedure. The objective functions of methods in this category, for both centralized and distributed ones, are mostly to maximise the overall benefits or to achieve certain overall performance of the whole population of DERs, rather than to maximise the benefits of each individual prosumer. Therefore, additional incentives are usually needed to be provided for prosumers to make them participate and allow the intrusive control of their DERs.

In the second category, the operators only provide a local market platform with necessary functions, in which all the prosumers trade or share energy with each other in order to maximise their own benefits individually. Therefore, in this framework, prosumers have full control of their own DERs, and no additional incentives are needed to motivate prosumers to participate. Moreover, reduced computational time and communication infrastructure are required due to its distributed nature [13]. This framework, which is the so-called “peer-to-peer (P2P) energy sharing”, is considered in this paper. A number of studies have been conducted in academia on designing proper mechanisms for P2P energy sharing [13–17], and also a rapidly growing number of commercial or pilot projects have been carried out in practice [18–27]. Detailed literature review will be presented in the next section.

Although there are booming research and practices in P2P energy sharing, there is still a lack of systematic methodology to evaluate and compare different P2P energy sharing mechanisms. This issue is of great significance both in academia and industry. A good evaluation method is able to assess the strengths and drawbacks of certain mechanisms, which lights the way for further improvement. In practice, the evaluation method is capable of comparing the performance of several candidate mechanisms, and hence implementing the best mechanism. Although there are a few evaluation indexes scattered in existing studies to assess the performance of P2P energy sharing mechanisms, such as total energy cost and peak-to-average ratio (PAR), there are still significant research gaps:

(1) The performance results derived in the existing studies are usually based on the simulation results with different assumptions of the prosumers’ decision-making model. Also, some existing mechanisms do not specify the implementation process. Therefore, a systematic and general simulation framework is needed, which includes all fundamental elements of P2P energy sharing mechanisms and does not rely on specific forms of decision-making or implementation models. The objective of such simulation framework

is to make the simulation results (e.g. energy cost of prosumers) under different P2P energy sharing mechanisms comparable to each other in a unified case (e.g. a community microgrid).

- (2) More aspects of economic performance remain to be reflected besides the total energy cost. Firstly, the cost saving potential that can be achieved by P2P energy sharing within an area actually has a theoretical upper limit. This upper limit can be used to measure how much potential has been gained and how much more still remains to be explored by adopting a certain P2P energy sharing mechanism. Secondly, an index needs to be defined to show whether the economic benefits obtained by each prosumer are large enough to keep the prosumer staying in the mechanism. Thirdly, it is worth to measure the income inequality among the prosumers in the mechanism besides evaluating the overall cost.
- (3) Some existing technical performance indexes need to be extended to assess P2P energy sharing mechanisms. For example, PAR is widely used to reflect the flatness of load curves. However, for a region with many DERs, the maximum loading of the grid transformer may occur when the total load (net load) is negative, so the definition of PAR needs to be extended.

To fill the above research gaps, a systematic methodology was proposed. The main contributions of the paper are presented as follows:

- (1) A general multiagent-based framework was established for the first time to simulate the behaviours of prosumers under various P2P energy sharing mechanisms. The framework consists of three types of agents and three corresponding models. Two techniques, i.e. step length control and learning process involvement, were proposed to facilitate the convergence of the mechanism. A last-defence mechanism was established to deal with the divergence. The simulation results are used for calculating the index values for evaluation.
- (2) A novel index system was established to evaluate the performance of P2P energy sharing mechanisms. The index system includes three economic indexes (i.e. value tapping, participation willing and income equality) and three technical indexes (i.e. energy balance, power flatness and self-sufficiency). These indexes are normalised and further synthesized into one systemic index to reflect the overall performance.
- (3) Three typical existing P2P energy sharing mechanisms were evaluated in current and future scenarios of the power systems in Great Britain (GB). The results verified the effectiveness of the proposed simulation and evaluation methodology, and provided some practical implications on applying P2P energy sharing in the power system in GB.

2. Literature review on P2P energy sharing

This section reviews and comments on existing academic studies and practical projects on P2P energy sharing.

2.1. Academic studies

Some P2P energy sharing mechanisms have been proposed by researchers in the world, although they might have different names in respective studies.

Cintuglu et al. [14] created a competitive market environment for DER owners in a grid-connected microgrid by designing a reverse auction model. In this model, the lumped load is able to be supplied with the lowest cost due to the competitive behaviours of DER owners. A multiagent system was designed and realised at the Florida International University smart grid test system to simulate and verify the proposed model. Three aspects of work remain to be done regarding this study: (1) the consumers were considered as an aggregated agent (rather than individual agents); (2) the decision-making process of energy storage owners was quite simple and heuristic; (3) no flexible

demand was considered.

Also targeting at a grid-connected community microgrid, Shamsi et al. [15] proposed a community energy market in which each prosumer is capable of trading electricity with others. Agent-based approach was used to simulate the behaviours of prosumers as well. Compared to the work in Ref. [14], each agent makes decisions by solving an optimization problem rather than follow heuristic rules, and a learning mechanism based 1-D recursive least squares was assumed for each agent to estimate and track the spot price and demand level for decision making. However, this study did not consider flexible demand either.

In contrast, Paola et al. [13] proposed price-based schemes for distributed coordination of flexible demand within a game-theoretical framework, but did not consider distributed generation or energy storage systems. Furthermore, some considerations were missing (e.g. the existence of the utility grid with infinite capacity at its set price) or not applicable (e.g. the strictly increasing monotonicity of the power price function with respect to power demand) for P2P energy sharing in microgrids or local distribution networks.

Chao et al. proposed three different market paradigms, i.e. bill sharing (BS), mid-market rate (MMR) and auction-based pricing strategy (APS), for P2P energy sharing [16]. Bill sharing is a pro rata cost sharing mechanism based on the proportion of each prosumer's energy production and consumption in those of the whole community. In the mid-market rate mechanism, the trading price among prosumers is set at the average of the selling and buying prices set by the retailer, with some adjustment based on the difference between the total energy production and consumption within the community. Auction-based pricing strategy is an auction market similar to that presented in Ref. [15] with some minor adjustments. Simple performance evaluation was conducted for the proposed mechanisms in a community microgrid without the presence of any energy storage and flexible demand.

Liu et al. designed an energy sharing model for P2P prosumers with photovoltaic (PV) arrays and price-based demand response in a microgrid, in which the internal prices are decided based on the supply and demand ratio (SDR) in the microgrid [17]. The proposed model was supported by theoretical analysis and simulation result. One drawback of the model is that the iterative pricing process might not converge and is affected by the demand response participation level.

In this paper, three of the above P2P energy sharing mechanisms, i.e. the bill sharing and mid-market rate mechanisms in Ref. [16] and the supply and demand ratio mechanism in Ref. [17], were chosen to be evaluated using the proposed simulation and evaluation methods, considering that they are applicable to prosumers with both local generation and flexible demand. Detailed description on the three mechanisms refer to [Appendix A.2](#).

Note that although this paper took two P2P energy sharing mechanisms from Ref. [16] to evaluate, this paper made significant novel contribution. Ref. [16] did not establish systematic simulation and evaluation frameworks for P2P energy sharing, and did not consider the flexibility contained in prosumers either, which both have been addressed in this paper.

2.2. Practical projects

Electric utilities, industrial enterprises and high-tech start-ups have shown increasing interests in P2P energy sharing and conducted a number of relevant projects with diverse focuses and characteristics.

A number of projects focus on creating a trading platform for generators, consumers and prosumers to directly trade energy with each other, such as Piclo in the UK [18], Vandebrom in the Netherland [19], SonnenCommunity in Germany [20] and Yeloha [21] and TransActive Grid [22] in the US. In these projects, the trading platforms are all realised as online websites for information acquisition and transaction conduction, and are most targeted at renewable energy. The main function of the platforms is to link the energy supply and demand by

providing information, metering and billing services.

In spite of the similarities, these projects differ in various ways. First of all, the projects aim at different geographical scales. For example, Piclo, Vandebrom and SonnenCommunity aim at national scale services, while Yeloha and TransActive Grid are for regional networks and microgrids respectively [23]. Besides that, some projects have specific focus, such as energy storage for SonnenCommunity and solar panels for Yeloha.

Moreover, the business models of the projects are significantly different in terms of business entities, customers, value propositions and profit structure, as summarized in Ref. [24]. First of all, the projects are run by different types of business entities including renewable energy supplier (Good Energy in Piclo), online platform operator (Vandebrom), battery manufacturer (sonnenBatterie in sonnenCommunity), energy sharing intermedium (Yeloha) and microgrid operator (LO3 Energy in TransActive Grid). As for customers, although the projects all try to link renewable energy suppliers and consumers, some of them focus on specific types of customers. For example, Piclo mainly engages large commercial consumers, while Yeloha pays special attention to the land owners who can provide sites for solar panel installation. Furthermore, the projects propose value propositions from different perspectives. Piclo and Vandebrom are characterized by matching preferences of energy suppliers and consumers, while Yeloha claims to reduce electricity bills both for solar energy suppliers and consumers. sonnenCommunity emphasizes the benefits brought by energy storage, while TransActive Grid highlights the increasing reliability supported by local power supply. Last but not least, the operators of the projects make profits in different ways. Piclo is a pilot project, thus relying on the government investment and venture capital. Vandebrom charges a monthly subscription fee (\$12 per month) from both energy suppliers and consumers. Yeloha shares benefits with solar power suppliers and charges fees from solar power consumers. sonnenBatterie mainly makes profits through the sale of batteries. The profit source of LO3 Energy in TransActive Grid is still not clear so far.

There are also projects focusing on the supporting technologies for P2P energy sharing. PeerEnergyCloud [25] and Smart Watts [26] in Germany focus on the information and communication technologies (ICT) that enable P2P energy sharing. TransActive Grid in the US [22] and National Lifestyle Villages in Australia [27] adopt an emerging “blockchain” technology to establish a decentralized but trustable P2P energy trading platform, so that the cost regarding involving an inter-media is able to be saved. Blockchain technology is a disruptive distributed information and computing paradigm that is able to create a trustable trading and billing environment without a centralized authority [28]. Blockchain technology is considered as a promising enabler in energy industry [29] and is able to support P2P energy sharing [30].

The rapid development of P2P energy sharing in the practical world highlights the importance of the research on relevant topics and methods, including the simulation and evaluation method studied in this paper.

3. Multiagent-based simulation framework for P2P energy sharing

This section describes a general multiagent-based simulation framework for P2P energy sharing and two heuristic techniques for facilitating convergence of simulation with a last-defence mechanism to deal with the divergence. Firstly, a brief introduction on P2P energy sharing is provided. After that, the multiagent-based simulation framework is presented in detail with the description for its necessity and components as well as the discussion of convergence issues. Note that the simulation results provide the basis for calculating the values of the evaluation indexes that are described in Section 4.

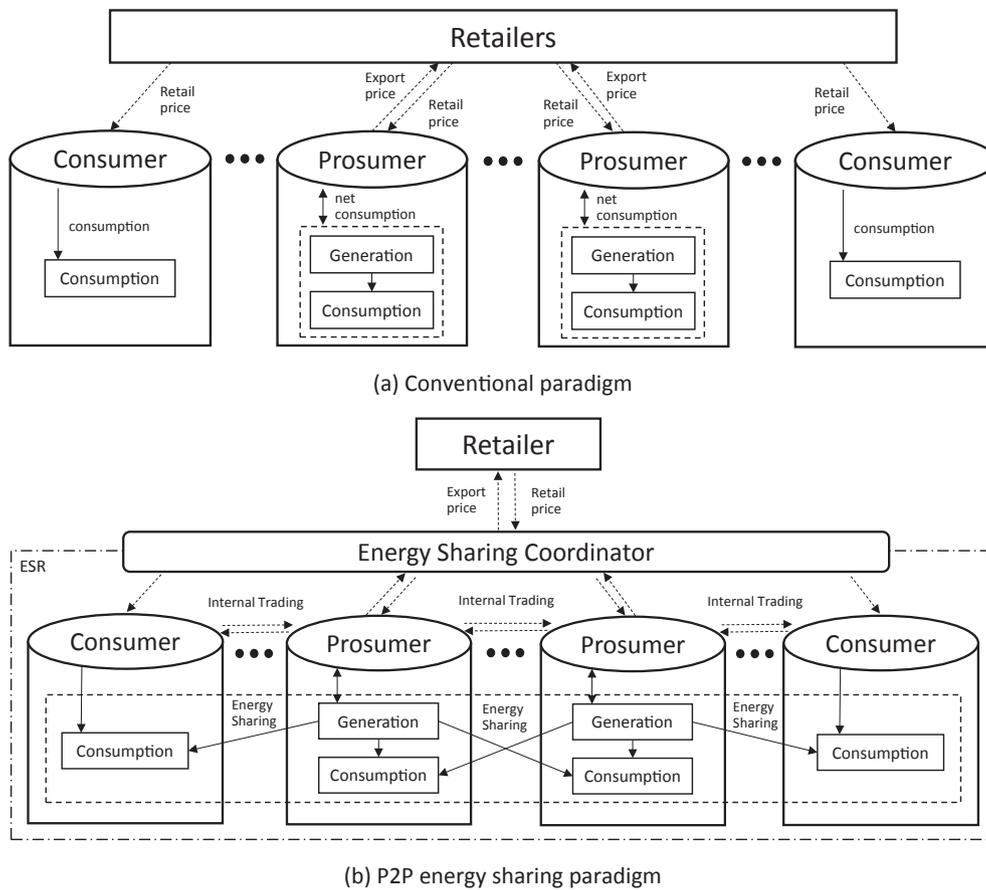


Fig. 1. Conventional and P2P energy sharing paradigms.

3.1. P2P energy sharing paradigm and mechanisms

P2P energy sharing involves novel technologies and business models at the demand-side of power systems, which is able to manage the increasing connection of DERs.

As illustrated in Fig. 1(a), in the conventional market paradigm, prosumers and consumers trade with retailers (the same retailer or different ones) independently based on their net consumption. For prosumers, when its consumption is greater than its generation, a prosumer buys the deficit electricity from a retailer at a retail price. When the consumption is less than the generation, the prosumer sells the surplus electricity to the retailer at an export price specified in the feed-in tariff (FIT) scheme.

However, in order to encourage prosumers to consume and balance distributed generation on site as much as possible, it is a common practice in many countries to set the export price in the FIT scheme lower than the retail price. This fact motivates the prosumers try sharing their surplus energy directly with their neighbours to seek higher revenues, which results in the so-called P2P energy sharing paradigm as shown in Fig. 1(b). In the P2P energy sharing paradigm, the prosumers and consumers first share their generation and consumption in a local market at an internal price, and then trade with a retailer to cover the remaining electricity deficit or surplus. The internal price is usually set between the export price and the retail price, so that each prosumer or consumer, no matter it is an electricity seller or buyer, benefits from the P2P energy sharing. Note that consumers can be seen as a special type of prosumers who do not own any local generation. Therefore, for convenience, both prosumers and consumers are collectively referred as prosumers in the rest of the paper. Detailed market rules in the P2P energy sharing paradigm are collectively termed as “P2P energy sharing mechanism”.

P2P energy sharing can be carried out among prosumers in a microgrid or a part of distribution network (referred to as “energy sharing region (ESR)” in this paper), supervised by a market operator (named “energy sharing coordinator”, short as “coordinator”, in this paper). A coordinator is usually needed in P2P energy sharing practice due to two reasons. First of all, a coordinator is needed to specify the rules for trading and supervise the energy sharing activities. The rules include the core pricing model and implementation process, as well as other relevant rules to guarantee the interests of every participant. Secondly, a trading platform as well as the associated metering and billing mechanisms needs to be provided and operated by a coordinator, based on which P2P energy sharing is able to be conducted. To the best of our knowledge, all the existing P2P energy sharing studies and practical projects involve coordinators [13–27], although in some decentralized blockchain-based projects the coordinators are played by machine codes rather than conventional intermedia run by manpower [22,27,30].

3.2. Multiagent-based simulation framework

P2P energy sharing mechanisms are evaluated based on the actual outcomes they lead to, including the power and energy exchange and the corresponding cash flows within the ESR and between the ESR and the retailer. However, in many cases, feasibility studies need to be conducted before a mechanism can be implemented. Moreover, simulation results are the basis of assessing the strengths and drawbacks of a mechanism during its development stage. Therefore, a simulation framework is necessary.

3.2.1. Framework overview

A multiagent system (MAS) includes multiple autonomous agents

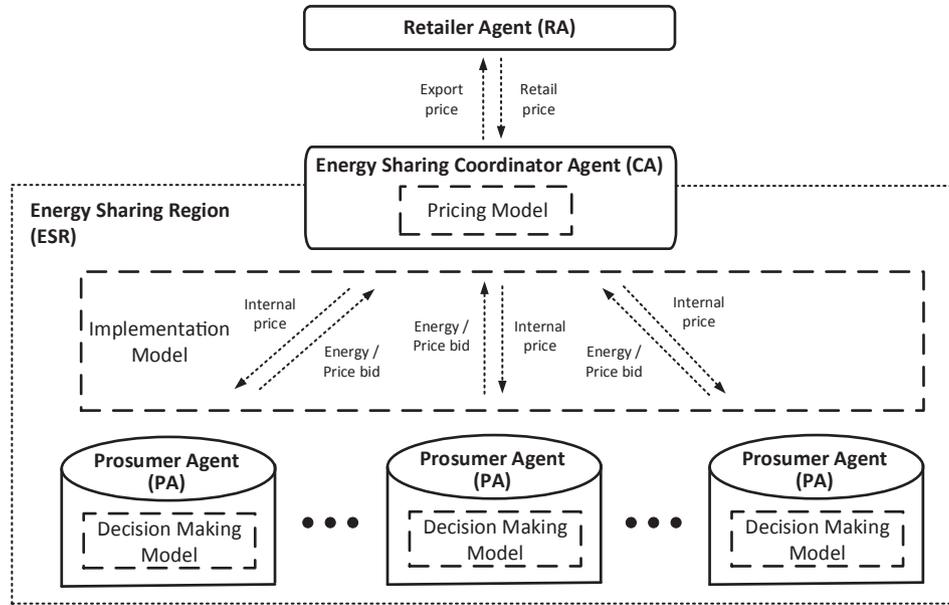


Fig. 2. Overview of the proposed multiagent-based simulation framework.

which interact, negotiate and cooperate with each other to achieve their individual objectives. MAS is considered suitable for conducting modelling and simulation tasks with flexible and extensible architecture in power engineering, as identified by the Multi-Agent Systems Working Group of IEEE Power and Energy Society [31]. Therefore, MAS is suitable for simulating the behaviours of the multiple prosumers that behave autonomously to maximise their individual benefits in P2P energy sharing mechanisms [32,33].

The overview of the proposed multiagent-based simulation framework is illustrated in Fig. 2. This framework includes three types of agents and three corresponding models. The agents are the energy sharing coordinator agent (CA), the prosumer agents (PAs) and the retailer agent (RA). The three models include (1) the pricing model in the CA to calculate and issue the internal price based on the bids of the PAs, (2) the decision-making model in the PAs to schedule the consumption and/or generation and produce the corresponding bids, and (3) the implementation model that specifies the type and rules of the interaction process between the CA and PAs.

The architectures and models of the agents are described in the following sub-sections. Note that they are described in a general and abstract way to highlight the major structure, functionalities and input/output relationship. A concrete example with detailed mathematical models and rules in the context of GB power system will be presented in Section 5.

3.2.2. Prosumer agents and decision-making model

Prosumer agents represent the autonomous prosumers in P2P energy sharing. Referring to the abstract architecture for agents described in [34], the set of prosumer agents is denoted as

$$\mathcal{PA} = \{PA_1, PA_2, \dots, PA_N\} \quad (1)$$

where N is the number of prosumers participating in the P2P energy sharing. Each agent perceives its environment to collect information needed for decision-making. The environment of a prosumer agent is denoted as

$$\mathcal{E}_{PA} = \{\mathbf{p}^{\text{internal}}, \mathbf{A}, \mathbf{D}, \mathbf{P}^{\text{renewable}}\} \quad (2)$$

where $\mathbf{p}^{\text{internal}}$ represents the set of internal prices in the P2P energy sharing mechanism; \mathbf{A} is the set of parameters of the electrical devices (i.e. appliances, energy storage systems and distributed generators); \mathbf{D}

is the set of demand of the prosumer (e.g. hot water use throughout the day); $\mathbf{P}^{\text{renewable}}$ is the set of power output of uncontrollable renewable generation owned by the prosumer. The environment actually describes the input data set of a prosumer agent, and the data can be provided by both external and internal entities such as the coordinator and the energy management system of the prosumer.

Based on the information perceived from the environment, the prosumer agent schedules its electrical devices to minimise its electricity cost/maximise its revenues in the P2P energy sharing. This process is simulated by the decision-making model, which is abstractly described as follows:

$$\begin{aligned} & \min_{\mathbf{x}} \text{Cost}_T(\mathbf{p}^{\text{internal}}, \mathbf{P}^{\text{renewable}}, \mathbf{x}) \\ & \text{s. t. } \mathbf{f}(\mathbf{x}, \mathbf{A}, \mathbf{D}) = 0 \\ & \mathbf{h}(\mathbf{x}, \mathbf{A}, \mathbf{D}) \leq 0 \end{aligned} \quad (3)$$

where T is the set of time steps considered throughout the scheduling horizon; \mathbf{x} is the decision variables, which are the operational status of the controllable electrical devices (e.g. ON/OFF status of washing machines, heating power of an electric water heater, etc.); Cost is a function of internal electricity price, renewable generation output and operational status of the electrical devices, of which the value is the total electricity cost throughout the scheduling horizon; \mathbf{f} and \mathbf{h} are the equality and inequality constraints that consider device physical limits and prosumer satisfaction. Detailed examples of Cost , \mathbf{f} and \mathbf{h} in Formula (3) refer to Appendix A.1.

Note that although the decision-making model is presented as an optimization problem, besides using optimization algorithms (e.g. interior point method, genetic algorithm, etc.) to solve it, it can also be realised as heuristic rules, such as those in Ref. [14]. It is also worth noting that in some cases the internal price, electricity demand and renewable generation output for future time steps cannot be obtained directly, and thus auxiliary forecast models are then needed to derive this information, based on the corresponding historical data, to support the decision-making model, such as those in Ref. [32].

The decision-making model derives the actions that a prosumer agent takes, which include the control signals for the controllable electrical devices, the energy bid (i.e. the resulting load profile over the scheduling horizon) and the price bid (e.g. the ascending cost plot of the generation units for economic dispatch as described in Ref. [15]) to be

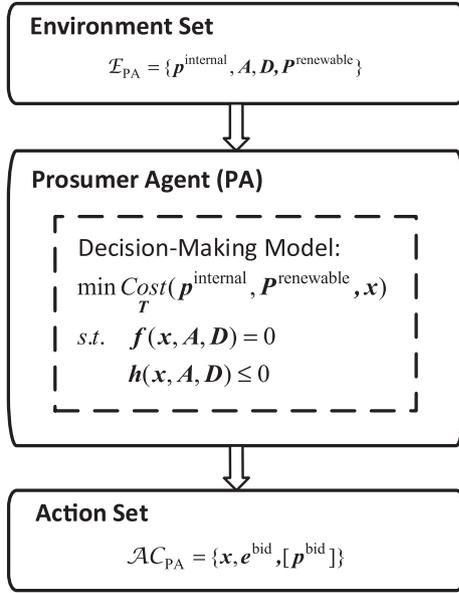


Fig. 3. Abstract architecture of a prosumer agent.

submitted to the coordinator agent. Therefore, the set of actions of the prosumer agent is denoted as

$$\mathcal{A}_{C_{PA}} = \{x, e^{bid}, [p^{bid}]\} \quad (4)$$

where e^{bid} and p^{bid} represent the energy bid and price bid, respectively. Note that in some mechanisms only energy bid is needed [16,17], so the p^{bid} is put into a bracket to show it is optional.

To summarize, the abstract architecture of a prosumer agent is illustrated in Fig. 3.

3.2.3. Coordinator agent and pricing model

The responsibility of the coordinator agent is mainly twofold: one is to receive the bids from the prosumer agents and issue internal price back to them, managing the local energy trading within the energy sharing region; the other is to trade with the retailer on behalf of the whole energy sharing region to purchase or sell electricity to balance the energy deficit or surplus in the region. Note that some coordinators also take care of physical network constraints within their energy sharing regions, but this is out of the research scope of this paper in which the coordinator is limited as a local market operator rather than a system operator.

Therefore, the environment of the coordinator agent is denoted as

$$\mathcal{E}_{CA} = \{p^{external}, e^{bid}, p^{bid}\} \quad (5)$$

where $p^{external}$ represents the electricity price at which the coordinator agent trades with the retailer, including the prices at which the coordinator buys and sells the electricity from and to the retailer (termed as “retail price” and “export price” respectively in this paper). Note that in this paper the retail and export prices are considered as non-dynamic ones, i.e. the prices are known exactly by the coordinator beforehand and will not change with the amount of power and energy exchanged in real time. This is the current status in many countries such as the UK and China.

Taking the information in the environment as input, the coordinator agent runs the pricing model to generate the internal trading price to be issued to the prosumer agents. The pricing model is described as:

$$p^{internal} = Pricing_T(p^{external}, e^{bid}, p^{bid}) \quad (6)$$

where *Pricing* is the abstract function for generating the internal price.

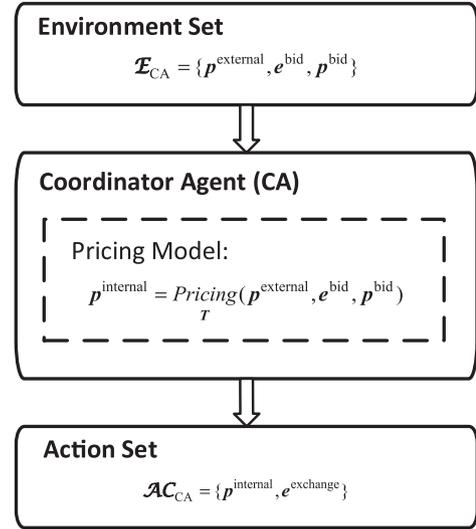


Fig. 4. Abstract architecture of a coordinator agent.

Major contribution of many existing work lies in the delicate design of this function, such as Ref. [16,17].

The actions taken by the coordinator agent include the internal price issued as well as the amount of electricity traded with the retailer. The action set is denoted as

$$\mathcal{A}_{C_{CA}} = \{p^{internal}, e^{exchange}\} \quad (7)$$

where $e^{exchange}$ denotes the energy traded with the retailer.

The architecture of the coordinator agent is summarized in Fig. 4.

3.2.4. Implementation model

The implementation model specifies the trading process between the coordinator agent and the prosumer agents, i.e. the bidding and pricing procedure during P2P energy sharing. According to the number of iterations needed to derive the internal price, there are one-shot implementation and iterative implementation. As presented in Section 3.2.2, the bid from a prosumer agent can include both energy bid and price bid, or only energy bid. The implementation model may also set additional regulations for the bidding process for improving the convergence performance or reducing the risk of market power exercise [15]. Detailed realisation of the implementation model will be demonstrated in Section 5.

3.2.5. Retailer agent

The retailer agent represents the retailer, acting as a passive agent which sells/buys electricity to/from the energy sharing coordinator agent on its requested amount at pre-announced retail/export prices. Note that it is assumed that the retailer does not adopt dynamic prices associated with the price fluctuation in the wholesale market. This assumption is consistent with the present practice in most regions of many countries such as GB and China.

Also note that the retailer can exercise demand response measures, such as direct load control, to actively interact with the coordinator and prosumers, but that is not considered in this paper. Although prosumers have been considered with demand response capabilities in some P2P energy sharing studies [17] and retailers have been considered to exercise demand response measures in some other studies without P2P energy sharing considerations [32,35,36], there have been no known studies in which retailers exercise demand response measures in P2P energy sharing.

It is worth pointing out that how to design P2P energy sharing mechanisms at the presence of an active retailer who adopts dynamic

prices or exercises demand response measures is still an open question and no known existing studies have addressed it. With an active retailer, all the existing P2P energy sharing mechanisms need to be re-designed because they all assumed that the retailer just passively provide electricity at pre-announced prices. Furthermore, an active retailer will be a player with very strong market power in P2P energy sharing compared to common prosumers, and thus additional rules need to be made to limit the market power of the retailer and protect the interests of prosumers. This is an interesting topic for future research but out of the scope of this paper.

In the paradigm shown in Fig. 2, the coordinator negotiates with the retailer on behalf of all the prosumers to buy/sell electricity for energy balance within the energy sharing region. P2P energy sharing in grid-connected microgrids with only one point of common coupling (PCC) follows this paradigm, because the physical network structure requires that the prosumers have to share their energy with each other first and then interact with the retailer in form of aggregated power [14–17].

Nevertheless, in some scenarios, where the prosumers are distributed in a low-voltage distribution network and virtually form an energy sharing region, the prosumers can directly negotiate with the retailer just as what they do with other prosumers. However, in this paper, it is assumed that the retailer passively offers/purchases unlimited power at pre-announced retail/export prices, and the export prices are assumed lower than retail prices, as all the known P2P energy sharing studies did [14–17]. Given this assumption, the scenarios where the prosumers directly negotiate with the retailer are equivalent with the paradigm shown in Fig. 2. This is because with this assumption, the internal prices have to be bounded between the retail and export prices (as shown in all the known P2P energy sharing mechanisms) and thus all the prosumers will first consider to trade with other prosumers and last choose to go to the retailer (only when the energy is not balanced) [14–17].

If the assumption does not hold, i.e. the retailer who participates in P2P energy sharing will actively adopt dynamic pricing associated with the wholesale market or exercise demand response measures, the proposed simulation framework definitely needs to be extended to consider the direct negotiation between the retailer and prosumers, and to involve the price fluctuation in the wholesale market and other factors that may affect the retailer's strategic decisions. However, this topic is out of the scope of this paper. To the best of our knowledge, there is no known studies on this topic and thus it is identified as a possible research direction for the future.

3.3. Convergence of the multiagent-based simulation

With the multiagent-based framework established, the behaviours of prosumers are able to be simulated under a P2P energy sharing mechanism that specifies the pricing and implementation models. However, this has to be based on an important condition: the simulation converges.

Iterative bidding and pricing procedure is usually needed in P2P energy sharing mechanisms, in which the bids provided by the prosumers would change in response to the dynamic internal price, and this change will in turn affect the internal price. This fact may lead to an outcome where the bidding and pricing iteration never ends with an ultimate internal price. Formally, the convergence is defined as the fact that the energy bids and internal price values finally converge to a fixed point after a finite number of iterations in the interaction between the coordinator agent and the prosumer agents. If energy bids and internal price values are not able to converge to a fixed point after a finite number of iterations, the simulation is considered to diverge [37].

Even for one-shot implementation, similar concern exists as well. The one-shot bidding can be taken as a non-cooperative game played by all the prosumer agents. Then the existence of Nash equilibrium in the

one-shot bidding corresponds to the convergence state in the iterative bidding.

Convergence is desired because electricity market designers, in this case the designers of P2P energy sharing mechanisms, intend to achieve an effective, efficient and fair allocation of interests among participants and an desired technical outcome (e.g. reduced peak power and enhanced energy balance within energy sharing regions) by the means of leading participants' behaviours to expected convergence through the 'invisible hand' of the market. If the divergence occurs, there are no stable outcomes that can be expected, which may result in undesired economic or technical outcomes with a high probability. That is why many existing studies tried to prove and achieve convergence for the market mechanisms they designed [13,15,17,37].

If convergence cannot always be guaranteed, an exit mechanism is usually designed in P2P energy sharing mechanisms, as that in Ref. [17], because in real life participants need to settle their trades finally and cannot just wait forever, although the specifics of the exit mechanism can vary. For example, in Ref. [17], if the simulation does not converge when the maximum number of iterations is reached, then the simulation is forced to exit, and all the prosumers are considered to directly trade with the retailer individually instead (i.e. P2P energy sharing is not used given divergence). For the exit mechanism used in this paper (which will be detailed later in Section 3.3.4), the simulation is also forced to exit at the maximum number of iterations if not converge, but the status at the last iteration is used for settling trades (i.e. P2P energy sharing is still used based on the results of the last iteration). The rationale behind this design is that the overall performance under P2P energy sharing can still be good even if the iteration does not converge, which will be demonstrated by numerical results in Section 5.2.2.

When conducting the multiagent-based simulation for the existing P2P energy sharing mechanisms, there are significant challenges in obtaining the convergence/equilibrium state. First of all, some existing mechanisms, such as those in Ref. [16], neither specified an implementation model nor provided any justification on the convergence of the mechanisms. Although some mechanisms, as that in Ref. [17], provided specific implementation model and proof of the existence of a fixed point, the implementation model could not guarantee that the fixed point is able to be found every time, and this depended on demand response participation level. Moreover, sometimes some existing mechanisms are extended to be used in broader scenarios in which their convergence is no longer guaranteed.

Faced with the above challenges, two heuristic techniques (step length control and learning process involvement) are proposed to facilitate the achievement of convergence, and a last-defence mechanism is devised to cope with the cases where it cannot converge in P2P energy sharing.

3.3.1. Step length control

This technique limits the number or ramping rate of the changing energy/price bids to increase the chance to find the convergence and try to avoid the "oscillation" (i.e. iterative large changes) between the bids and the internal price. It is a common technique in simulation practice to adjust the length of steps for better convergence [13,38]. Taking the energy bidding process in iterative implementation as an example, the step length control can be achieved by requiring each prosumer agent to limit the ramping rate of the bid at each iteration:

$$\max(e_{i-1}^{\text{bid}} - \Delta, e^{\text{min}}) \leq e_i^{\text{bid}} \leq \min(e_{i-1}^{\text{bid}} + \Delta, e^{\text{max}}) \quad \Delta = \text{rmp} \cdot |e_{i-1}^{\text{bid}}| \quad (8)$$

where i is the index of the current iteration during which the bid decision needs to be made, and rmp represents the ramping rate that takes a non-negative value. Formula (8) can be basically interpreted as follows: the value of the current energy bid, e_i^{bid} , should be bounded in a range, $[e_{i-1}^{\text{bid}} - \Delta, e_{i-1}^{\text{bid}} + \Delta]$, which is specified by the ramping rate and the

bid of the previous iteration with $\Delta = rmp \cdot |e_{i-1}^{\text{bid}}|$. Besides, if the upper bound specified in this way exceeds the maximum limit of the energy bid e^{max} , it should be reduced to e^{max} by having $\min(e_{i-1}^{\text{bid}} + \Delta, e^{\text{max}})$. Similar operation applies to the case of the lower bound. Formula (8) should act as an additional constraint in the decision-making model (as described by Formula (3)) of each prosumer agent.

The step length control can also be achieved by limiting the number of the bids allowed to be changed at each iteration. That is,

$$e_{i,j}^{\text{bid}} = e_{i-1,j}^{\text{bid}} \quad j \in \mathcal{PA}_i^{\text{forbid}} \subset \mathcal{PA} \quad (9)$$

where j is the index of prosumer agent. $\mathcal{PA}^{\text{forbid}}$ is the set of prosumer agents who are forbidden to change their energy bids at the i th iteration. The number of the elements in $\mathcal{PA}^{\text{forbid}}$, i.e. $|\mathcal{PA}^{\text{forbid}}|$, is pre-defined. During simulation, Formula (9) should be added to the decision-making model (as described by Formula (3)) of j th prosumer agent to make it function.

The reasoning behind this measure is that if all the prosumers are allowed to change their bids at each iteration, the change in power and energy within the region may be too large so that the price may oscillate heavily and it is more difficult for the simulation to converge. Therefore, only a portion of prosumers are allowed to change their bids at each iteration to reduce the magnitude of total power and energy changes within the region. For example, in Algorithm 1 – Iterative Scheme of Ref. [13], at each iteration only one device is allowed to change its power consumption to guarantee the convergence.

At each iteration, the elements of $\mathcal{PA}^{\text{forbid}}$, i.e. the prosumers who are forbidden to change their bids, are evenly randomly selected by the coordinator to ensure the fairness among prosumers. The number of prosumers forbidden affects the magnitude of energy and price change in the region at each iteration, thus potentially affecting the convergence performance. The effects of this measure with different portions of prosumers forbidden were examined and presented in Case 1-2 of Section 5.

Note that the two types of step length control patterns are able to be used in a combined way to obtain smaller step limits. That is, one can first limit the number of bids allowed to be changed as described in Formula (9), and then limit the change of the allowable bids by using Formula (8). For example, a broader ramping rate, denoted as rmp' , can be defined, indicating that $rmp' \times 100\%$ of the bids are allowed to be changed and the change for each bid should not exceed $\pm rmp' \times 100\%$.

Detailed analysis on why and how the step length control is able to facilitate convergence refers to Appendix B.

3.3.2. Learning process involvement

Another technique is to involve a learning process in the decision-making model of each prosumer agent. Traditionally, as described in Formula (3), the objective of each prosumer agent is to maximise its economic benefits given the current market environment (i.e. the internal price at the current iteration), while with a learning process, it is assumed that the prosumer agents make decisions not only considering the current situation but also referring to the historical experience and/or the forecast for the future. This assumption is basically sensible because the prosumer agents, either human beings or computer programs, can have the intelligence to learn from the past and predict the future when making decisions. If the learning process is designed properly, the convergence of the simulation is able to be enhanced.

For example, in Ref. [15], a 1-D recursive least squares based learning process is adopted for each prosumer agent to estimate the internal price based on which the bidding decision is made. With this learning process assumption, the simulation is proven to converge but does not guarantee a boundary on the error. In another example as presented in Ref. [39], reinforcement learning is used in the decision making process of the agents to enhance the convergence of the

diagonalization algorithm, in which the knowledge on the success of the agents' past behaviour is used to adjust the supply offers. In this paper, a modified reinforcement learning based on the basic idea in Ref. [39] is devised as a technique to enhance the simulation convergence. Specifically, if the technique is adopted, the objective function in the decision-making model of each prosumer agent, as shown in Formula (3), is replaced with the following formula:

$$\min_T \text{Cost}(\hat{\mathbf{p}}^{\text{internal}}, \mathbf{P}^{\text{renewable}}, \mathbf{x}). \quad (10)$$

The estimated internal price, $\hat{\mathbf{p}}^{\text{internal}}$, is defined as

$$\hat{\mathbf{p}}_i^{\text{internal}} = 0.5(1-\gamma)\mathbf{p}_{i-1}^{\text{internal}} + \gamma \sum_{k=i-W}^{i-1} (\omega_k \mathbf{p}_k^{\text{internal}}) + 0.5(1-\gamma)[\mathbf{p}_{\min}^{\text{internal}} + \mu(\mathbf{p}_{\max}^{\text{internal}} - \mathbf{p}_{\min}^{\text{internal}})] \quad (11)$$

in which

$$\omega_k = \frac{\text{Income}'_k}{\sum_{k=i-W}^{i-1} \text{Income}'_k} \quad (12)$$

where

$$\text{Income}'_k = \begin{cases} -\text{Cost}_k & \text{if } U \geq 0 \\ -\text{Cost}_k + |U| & \text{if } U < 0 \end{cases}, \quad U = \min_{k \in \{i-W, \dots, i-1\}} (-\text{Cost}_k) + \epsilon. \quad (13)$$

In Formula (11)–(13), i represents the index of the current iteration; γ represents the learning rate that takes value in $[0,1]$; W is the number of the previous iterations which the prosumer agent considers to make its decision; ω_k is the weighting factor for the internal price of the k th iteration; $\mathbf{p}_{\max}^{\text{internal}}$ and $\mathbf{p}_{\min}^{\text{internal}}$ are the upper and the lower bounds of the internal price, which equal to the retail price and export price (with the retailer) respectively in most P2P energy sharing mechanisms; μ is a random number ranging from 0 to 1; Income'_k represents the income of the prosumer at k th iteration with an offset; U is the offset constant which is defined in Formula (13) and intended to make all the incomes considered in Formula (12) to be non-negative; ϵ is a very small positive number to avoid the denominator of Formula (12) to equal to zero in some rare cases.

As shown in Formula (10), the prosumer agent makes its decision based on an estimation of the internal price which is a combination of the current price, the weighted sum of the previous prices and a random adjustment as described in Formula (11). In the proposed learning process as shown in Formula (10)–(13), there are two modifications compared to the existing one in Ref. [39] and the corresponding rationales are as follows.

First of all, the prosumer income (i.e. the opposite number of the cost calculated in Formula (3)) in the weighting factor calculation Formula (12) is replaced with the income with an offset as calculated in Formula (13). This is because in Ref. [39] only producers were considered so that the income was always non-negative. However, in the P2P energy sharing, the prosumers may also consume much electricity, which may result in a negative income. Therefore, an offset constant is introduced to increase all the incomes up to non-negative values, so that each weighting factor takes values within $[0,1]$ with the sum of them being exactly 1.

The other modification is the introduction of the random term (the third term) in the price estimation Formula (11). With this term, the agent makes decisions based not only on the current market information and the past experience but also on a random attempt. The rationale behind the involvement of the random attempt is that, if an agent always makes decisions based on the optimal decisions in the past only, it will be easier to fall into local optimums and be more vulnerable in a variable market environment. The random attempt at each iteration is able to broaden the agent's experience, and thus potentially helps the

agent to make better decisions in the iteration process. Similar ideas are usually applied in intelligent optimization algorithms, such as the random numbers in the velocity update equations in particle swarm optimization (PSO) [40].

The involvement of the learning process can enhance the convergence of the simulation because each prosumer agent makes more stable decisions with the consideration of the historical experience, as demonstrated in Ref. [39]. Detailed analysis on this issue refers to Appendix B. Furthermore, a decreasing learning rate in the process of iteration can be used instead of a constant learning rate to significantly enhance the convergence or even guarantee a convergence, although still no boundary on the error will be guaranteed (i.e. the final convergence obtained in this way may be far from the feasible optimum).

3.3.3. Practical implications of the two techniques

The previous two sub-sections (Sections 3.3.1 and 3.3.2) discuss the convergence techniques from the simulation point of view. However, the purpose of simulation is to reflect and assess the reality, and thus it will be pointless if the simulation with the techniques deviates from the reality. Therefore, it is of great importance to discuss the practical implications of the two convergence techniques.

The first technique, step length control, limits the ramping rate of the bids in the bidding process. In practice, this can be realised by the coordinator through setting bidding rules in the implementation model, as described in Section 3.2.4, in a P2P energy sharing mechanism. For example, the mechanism can achieve this by requiring that the coordinator should reject any bid that exceeds the prescribed ramping rate so that all the prosumers have to obey the ramping rate limit. Therefore, the step length control technique in simulation is able to suggest better bidding rules in the implementation model in practice.

The second technique, learning process involvement, models the decision-making process of the prosumers in a more practical way by considering the learning and predicting capability of theirs. However, for a real population of prosumers, the learning process is somehow an inherent attribute of theirs, rather than something that can be easily changed from the outside. In this sense, strictly speaking, the parameter values in Formula (11), such as the learning rate γ and the learning window W , should be identified based on field investigation and actual behaviour data of the prosumers, rather than be assigned some value to derive better convergence in simulation. A number of studies on electricity markets used learning-based multiagent methodology, in which the learning rates were usually specified heuristically and sensitivity analysis was conducted in some studies [39,41–45]. However, no practical field test has been found on this issue either in academia or industry to the best of our knowledge. In spite of this, to study what learning process can best improve the convergence is still of some significance, which reveals the desired outcome when designing the incentive mechanisms.

3.3.3.1. Remarks on P2P energy sharing with the two techniques compared with distributed optimization approaches. It is worth noting that the proposed heuristic techniques for facilitating convergence somehow interfere the local decision-making process of prosumers. Specifically, the step length control technique limits a prosumer's decision domain by imposing a ramping rate limit for the bids, and the learning process involvement technique assumes certain decision-making logic for prosumers. Considering this fact, the following three questions rise:

- (1) Are the techniques necessary?
- (2) Will the techniques undermine the unique features of P2P energy sharing, compared to distributed optimization approaches?
- (3) Compared with P2P energy sharing with the proposed heuristic techniques, can we say that distributed optimization approaches are better, considering they may have theoretically verified

convergence properties and the advantage of converging towards a social welfare maximizing solution through a specially designed cost function?

The answer to the first question is that, the techniques are not essential parts of P2P energy sharing mechanisms, and they are just additional measures to help facilitate convergence and had to be used in the case studies of this paper. They are not essential because if the P2P energy sharing mechanisms were well designed with very good convergence performance, then the simulation and evaluation could be conducted smoothly by using the multiagent-based simulation and evaluation system proposed in this paper, without imposing any additional techniques for facilitating convergence. However, the fact is that the convergence performance of all the existing mechanisms examined in this paper is so poor that it will be pointless to simulate and evaluate them directly because they will just diverge in most cases. Therefore, the heuristic adjustment techniques were proposed to facilitate the convergence for better evaluation, as an additional contribution (but not key focus) of this paper, although they indeed have the drawback of interfering local decision-making process of prosumers to some extent.

Regarding the second question, The P2P energy sharing paradigm is claimed to be distinguished from distributed optimization approaches in terms of two features, i.e. 'prosumers have full control of their own DERs' and 'no additional incentives are needed to motivate prosumers to participate (because every prosumer in P2P energy sharing makes decisions only to maximise its own interests)'. First of all, we note again that the proposed heuristic adjustment techniques are not essential but just additional measures to facilitate convergence. If P2P energy mechanisms were designed with good convergence performance, the heuristic techniques might not need to be used, so that the two distinguishing features are able to be kept. Secondly, although the step length control technique indeed weakens the full control of prosumers over their DERs, this conclusion may not apply to the learning process involvement technique. If a learning rate is imposed from the external by the coordinator, the full control is indeed interfered; but if the learning rate is just a description of the reality (e.g. a group of prosumers intrinsically having that learning rate are aggregated to conduct P2P energy sharing), then there will be no point to say that the full control is interfered. Last but not least, even if the full control is interfered, it is interfered indirectly and fairly, i.e. the coordinator does not control any device directly but just issues unified rules (e.g. bid change limitation in the step length control technique) fairly to everyone. Moreover, the other distinguishing feature of P2P energy sharing (i.e. self-motivated) always holds, because even with any of the two heuristic techniques, each prosumer still makes its decision only to maximise its individual interest, but this is not always the case for distributed optimization approaches, as noted in Ref. [13].

Regarding the third question, distributed optimization approaches cannot always guarantee the convergence in many cases (including the cases studied in this paper), and thus heuristic measures actually have to be involved anyway. The cases studied in this paper include EVs and TCLs, which are reschedulable loads that may involve inter-temporal demand shift. As a result, the decision-making model of a prosumer, as detailed in Appendix A.1, is nonconvex [46]. However, most existing distributed optimization approaches, including LR and augmented LR based approaches such as ADMM and auxiliary problem principle (APP), are able to guarantee the convergence only if the problems are convex [47]. Therefore, even for distributed optimization approaches, heuristic modifications are inevitable for the cases considered in this paper, and little theory exists to guide the search of near-optimal feasible solutions [48]. Additionally, the step length control technique proposed in this paper actually accidentally have some similarities, in terms of high-level ideas, with the LR heuristics for the distributed optimization approach described in Ref. [48], although focusing on

problems at different scales. It is thus an interesting research topic for the future to see if the proposed heuristic techniques can be improved through observing some ideas from the studies in the field of distributed optimization.

Finally, regarding converging towards a social welfare maximising solution, P2P energy sharing may be able to achieve that as well, but again, it is mostly the responsibility of P2P energy sharing mechanism designers. A good mechanism is expected to lead to good social welfare, by providing a smart market design that motivates prosumers to behave right for the whole society at the same time they pursue their personal interests. This is somehow out of the scope of this paper. The evaluation method proposed in this paper is able to evaluate whether and how well they achieve that, but not to figure out how they can achieve that.

3.3.4. Last-defence mechanism

Although the techniques are generally able to enhance the convergence of the simulation for P2P energy sharing, there are no guarantee that they are always able to find the convergence. The reasons may be that the convergence does not exist at all, or that it is just not found although it exists (e.g. Ref. [17] proves the existence of convergence by applying Brouwer Fixed Point Theorem, but the algorithm it provides cannot guarantee that the convergence is able to be found in every case). Therefore, a last-defence mechanism needs to be established to deal with the situation where all the other efforts for reaching convergence have failed. Note that how many cases in which we need the last-defence mechanism when a convergence exists, mostly depends on how well the P2P energy sharing mechanism that we are evaluating is designed. To a great extent, that is not the responsibility and core focus of this paper.

The proposed last-defence mechanism is just to end the simulation after a pre-defined finite number of iterations, no matter the convergence is achieved or not. If the simulation ends in that way, the status at the last iteration is used in this paper to calculate the index values for evaluation. It is fair to do so because in practice, the bidding and pricing iteration cannot carry on forever and there is a deadline at which the iteration has to stop and the trading is settled.

In the proposed last-defence mechanism, the maximum number of iterations allowed is an important parameter, and should be chosen to be large enough so that the simulation is not forced to be stopped before it converges. However, there is no way to decide a perfect maximum number of iterations a priori, because we never know whether a convergence exists or how many iterations are needed to reach it until we actually reach it. Therefore, heuristic values are used in this paper. The sensitivity analysis of this parameter has been provided to show its impact and support the choice of its value in Section 5.2.5.

3.3.5. Remarks on strategic behaviours of prosumers

In P2P energy sharing, strategic behaviours of prosumers are of great significance, not only directly affecting how much interest a prosumer is able to obtain, but also shaping the overall economic and technical outcome and performance of the P2P energy sharing mechanism within the region. Remarks are presented as follows to discuss strategic behaviours of prosumers in the proposed multiagent-based simulation framework and broader P2P energy sharing background.

As shown in the decision-making model of a prosumer agent in the proposed multiagent-based simulation framework (Section 3.2.2), a prosumer is considered to make its decision just to maximise its own interests. From this point, the bidding process formulated in this paper is actually a non-cooperative game. If the simulation converges, which means that nobody changes its bid because no more benefits can be achieved by doing this, a Nash equilibrium is found. If the simulation does not converge within the maximum number of iterations, no Nash equilibrium is found, and the trading is tackled as specified in the last-defence mechanism (Section 3.3.4). Note that whether Nash

equilibriums exist and can be found largely depends on the design of the P2P energy sharing mechanism under evaluation.

Actually, the above work presented in this paper is just a small part of the many issues regarding strategic behaviours of prosumers, and a number of topics remain to be further explored.

First of all, the interactions among prosumers can range from intense competition to collusion, but this paper just considers the complete competition case by modelling the problem as a non-cooperative game. Uncompetitive situations may happen, and need to be modelled and studied as cooperative games or Stackelberg games. Even in competitive situations, a number of other “conjunctural variations” (i.e. the assumption a prosumer makes about its rivals’ response to its actions) can be adopted [49], besides the one used in this paper, which assumes that rival prosumers make their decisions assuming that other prosumers will not change theirs.

Moreover, in the case studies in Section 5, the prosumers are considered as price takers, as detailed in Appendix A.1. Although it is a common assumption especially in P2P energy sharing studies, it will make more sense to assume some prosumers as price makers in some cases [5], especially when the prosumers under consideration have large generation or demand capacity and will affect the market price a lot.

Last but not least, the market power of prosumers are not examined in this paper. Some capable prosumers may intentionally manipulate the market price by taking advantage of the market rules, pricing mechanisms, their own operational parameters or even the network conditions if the physical power networks are considered in the future [42]. Market power of prosumers may affect the performance of a P2P energy sharing mechanism, and is thus an important aspect that needs to be considered and evaluated.

All the above topics to be explored are interesting and of great significance, and noted as potential research directions in the future.

4. Evaluation indexes for P2P energy sharing

This section presents the indexes proposed to evaluate the performance of P2P energy sharing mechanisms. Three economic indexes and three technical indexes are defined, which are then normalised and synthesized as a systemic index to evaluate the overall performance. Note that the values of the indexes are calculated based on the simulation results derived by the multiagent framework described in Section 3 or on the actual outcome if the P2P energy sharing mechanisms have been implemented in practice.

4.1. Economic indexes

4.1.1. Value tapping index

The value tapping index measures the overall benefits of the whole population within the P2P energy sharing region, reflecting how much cost-saving potential has been tapped and how much more still remains to be explored by adopting a certain P2P energy sharing mechanism.

As presented in Section 3.1, the difference between the retail price and the export price between the retailer and prosumers provides the fundamental incentive for prosumers to participate in P2P energy sharing. Each prosumer can benefit, either acting as an electricity producer or consumer, by agreeing an internal price between the retail and export price. However, obviously the total benefits brought by P2P energy sharing have an upper limit, at which the prosumers share their local generation and consumption to the maximum extent that results in the minimum total energy cost paid to the retailer. Therefore, the maximum possible benefits, i.e. the maximum value potential of P2P energy sharing, are specified by

$$value_{max} = \max \left\{ - \sum_T p^{external} \left| \sum_{\mathcal{P}, \mathcal{A}} \left(\sum_L l + \sum_G g \right) \right| \Delta t \right\} \tag{14}$$

where

$$p^{external} = \begin{cases} p^{retail} \sum_{\mathcal{P}, \mathcal{A}} \left(\sum_L l + \sum_G g \right) \geq 0 \\ p^{export} \sum_{\mathcal{P}, \mathcal{A}} \left(\sum_L l + \sum_G g \right) < 0 \end{cases} \tag{15}$$

subject to

$$\begin{aligned} F(x) &\geq 0 \\ H(x) &= 0 \end{aligned} \tag{16}$$

where L and G are the set of devices that consume and produce electricity, and l and g represent the electricity consumed and generated respectively (l is positive and g is negative). Note that for an energy storage system, when it is charging, it belongs to L , and when it is discharging, it belongs to G . F and H are the union of the f and g in Formula (3), i.e. the union of the device and user requirement limits of each device of each prosumer.

If we compare the total benefits of all the prosumers under some P2P energy sharing mechanism with the maximum value identified by Formula (14), we are able to have an idea about to what extent the adopted mechanism has tapped the potential value among the prosumers and how much space has been left for further improvement. Therefore, the following value tapping index is defined:

$$VI = \frac{value_{mechanism} - value_{ref}}{value_{max} - value_{ref}} \tag{17}$$

in which $value_{mechanism}$ represents the total income of prosumers under the adopted P2P energy sharing mechanism, and $value_{ref}$ represents total income of prosumers in the non-P2P conventional paradigm where each prosumer trades with the retailer separately as illustrated in Fig. 1(a).

It is worth noting that the value tapping index, VI , derived by Formula (17) is a normalised index without units, which represents a proportion. The larger the index value is, the higher the overall income of the prosumers is, i.e. the higher value has been tapped. With the normalised index, it is convenient to compare the overall benefits under different P2P energy sharing mechanisms and figure out the potential value left to be further tapped. The normalised index is also essential for the further synthesization of multiple indexes.

In addition, it is also worth noting that the VI takes value in $[0,1]$, unless $value_{mechanism} < value_{ref}$. If $value_{mechanism} < value_{ref}$, it means that the total income under the adopted P2P energy sharing mechanism is even less than that in the non-P2P conventional paradigm, and then VI takes negative values, which rarely happens as shown in Section 5.3.2.

4.1.2. Participation willingness index

The participation willingness index measures the percentage of the prosumers who obtain more benefits after participating in certain P2P energy sharing mechanism, reflecting the overall participation willingness of the whole population.

Besides the overall benefits of the whole population as evaluated by Formula (17), the benefits of each single prosumer counts as well. If the energy cost of a prosumer under some P2P energy sharing mechanism is higher than that under direct trading with the retailer, the prosumer will have the incentive to exit the P2P energy sharing mechanism and seek to trade with the retailer directly. In this case, it is difficult for the mechanism to keep the population of the participants. Therefore, the participation willingness in a P2P energy sharing mechanism can be measured by the proportion of the prosumers who have lower energy

cost compared to that under direct trading with the retailer:

$$PI = \frac{N_{Lower,Cost}}{N} \tag{18}$$

where $N_{Lower,Cost}$ represents the number of prosumers who have lower energy cost in P2P energy sharing than that under direct trading with the retailer; N is the total number of prosumers participating in the P2P energy sharing mechanism.

Note that the index value calculated by Formula (17) is also normalised in $[0,1]$, with higher value representing higher participation willingness.

4.1.3. Equality index

The equality index measures the income distribution among the prosumers in the adopted P2P energy sharing mechanisms, reflecting the income equality within the population.

The equality is an important issue in many aspects of human society and the energy sector is not an exception. Strong inequality affects the harmony within the community, and hinders the acceptance and adoption of the P2P energy sharing mechanisms among prosumers. Borrowing the idea of Gini coefficient in economics, the relative mean absolute difference of the levelled up income of the prosumers is defined as the index to measure the inequality:

$$IEI = \frac{\sum_{n=1}^N \sum_{m=1}^N |Income'_n - Income'_m|}{2N \sum_{n=1}^N Income'_n} \tag{19}$$

where $Income'$ represents the levelled up income that is defined to level the income up to positive values. The definition of $Income'$ in Formula (19) is similar to Formula (13), but defined among the prosumers rather than throughout the previous iterations:

$$Income'_n = \begin{cases} -Cost_n & \text{if } U \geq 0 \\ -Cost_n + |U| & \text{if } U < 0 \end{cases}, \quad U = \min_{n \in \{1,2,\dots,N\}} (-Cost_n) + \varepsilon. \tag{20}$$

Note that the value of IEI also ranges from 0 to 1, according to the property of Gini coefficient. The larger the index is, the larger the inequality is. The inequality index, IEI , is transformed to equality index, EI by

$$EI = 1 - IEI \tag{21}$$

to be consistent with the other two economic indexes VI and PI in terms of being better with higher values. This is a preparation for further synthesization which will be detailed in Section 4.3.

4.2. Technical indexes

Technical indexes are defined to measure the performance that is concerned from the perspective of power systems. Three indexes are defined, including energy balance index, power flatness index and self-sufficiency index.

4.2.1. Energy balance index

The energy balance index measures the total amount of energy exchange with the bulk power grid in both import and export directions, reflecting the energy balance of the P2P energy sharing region.

One of the key motives of encouraging P2P energy sharing from the power systems' points of view is to facilitate the local consumption of distributed generation to alleviate the problems brought by its increasing penetration, as discussed in Section 1. Therefore, the energy balance within the P2P energy sharing region is considered as an important index. First of all, the energy imbalance is measured by

$$EII = \frac{\sum_{t \in T} \left| \sum_{n \in \mathcal{P}, \mathcal{A}} \left(\sum_{j \in L} l_{n,j,t} + \sum_{j \in G} g_{n,j,t} \right) \right|}{\sum_{t \in T} \sum_{n \in \mathcal{P}, \mathcal{A}} \left| \sum_{j \in L} l_{n,j,t} + \sum_{j \in G} g_{n,j,t} \right|} \quad (22)$$

where the numerator is the summation of the energy imbalance (either surplus or deficit) throughout the considered time horizon, and the denominator is the total amount of the generation and consumption throughout the horizon, which is used to normalise the index. Based on the energy imbalance index, *EII*, the energy balance index is defined as

$$EBI = 1 - EII \quad (23)$$

which takes value in [0,1]. Similar to other economic indexes defined earlier, this operation is to make it “the larger, the better” for further synthesisization.

Remarks: Another common used index is local self-consumption, which measures how much local generation has been consumed on site. It basically focuses on where the local generation goes (either consumed by local loads or exported to the main grid), but does not care about how much power is imported from/exported to the main grid. In comparison, the energy balance index defined in this paper measures the sum of the absolute value of the net power exchange between the P2P energy sharing region and the main grid throughout the time horizon considered, reflecting the energy exchange in both import and export directions. The reason for caring about this is that, large exchange power in either import or export direction may be concerned by the network operator, because large power flow in either direction may require costly network reinforcement.

Note that the local self-consumption index and energy balance index are not equivalent to each other. For example, even with a high self-consumption level, a prosumer may still need to import a large amount of electricity at times when the local demand is high but local generation is low, which results in a low energy balance level. Therefore, the local self-consumption index and energy balance index reflects different aspects of performance, and both of them are of practical meaning. People who conduct the evaluation can choose proper indexes according to their specific needs. The evaluation index system proposed in this paper is open to and compatible with other additional indexes like local self-consumption index.

4.2.2. Power flatness index

The power flatness index measures peak power considering both positive and negative directions.

Besides the energy balance, the peak power of the P2P energy sharing region is another important concern from the perspective of power systems, because high peak power results in the expensive network reinforcement and heavy burden on the operation of power systems. Moreover, flatter power profiles are able to increase the utilisation rate and operational efficiency of the power equipment. Therefore, an index is needed to measure the flatness of the power profiles in the P2P energy sharing region.

Traditionally, the flatness of load profiles is measured by the peak-to-average ratio (PAR), which is usually defined as the quotient of the peak load and average load over a period of time. However, in the P2P energy sharing region composed of prosumers, the net consumption is either positive or negative, rather than always being positive. Therefore, an extended PAR is defined as follows:

$$EPARI = \frac{\max_t \left(\left| \sum_{n \in \mathcal{P}, \mathcal{A}} \left(\sum_{j \in L} l_{n,j,t} + \sum_{j \in G} g_{n,j,t} \right) \right| \right)}{\frac{1}{T} \sum_{t \in T} \left| \sum_{n \in \mathcal{P}, \mathcal{A}} \left(\sum_{j \in L} l_{n,j,t} + \sum_{j \in G} g_{n,j,t} \right) \right|} \quad (24)$$

in which both the power surplus and deficit are considered. Based on the extended PAR, the power flatness index is defined as

$$PFI = 1 - \frac{EPARI}{EPARI_{ref}} \quad (25)$$

where $EPARI_{ref}$ is used to normalised the index value into the interval [0,1], which can be chosen as the maximum *EPARI* when several P2P energy sharing mechanisms are compared.

4.2.3. Self-sufficiency index

The self-sufficiency index measures how much local demand is able to be supplied by local generation, reflecting the dependency of the P2P energy sharing region on the external bulk power grid.

Self-sufficiency has been increasingly valued by many communities in recent years. One consideration is that with higher self-sufficiency supported by local generation, the reliability of power supply will be better guaranteed, in case of power outages in the external power systems. Another consideration is the so-called “energy autonomy”, which is considered able to deliver a host of social, financial and environmental benefits [50]. Therefore, the self-sufficiency in a P2P energy sharing region is measured as a performance index. First of all, the proportion of energy relying on import is calculated as

$$SII = \frac{\sum_{t \in T^+} \sum_{n \in \mathcal{P}, \mathcal{A}} \left(\sum_{j \in L} l_{n,j,t} + \sum_{j \in G} g_{n,j,t} \right)}{\sum_{t \in T} \sum_{n \in \mathcal{P}, \mathcal{A}} \sum_{j \in L} l_{n,j,t}} \quad (26)$$

where

$$T^+ = \left\{ t \mid \sum_{n \in \mathcal{P}, \mathcal{A}} \left(\sum_{j \in L} l_{n,j,t} + \sum_{j \in G} g_{n,j,t} \right) > 0, t \in T \right\} \quad (27)$$

Based on Formula (26), the self-sufficiency index is defined as

$$SSI = 1 - SII. \quad (28)$$

4.3. Index synthesisization

The economic and technical indexes proposed in Section 4.1 and 4.2 are able to evaluate the performance of P2P energy sharing mechanisms from different perspectives. They can also be synthesized for assessing the overall performance.

All the six individual indexes proposed are normalised, generally ranging from 0 to 1, and are also defined to be consistent (i.e. the larger the index value is, the better the performance is). It is now feasible to use the simple and straightforward weighting factors to synthesize the indexes. Specifically, the economic performance index, *EPI*, is defined to reflect the overall economic performance of P2P energy sharing mechanisms:

$$EPI = \alpha_1 \cdot VI + \alpha_2 \cdot PI + \alpha_3 \cdot EI, \quad \sum_{w=1}^3 \alpha_w = 1, \quad \alpha_w \in [0,1], w \in \{1,2,3\}. \quad (29)$$

Similarly, the technical performance index, *TPI*, is defined to assess the overall technical performance:

$$TPI = \beta_1 \cdot EBI + \beta_2 \cdot PFI + \beta_3 \cdot SSI, \quad \sum_{w=1}^3 \beta_w = 1, \quad \beta_w \in [0,1], w \in \{1,2,3\}. \quad (30)$$

The economic and technical performance index can be further combined to compose an index to evaluate the overall performance of P2P energy sharing mechanisms:

$$OPI = \gamma_1 \cdot EPI + \gamma_2 \cdot TPI, \quad \sum_{w=1}^2 \gamma_w = 1, \quad \gamma_w \in [0,1], w \in \{1,2\}. \quad (31)$$

In summary, the hierarchy of the indexes proposed is illustrated in Fig. 5. The value of the weighting factors can be flexibly chosen to reflect the relative importance of the different aspects of the performance, according to the specific need and concerns in practice.

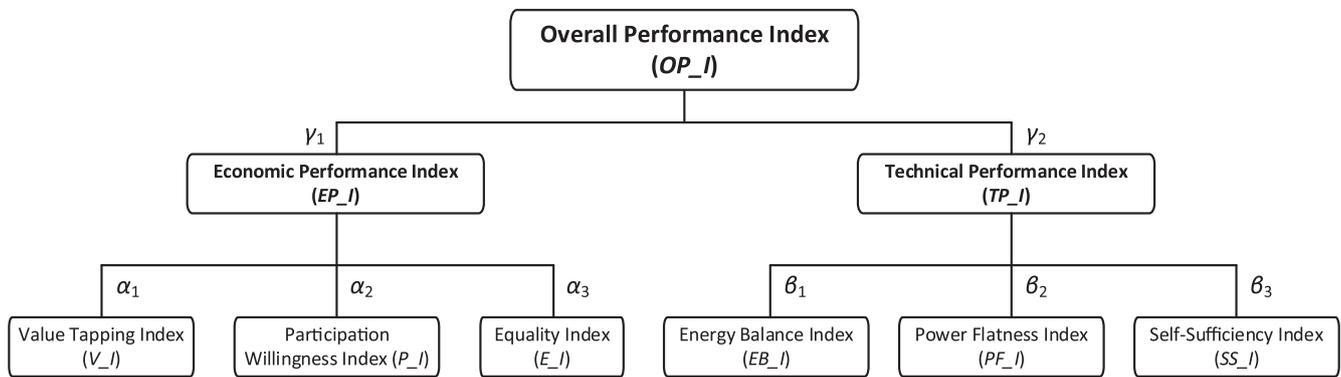


Fig. 5. The hierarchy of the evaluation indexes.

The six individual indexes proposed in this paper measure and reflect different but important aspects of technical and economic performance of P2P energy sharing mechanisms, as have already explained in previous sub-sections for all the indexes. They have successfully filled the research gaps identified in Section 1 of this paper to a great extent. We note that the proposed index system as shown in Fig. 5 is an open system, and the index system could be extended by other researchers in the future.

Remarks: The relationship between the indexes proposed in this paper is discussed as follows. First of all, the indexes are divided into two groups, economic index and technical indexes. The former ones concern the cost / income of the participants in P2P energy sharing, while the latter ones focus on the technical implications that may be concerned by electricity network operators or customers. Basically, economic indexes and technical indexes have different focuses, so they do not have a direct relationship.

Among the economic indexes, the value tapping index measures the overall cost of the whole population in the P2P energy sharing region, to evaluate whether and to what extent the adopted P2P energy sharing mechanism has brought benefits for the whole population. The equality index further examines how the overall benefits are distributed among the population. The participation willingness index examines each single participant to check if the incentive is strong enough to keep the participant within the adopted P2P energy sharing mechanism. Although the three economic indexes seem to have some relationship, to what extent they are correlated with each other varies with specific application scenarios and the P2P energy sharing mechanisms adopted. For example, we cannot assert that higher overall income must lead to higher income for everybody. Therefore, it is wise to just keep all the indexes in the evaluation system as shown in Fig. 5, and adjust their effects by assigning corresponding weight values according to practical needs and concerns. Similar analysis applies to the technical indexes as well.

5. Case Study: evaluating P2P energy sharing mechanisms for residential customers in present and future scenarios of Great Britain

Three existing P2P energy sharing mechanisms were simulated and evaluated in present and future scenarios of GB in this paper. The objectives were to validate the proposed simulation and evaluation methods, as well as to derive some practical implications on applying P2P energy sharing in GB.

Specifically, the three mechanisms evaluated were supply and demand ratio (SDR), mid-market rate (MMR) and bill sharing (BS) mechanisms. SDR mechanism established an internal price model for energy sharing, in which the internal prices are defined as piecewise function of SDR [17]. MMR mechanism basically sets the internal trading price as the average of retail and export prices, with an additional adjustment mechanism for situations where local generation does

not equal to local consumption [16]. BS mechanism a pro rata cost sharing mechanism, in which the income and cost of each participant are proportional to its electricity production and consumption [16]. Detailed description and definition on these three mechanisms refer to Appendix A.2.

Residential customers in GB were considered to participate in the chosen mechanisms. Electrical demand and PV generation were modelled by CREST model that incorporates appliance composition, electrical parameters and human occupancy models based on realistic statistics of GB [51]. The parameters and travelling behaviours of EVs were obtained from the EV database [52] which is based on realistic GB statistics as well. Future scenarios were modelled by increased penetration of PV panels and EVs compared to the current baseline.

Note that EVs were considered in future households because there is a clear trend that EVs will play an important role in future GB [53] as well as many other countries in the world [54]. Compared to EVs, it is still not clear whether other energy storage systems, e.g. dedicated household batteries like Tesla Powerwall [55], will be widely used in households or not, so they were not included in this case study. In spite of this, it is worth noting that actually an EV participates in P2P energy sharing using its batteries, so it can be seen as a special case of battery energy storage systems so that the implications of this case study can be extended to battery energy storage systems.

With these settings, the abstract agents and models in the multi-agent-based simulation framework described in Section 3 were realised as detailed mathematical models, which refer to Appendix A.

5.1. Case design and simulation settings

Two sets of cases were designed and simulated. The first set of cases were basically conducted in one typical weekend day in summer with fixed PV and EV penetration levels and only one single retail price scheme. The main objective is to test and validate the proposed simulation and evaluation methods, including: (1) to test the multiagent-based simulation framework, (2) to demonstrate the calculation and implications of the evaluation indexes, (3) to verify the performance of the proposed techniques for convergence, and (4) to evaluate the influence of relevant parameters on the simulation results. The second set of cases compared three existing P2P energy sharing mechanisms in current and future scenarios in GB, and the sensitivities of various factors, including PV and EV penetration levels, seasons and day types and retail price schemes, were examined. The main objective is to derive some practical implications on applying P2P energy sharing mechanisms in GB. Note that the related parameters, including ramping rates, learning rates, initial values and maximum number of iterations, were assessed in the first set of cases, and suitable values were chosen and adopted to conduct the second set of cases.

In both sets of cases, a population of 20 residential customers in a community were considered. The types and parameters of the appliances, the occupancy and the customer demand were obtained by

randomly sampling from the CREST model. The flexible appliances considered included: (1) wet appliances, including dish washers, tumble dryers, washing machines and washer dryers, modelled as non-interruptible appliances by Formulas (A4)–(A7) in Appendix A.1, and (2) water heating appliances, such as domestic electric storage water heaters, modelled as thermostatically controlled appliances by Formulas (A8)–(A11) in Appendix A.1. Inflexible, i.e. the must-run, appliances included consumer electronics, like televisions, personal computers and printers, and cooking appliances like microwaves and kettles. The complete list of appliances, including 34 appliances, refer to the “Appliance Model Configuration” sheet of the CREST model. Note that not all the appliances in the list appeared in every premise. Whether a customer owned an appliance was a result of the sampling from a given probability distribution based on realistic GB statistics. As for EVs, the parameters for Formulas (A12)–(A17) in Appendix A.1 were obtained by sampling from the EV database based on the GB statistics.

For both sets of cases, within a day, the bidding and pricing process was assumed to be conducted on a day-ahead basis, in which all the generation and demand forecast for each customer were assumed to be accurate. The time step of simulation, Δt , was assumed to be 1 h. The simulation stopped if the maximum internal price difference between two consecutive iterations was less than 0.001 £/kWh, indicating that the simulation converged. The maximum number of iterations was set as 200 as a part of the last-defence mechanism as discussed in Section 3.3.4. The simulation under conventional trading arrangements between customers and retailers, as shown in Fig. 1(a) was conducted in some cases as a reference for comparison.

When evaluating both sets of cases, the weighting factors were assumed as $\alpha_1 = \alpha_2 = \alpha_3 = 0.33$, $\beta_1 = \beta_2 = \beta_3 = 0.33$ and $\gamma_1 = \gamma_2 = 0.5$, indicating that all the indexes are of the same importance. Note that this will not lose any generality, and in practice, the values of weighting factors can be chosen according to specific considerations and needs.

All the cases were simulated using MATLAB, and the decision-making models of prosumer agents were solved using CPLEX.

Remarks: Note that this paper is aimed to use some practical present and future scenarios of GB mainly to validate the proposed simulation and evaluation methodology and also to give some (but not complete) implications on the potential benefits of P2P energy sharing, rather than have the ambitions to comprehensively evaluate the impact of P2P energy sharing on present and future GB. If one wants to comprehensively evaluate present and future scenarios in GB, it is important to consider the composition of P2P energy sharing communities/regions, because the proportion of local generation and flexible demand and the extent to which they are complementary with each other may affect the final benefits significantly, which has been preliminarily revealed by another piece of our research [56]. However, in practice, how the customers will be grouped is a result of the market competition among the companies who engage the customers to run P2P business, and is also affected by other factors including market policies and the capacity of physical electricity networks. Moreover, the geographical distribution of customers may be quite uneven across GB, resulting in the fact that the PV and EV penetration and demand profiles of one area may significantly differ from those in another area. Therefore, to use the data randomly sampled from the CREST model, which just reflects the average situation of GB, is not sufficient to given detailed evaluation for the whole GB. More detailed data models with geographical distribution information are essential, and a number of other factors like market policies and network constraints need to be considered to conduct more comprehensive evaluation for GB. This is a valuable piece of work to be done in the future but out of the scope of this paper.

5.2. The first set of cases

In the first set of cases, the SDR mechanism was adopted. Half (i.e. 10) of the customers owned PV panels but no EVs, and in contrast the other half (also 10 customers) owned EVs but no PV panels. A weekend

day in July was assumed for using the CREST model to generate the PV generation and appliance demand data and using the EV database to generate the EV data. A flat retail price, 14.57 pence/kWh, was considered, and the export price in the GB feed-in tariff scheme was used, being 5.03 pence/kWh. The initial internal selling and buying prices in the SDR mechanism were set as the export and retail prices respectively, except the final. With the above settings, five cases were simulated:

- Case 1–1: base case without using any extra convergence techniques, mainly for testing the basic simulation and evaluation processes;
- Case 1–2: Technique 1, step length control was used;
- Case 1–3: Technique 2, learning process involvement was used;
- Case 1–4: the influence of initial values was examined;
- Case 1–5: the influence of the maximum number of iterations in the last-defence mechanism was examined.

5.2.1. Case 1-1: Base case without convergence techniques

Fig. 6 illustrates the overall net consumption (i.e. consumption minus generation) as well as PV generation in the energy sharing region throughout the day. Both the results under the SDR mechanism and the conventional paradigm are presented.

In Fig. 6(a), the surplus energy sold to the retailer from 6:00 to 19:00 was much less than that of the same time period in Fig. 6(b), and the net consumption from 20:00 to 24:00 became negative in Fig. 6(a), compared to that in Fig. 6(b). This fact indicates that, under the SDR mechanism, some EVs charged more during 6:00–19:00 and then discharged during 20:00–24:00 to supply the demand of other prosumers, i.e. the prosumers did share energy with each other using the flexibility contained in the EVs. Whether this sharing was able to bring more economic and technical benefits, is still not straightforward from Fig. 6.

The net energy cost (i.e. energy cost for buying electricity minus earnings from selling electricity) distribution is shown in Fig. 7 to compare the economic benefits under the two mechanisms.

In Fig. 7, it is observed that, under the SDR mechanism, most prosumers (15 of 20) had lower net energy cost than that under the conventional paradigm, indicating that most prosumers benefit and are willing to stay in the SDR mechanism. However, it is also noticed that 5 prosumers, numbered from 16 to 20, had higher net energy cost in the SDR mechanism, thus having the incentives to opt out of the mechanism. Besides, there was huge cost difference among the prosumer population for both mechanisms, but it is not straightforward in which mechanism the difference was larger.

To assess the performance of the mechanisms quantitatively, the values of the evaluation indexes defined in Section 4 were calculated, as presented in Table 1.

Regarding the economic indexes in Table 1, it is observed that the total economic benefits (indicated by the value tapping index) and the equality among the prosumers under the two mechanisms were almost the same, but some prosumers had increased energy cost (as illustrated in Fig. 7), resulting in a lower mark in participation willing index and thus a lower economic performance index for the SDR mechanism. Regarding the technical indexes, the SDR mechanism had prominently higher marks in energy balance and self-sufficiency index. In summary, the SDR mechanism had a slightly higher overall performance than the conventional paradigm, with a worse economic performance but an even better technical performance.

The values of the evaluation indexes, as listed in Table 1, can be interpreted mainly from two perspectives. First of all, taking the value of the overall performance index under SDR mechanism as an example, 0.53 gives a preliminary impression that it is a good score which is slightly higher than the median of the score band. The reasoning behind this impression is that generally we could consider that the range of the score is within [0,1], and the ideal maximum value, 1, is almost impossible to be reached because some indexes are contradictory to each

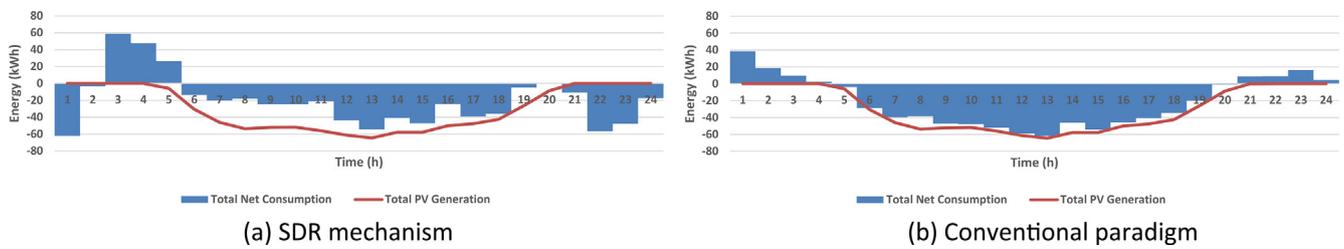


Fig. 6. Overall net consumption and PV generation in the energy sharing region.

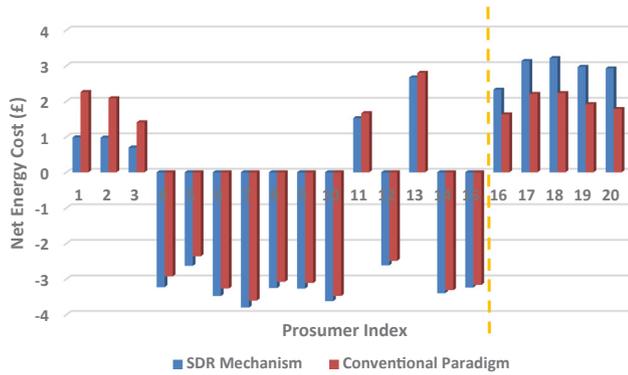


Fig. 7. Net energy cost distribution in the energy sharing region.

Table 1
Evaluation index values for Case 1-1.

Index	SDR Mechanism	Conventional Paradigm
Value Tapping Index (V_I)	0.02	0.00
Participation Willing Index (P_I)	0.75	1.00
Equality Index (E_I)	0.59	0.59
Economic Performance Index (EP_I)	0.45	0.52
Energy Balance Index (EB_I)	0.47	0.20
Power Flatness Index (PF_I)	0.66	0.65
Self-Sufficiency Index (SS_I)	0.71	0.46
Technical Performance Index (TP_I)	0.61	0.44
Overall Performance Index (OP_I)	0.53	0.47

other in many cases (for example the power flatness index equals to 1 when the aggregated load curve throughout the time horizon is completely flat, but if that happens given a time-of-use retail price scheme, it indicates that the load curve does not respond to the retail price at all, so it is highly possible that the values of economic indexes do not take their maximum value, 1, at the same time).

After having this preliminary impression, the score can be compared with that under the reference case (i.e. the conventional paradigm). Considering that all the scores have been normalised, they are able to be compared directly. For example, with 0.53 for SDR mechanism and 0.47 for conventional paradigm, it can be stated that the SDR mechanism is 12.7% $((0.53 - 0.47) / 0.47 * 100\%)$ better than the conventional paradigm in terms of the overall performance in this case. If more mechanisms are involved and calculated, the performance of multiple mechanisms can be compared, as shown in Section 5.3 later. Furthermore, the comparison in individual indexes has more straightforward meaning. For example, it can be stated that the SDR mechanism helps the whole population save 2% electricity cost than the conventional paradigm, by comparing the value tapping index of the two mechanisms in Table 1.

Finally, the internal prices (taking the ones at the 5th hour as

examples) and overall net energy cost throughout the iterative implementation procedure under the SDR mechanism are illustrated in Fig. 8.

From Fig. 8, it is seen that both the internal selling and pricing price entered “oscillation” states in which the price jumped between two values across the iterations. This oscillation resulted in the oscillation of the total net energy cost of the energy sharing region. These facts show that the iteration, i.e. the bidding and pricing process within the SDR mechanism, actually did not converge. The final state of the price and energy cost would be uncertain, depending on when the iteration was forced to be stopped. In this case, the iteration was ended when the maximum number of iterations, 200, was achieved.

Therefore, the performance of the SDR mechanism actually can be better than that presented in Table 1, if proper techniques for convergence are applied.

5.2.2. Case 1-2: validation of the step length control technique

In this part of simulation, the SDR mechanism was adopted, and the step length control technique, was applied. Note that Formulae (8) and (9) were used in a combined way to achieve the step length control, and the ramping rate took the broader meaning, as presented in Section 3.3.1, in this case. The results with different ramping rates are illustrated in Figs. 9 and 10.

Fig. 9 illustrated the number of iterations under different ramping rates, from which the convergence state could be observed. When the ramping rate was between 0 and 0.1, the number of iterations was only one, indicating that no change was made by any prosumer because the allowed change was too small. When the ramping rate was between 0.1 and 0.4, the simulation converged at some iterations. A specific example is shown in Fig. 11(a), in which the simulation converged at the 8th iteration. When the ramping rate was larger than 0.4, the simulation diverged, being stopped at the maximum number of iterations, 200.

The dark blue¹ line in Fig. 10 illustrates the values of the overall performance indexes under different ramping rates. It is observed that the overall performance was desirable with moderate ramping rates (roughly from 0.15 to 0.7). It is worth noting that the simulation actually diverged with a ramping rate larger than 0.4, but the performance was still not bad with a ramping rate from 0.4 to 0.7. The reason is that although the simulation diverged, the results oscillated mildly around a good value, as shown in Fig. 11(b). Therefore, the final result might be acceptable when the simulation stopped at the maximum number of iterations.

As shown by the dark blue line in Fig. 10, the best overall performance was achieved when the ramping rate equalled to 0.45, but within the cases that converged, the best performance was achieved with the ramping rate being 0.3. The corresponding values of the evaluation indexes are presented in Table 2 (compared with the values in Case 1-1).

From Table 2, it is seen that with proper ramping rate setting, the performance of the SDR mechanism became much better. Almost all the

¹ For interpretation of color in Figs. 10, 15 and 17, the reader is referred to the web version of this article.

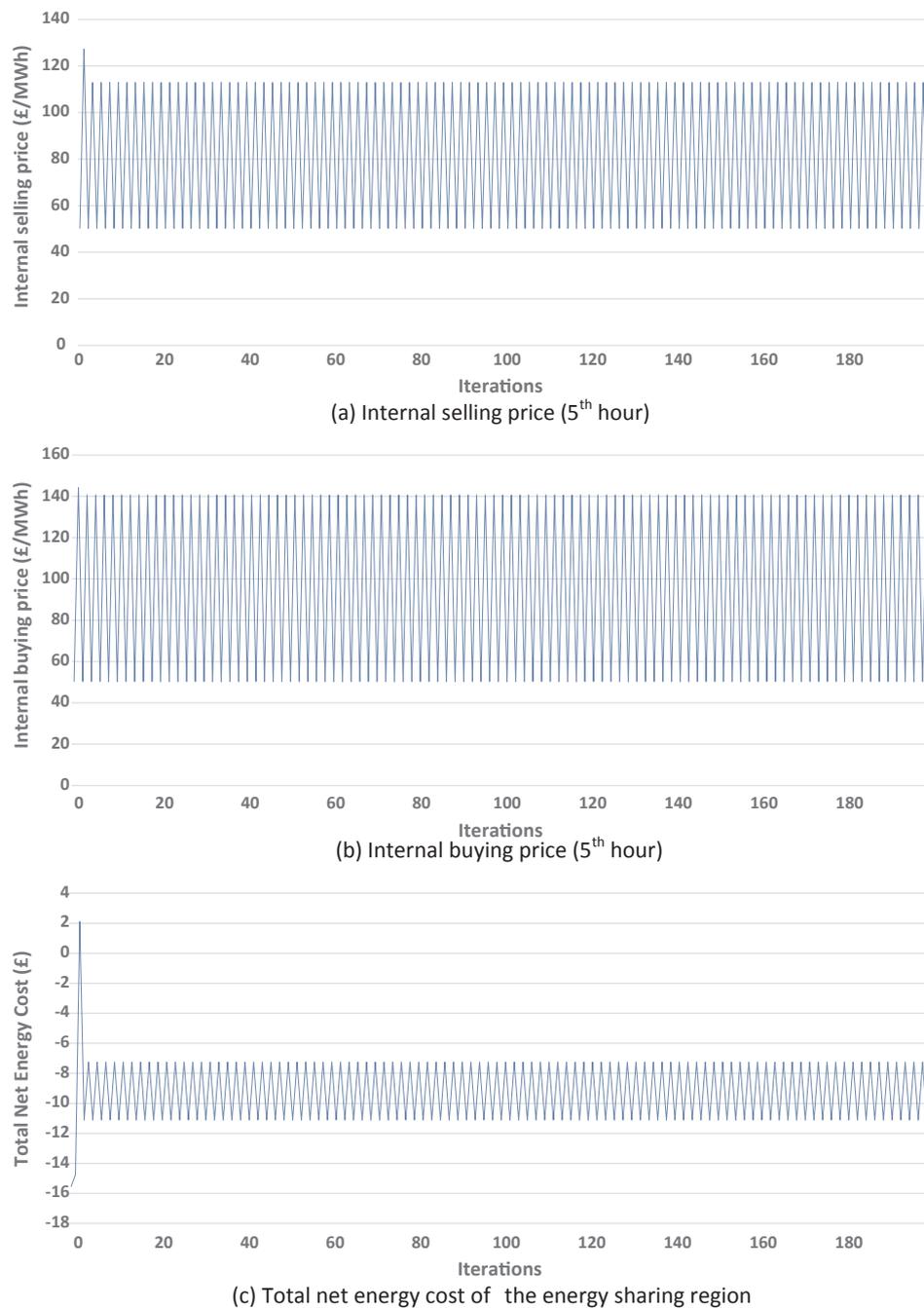


Fig. 8. Iterative implementation procedure under the SDR mechanism.

indexes were significantly higher than those under the same mechanism without any convergence technique and the conventional paradigm, except the equality index and power flatness index being slightly lower. In summary, the results demonstrate that P2P energy sharing, such as the SDR mechanism with a ramping rate limit being 0.3, was able to bring 59.57% more overall benefits measured by the overall performance index, compared to the conventional paradigm. Moreover, the ramping rate setting affected the performance of P2P energy sharing mechanisms, being able to improve the performance to 141.51% in a case of the SDR mechanism.

Note that in Fig. 10, the impact of the different prosumer demand profiles on the overall performance under different ramping rates has been illustrated. The eight light blue lines are the results given 8 typical demand scenarios randomly sampled from the CREST model and EV database (being typical weekdays and weekends in four seasons, so 2

(day types) * 4 (seasons) = 8 (scenarios)). It can be observed that the demand profiles affect the overall performance significantly, but the conclusion that the overall performance is desirable with moderate ramping rates still holds. Compared to the results with the base case setting as shown by the dark blue line, the optimal ramping rate is no longer 0.45 in some other scenarios as shown by the light blue lines. However, in those cases, the optimal ramping rates are still around 0.45 (ranging from 0.3 to 0.5), and the optimal performance was close to the performance with the ramping rate being 0.45. Therefore, in practice, it basically makes sense to use the parameter values derived from typical cases, if no detailed historical or forecast demand profiles are available.

5.2.3. Case 1-3: validation of the learning process involvement technique

As presented in Section 3.3.2, involving learning process in the decision-making model of each prosumer agent can improve the

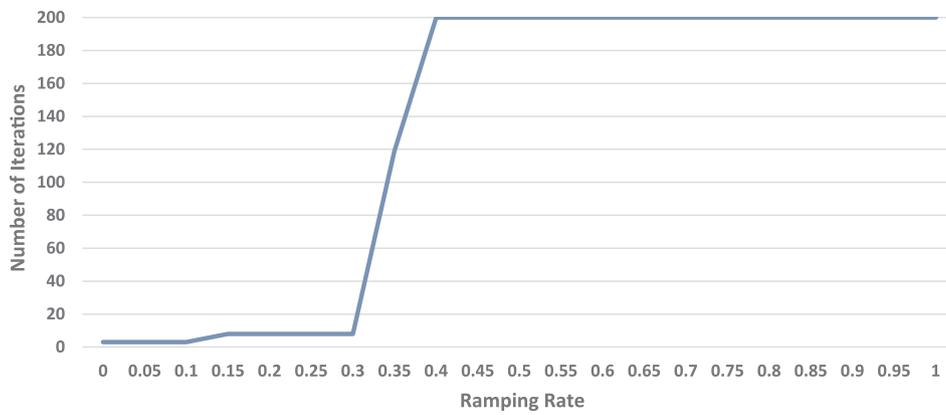
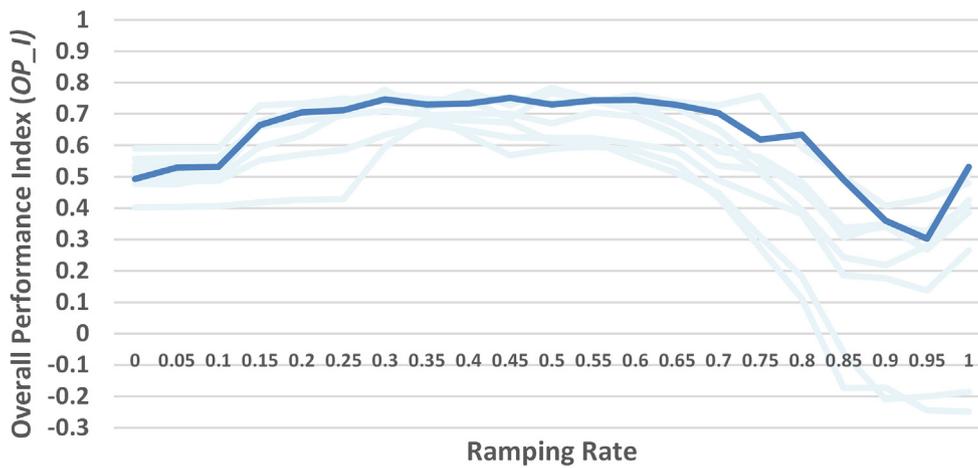
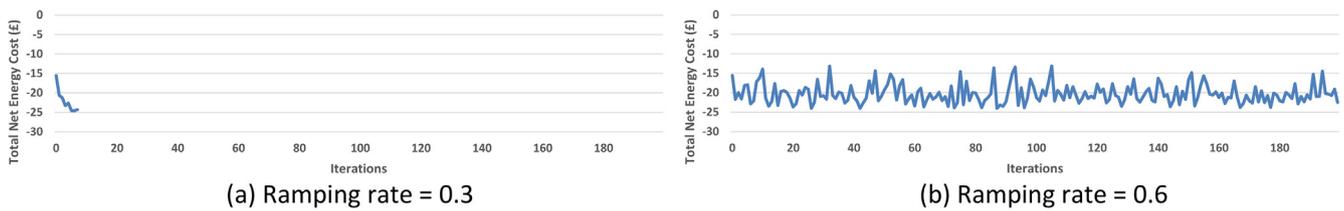


Fig. 9. The number of iterations under different ramping rates.



— Results with various demand profiles — Results with Base Case Setting

Fig. 10. The overall performance under different ramping rates.



(a) Ramping rate = 0.3

(b) Ramping rate = 0.6

Fig. 11. The total net energy cost throughout the iterations with different ramping rates.

Table 2

Evaluation index values for Case 1–2.

Index	<i>SDR Mechanism</i> (best, ramping rate = 0.3)	SDR Mechanism (with no technique)	Conventional Paradigm
Value Tapping Index (<i>V_I</i>)	0.88	0.02	0.00
Participation Willing Index (<i>P_I</i>)	1.00	0.75	1.00
Equality Index (<i>E_I</i>)	0.52	0.59	0.59
Economic Performance Index (<i>EP_I</i>)	0.79	0.45	0.52
Energy Balance Index (<i>EB_I</i>)	0.61	0.47	0.20
Power Flatness Index (<i>PF_I</i>)	0.57	0.66	0.65
Self-Sufficiency Index (<i>SS_I</i>)	0.97	0.71	0.46
Technical Performance Index (<i>TP_I</i>)	0.71	0.61	0.44
Overall Performance Index (<i>OP_I</i>)	0.75	0.53	0.47

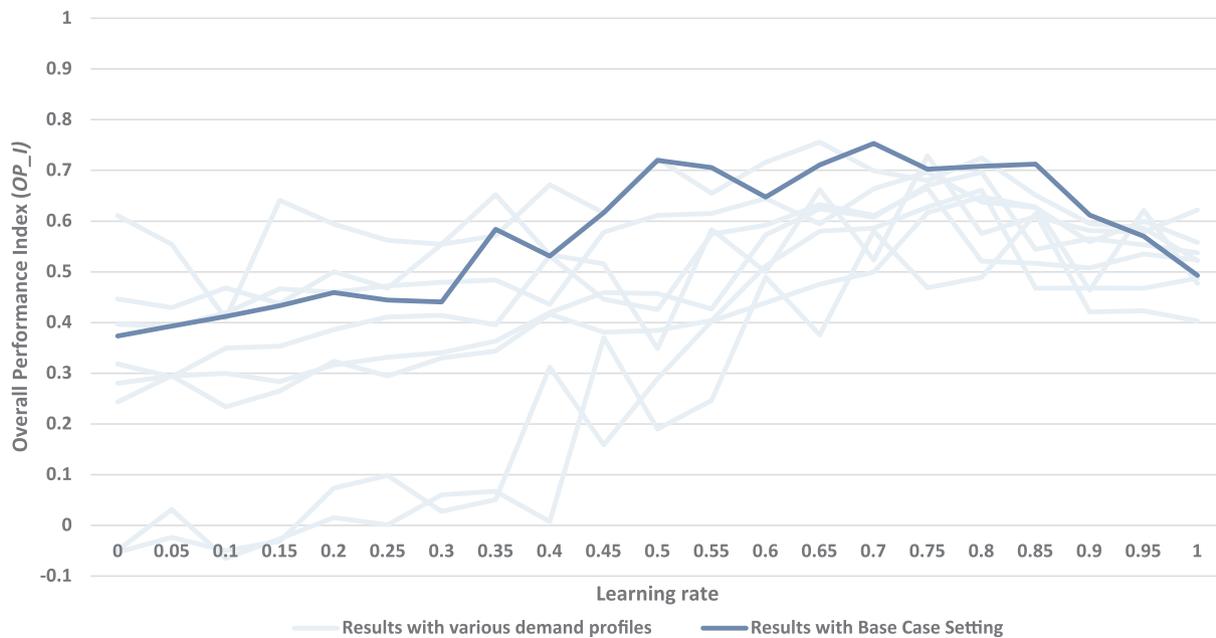


Fig. 12. The overall performance under different learning rates.

convergence of the simulation. It was assumed that each prosumer agent made its decision based on the estimation described by Formula (11), in which the length of learning window, W , was set as 10. The results with different learning rates are illustrated in Fig. 12.

As shown in the dark blue line in Fig. 12, it is seen that the overall performance was able to be improved by choosing proper learning rates, which were roughly located between 0.5 and 0.9. The best overall performance was achieved when the learning rate was 0.7. The detailed results at this point are presented in the first column Table 3. It is seen that with a proper learning rate, the performance with the learning process involvement technique is almost as good as that with the step length control technique, only with very slight differences in a few indexes.

With the above results, it is naturally to think that better performance may be obtained if the two techniques, i.e. the step length control and learning process involvement, are adopted at the same time. Therefore, a simulation was conducted using the two techniques at the same time. The ramping rate and learning rate were set at their respective best values (i.e. 0.3 and 0.7 respectively). The results are presented in the third column of Table 3. Unfortunately, it is seen that better results cannot be obtained by simply combining the two techniques.

Note that in Fig. 12, the impact of the different prosumer demand profiles on the overall performance under different learning rates has

been illustrated. The eight light blue lines are the results given the 8 typical demand scenarios that are the same as those used in Case 1-2. It can be observed that the demand profiles affect the overall performance significantly, but the impact patterns of the learning rate on the overall performance are similar, all being low performance at low learning rates, higher performance at moderate and high learning rates and a bit lower performance at very high learning rates that are close to 1. Compared to the results with the base case setting as shown by the dark blue line, the optimal learning rate is not always 0.7 in other scenarios as shown by the light blue lines. However, in those cases, the optimal learning rates are still around 0.7 (ranging from 0.65 to 0.85), and the optimal performance did not deviate severely from that with the learning rate being 0.7.

5.2.4. Case 1-4: Influence of initial values

The results of the above three cases, Case 1-1 to Case 1-3, were all derived based on the same initial value of the internal price. This case examined whether or not and to what extent the results would be affected by the selection of initial values. For each typical ramping rate in Case 1-2, 10 simulations with randomised initial values were conducted, and the results (the light red curves) with their average (the dark red curve) were plotted in Fig. 13, compared to the results derived by only one simulation with fixed initial value in Case 1-2 (the blue curve). Similar work was done for each typical learning rate in Case 1-3

Table 3
Evaluation index values for Case 1-3.

Index	<i>SDR Mechanism</i> (best; learning rate = 0.7)	SDR Mechanism (best; ramping rate = 0.3)	<i>SDR Mechanism</i> (ramping rate = 0.3, and learning rate = 0.7)	Conventional Paradigm
Value Tapping Index (V_I)	0.84	0.88	0.90	0.00
Participation Willing Index (P_I)	1.00	1.00	1.00	1.00
Equality Index (E_I)	0.57	0.52	0.50	0.59
Economic Performance Index (EP_I)	0.79	0.79	0.79	0.52
Energy Balance Index (EB_I)	0.59	0.61	0.48	0.20
Power Flatness Index (PF_I)	0.61	0.57	0.52	0.65
Self-Sufficiency Index (SS_I)	0.96	0.97	0.94	0.46
Technical Performance Index (TP_I)	0.71	0.71	0.64	0.44
Overall Performance Index (OP_I)	0.75	0.75	0.72	0.47

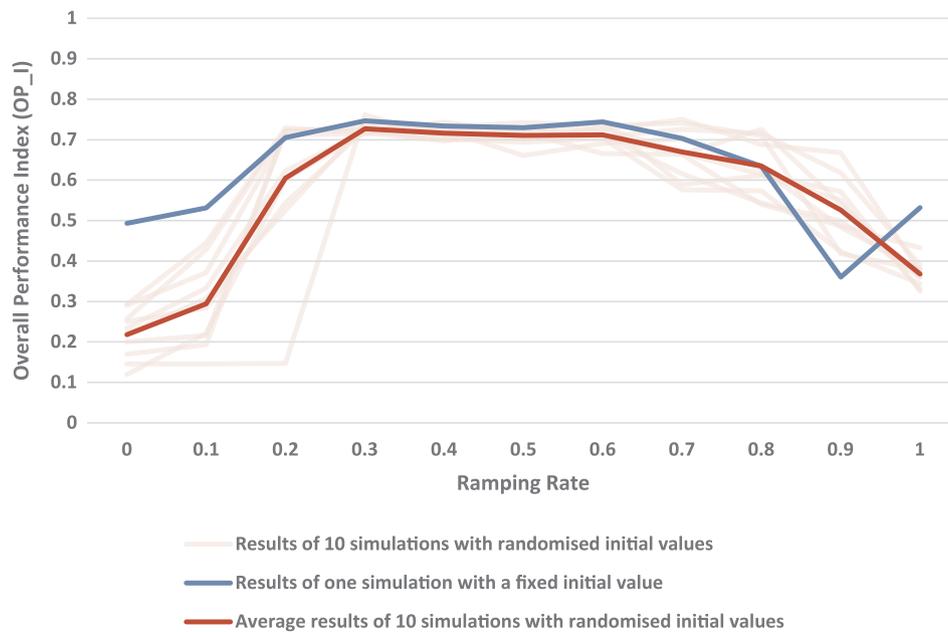


Fig. 13. The overall performance under multiple ramping rates with different initial value settings.

as well, and the results are presented in Fig. 14. Note that the initial values were randomly sampled between the export price and the retail price evenly.

In Figs. 13 and 14, the initial values did affect the simulation results, especially if the ramping/learning rate took an extreme value (i.e. close to the lower limit, 0, or to the upper limit, 1). In spite of this, as shown in Fig. 13, initial values had small effects on the final results, when the ramping rate took moderate values between 0.3 and 0.6.

5.2.5. Case 1-5: influence of the maximum number of iterations in the last-defence mechanism

In the previous cases (Case 1-1 through Case 1-4), the maximum number of iterations in the last-defence mechanism was assumed as 200. However, if different numbers are taken, the evaluation results may change. This is because the simulation may be forced to stop before convergence if the number taken is too small. Therefore, this sub-

section assesses the influence of the maximum number of iterations and figures out the suitable number to be used in later cases.

A series of simulation adopting the SDR mechanism with the step length control technique were carried out, given a variety of maximum number of iterations and ramping rates. The results are presented in Figs. 15 and 16.

Fig. 15 illustrates the number of iterations when the simulation stopped, given different maximum number of iterations and ramping rates. In the scenarios marked as green colour, the number of iterations used are all smaller than the maximum number of iterations, revealing that the simulation converged for these scenarios. On the other hand, in the scenarios marked as red colour, the number of iterations used are all exactly equal to the maximum number of iterations, showing that the simulation did not converge when it was forced to stop because the maximum number was reached. It can be observed that lower ramping rates resulted in quicker convergence. Therefore, the choice of

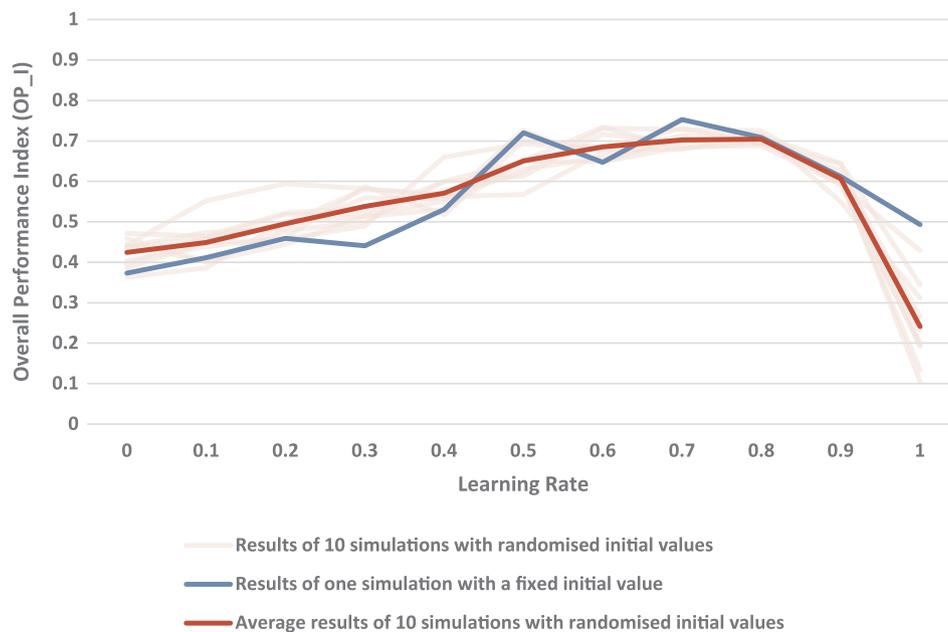


Fig. 14. The overall performance under multiple learning rates with different initial value settings.

Maximum Iterations												
10	3	3	8	8	10	10	10	10	10	10	10	10
20	3	3	8	8	20	20	20	20	20	20	20	20
50	3	3	8	8	50	50	50	50	50	50	50	50
100	3	3	8	8	100	100	100	100	100	100	100	100
200	3	3	8	8	200	200	200	200	200	200	200	200
500	3	3	8	8	214	214	500	500	500	500	500	500
1000	3	3	8	8	214	214	1000	1000	1000	1000	1000	1000
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	
	Ramping Rate											

Legend	Converged					Diverged						
--------	-----------	--	--	--	--	----------	--	--	--	--	--	--

Fig. 15. The number of iterations when the simulation stopped given different maximum number of iterations and ramping rates.

maximum number of iterations depends on the choice of ramping rates.

As concluded in Case 1-2, which is again verified by the results in Fig. 16, with the ramping rate being 0.3, the overall performance is stably the best, and thus should be chosen. As shown in Fig. 15, the simulation converges very fast given the ramping rate equals to 0.3, and thus the maximum number of iterations can be chosen as a very small number. However, considering that the iterations needed may vary with different scenarios (e.g. different PV/EV penetration, seasonal factors, etc.), a much larger number, 200, was chosen for later cases, to leave great margin. Note that there is no way to decide a perfect maximum number of iterations a priori, because we never know whether a convergence exists or how many iterations are needed to reach it until we actually reach it. Also, it is neither practical nor necessary to do the similar sensitivity analysis for each case later, because that will be very computationally expensive and repetitive. Considering all the above results and facts, it is basically reasonable to assign 200 as the maximum number of iterations in the following set of cases.

5.3. The second set of cases

In the second sets of cases, three P2P energy sharing mechanisms, i.e. SDR, MMR and BS, were simulated and compared in current and future scenarios of GB. First of all, a base case was established with a preliminary comparison among the three mechanisms. After that, the sensitivities of a series of factors were examined on top of the base case. Specifically, four cases were studied:

- Case 2-1: base case in which the three mechanisms were simulated and evaluated;
- Case 2-2: current and future scenarios with different PV and EV penetration levels were examined;
- Case 2-3: results with different seasons and day types were examined;
- Case 2-4: results with different retail price schemes were examined.

5.3.1. Case 2-1: Base case with the three mechanisms simulated and compared

The settings of this case kept the same as those of Case 1-1, except that the step length control technique was used in this case to facilitate the convergence and to obtain better performance. The ramping rate was set as 0.3 considering its good performance as shown in Case 1-2 and Case 1-4. The three P2P energy sharing mechanisms were simulated and evaluated, and the results are presented in Table 4.

From Table 4, it is observed that, in terms of the overall performance, the SDR mechanism performed the best, followed by the MMR mechanism with lower marks, and both of them were much better than the BS mechanism and the conventional paradigm.

The SDR and MMR mechanisms tapped much cost-saving potentials in P2P energy sharing while guaranteeing that all the participants obtained no less benefit than that under the conventional paradigm. Moreover, the SDR and MMR mechanisms largely increased local energy balance and self-sufficiency of the region. Therefore, both the economic and technical index values of the SDR and MMR mechanisms were much higher than those under the conventional mechanism. In spite of the above advantages, it is also noticed that the SDR and MMR mechanisms slightly decreased the income equality and power flatness within the region.

As for the BS mechanism, its overall performance was very close to (even slightly worse than) the conventional paradigm. Although it tapped 34% more economic values than the conventional paradigm, half of the participants of the BS mechanism received lower income than that under the conventional income. The reason was that in the BS mechanism, all the participants shared the total energy cost/income averagely, so that the ones with larger contribution (e.g. with high local power generation) were not remunerated fairly.

5.3.2. Case 2-2: results in current and future GB scenarios with different PV and EV penetration levels

Although there are some PV panels and EVs owned by residential customers in GB, the overall number is still small. Therefore, the zero

Maximum Iterations												
10	0.49	0.53	0.70	0.75	0.74	0.72	0.70	0.63	0.67	0.58	0.53	
20	0.49	0.53	0.70	0.75	0.69	0.72	0.71	0.68	0.62	0.53	0.53	
50	0.49	0.53	0.70	0.75	0.75	0.70	0.74	0.72	0.63	0.55	0.53	
100	0.49	0.53	0.70	0.75	0.76	0.69	0.59	0.62	0.46	0.36	0.53	
200	0.49	0.53	0.70	0.75	0.73	0.73	0.74	0.70	0.63	0.36	0.53	
500	0.49	0.53	0.70	0.75	0.71	0.72	0.61	0.69	0.47	0.42	0.53	
1000	0.49	0.53	0.70	0.75	0.71	0.72	0.64	0.58	0.42	0.45	0.53	
	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	
	Ramping Rate											

Legend	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
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Fig. 16. The overall performance given different maximum number of iterations and ramping rates.

Table 4
Evaluation index values for Case 2–1.

Index	SDR Mechanism	MMR Mechanism	BS Mechanism	Conventional Paradigm
Value Tapping Index (V_I)	0.92	0.62	0.34	0.00
Participation Willing Index (P_I)	1.00	1.00	0.50	1.00
Equality Index (E_I)	0.51	0.55	0.57	0.59
Economic Performance Index (EP_I)	0.80	0.71	0.46	0.52
Energy Balance Index (EB_I)	0.57	0.30	0.21	0.20
Power Flatness Index (PF_I)	0.53	0.59	0.65	0.65
Self-Sufficiency Index (SS_I)	0.98	0.69	0.47	0.46
Technical Performance Index (TP_I)	0.69	0.51	0.44	0.44
Overall Performance Index (OP_I)	0.74	0.61	0.45	0.48

PV and EV penetration scenario was set as the baseline representing the current situation in GB. Future scenarios were generated by gradually increasing the PV and EV penetration levels with a step of 10%. The simulation settings were the same as those of Case 2-1, except that the ownership of PV and EV for each customer was randomly decided according to the pre-set penetration levels. For example, if the PV/EV penetration was 10%, then 10% of customers would own PV/EV, and the corresponding PV/EV parameters would be derived from the CREST model / EV database. The three P2P energy sharing mechanisms were simulated and evaluated in these scenarios, and the results are presented in Fig. 17.

In Fig. 17, the overall performance scores of the three P2P energy sharing mechanisms as well as the conventional mechanism are presented with colours corresponding to their values. The colour changes from red, to yellow, then to green gradually, with the increase of the index value from 0 to 1. The first observation is that the SDR mechanism performed the best in most scenarios with a large area of green and light yellow data. The MMR mechanism had good performance mainly in scenarios with moderate PV penetration levels (from 10% to 60%). The BS mechanism generally did not outperform the reference conventional paradigm, except some scenarios where the EV penetration was very low.

It is also noted that both the MMR and BS mechanisms obtained better performance than the conventional paradigm in scenarios where the EV penetration is very low (especially zero). This is because the MMR and BS mechanisms were designed to share local surplus generation without considering stimulating flexible demands [16]. Therefore, they performed well with low EV penetration, but not that well with the increase of EV penetration.

Another interesting result is that the conventional paradigm performed even better than all the three P2P energy sharing mechanisms when (1) the PV penetration equalled to zero or (2) both the PV and EV penetration were equal or very close to 100%. The reasons are as follows: (1) when there was no local PV generation in the whole region, no energy could be shared among the customers, so to optimise the power schedule individually was the best solution; (2) when almost every prosumer owned PV and EV, to a very large extent they were able to consume their own PV generation by using the flexibility of their own EVs, so to optimise schedules individually in the conventional paradigm was still able to derive good solutions.

In addition, it is noted that in three scenarios under the MMR mechanism (i.e. PV 100% & EV 80–100%) as shown in Fig. 17(b), the overall performance scores were negative, which indicates that the total incomes in these scenarios were even less than those in the conventional paradigm (referred to Section 4.1.1).

5.3.3. Case 2-3: results of different seasons and day types

At first, the impact of seasons were examined. Besides the summer weekend day of July in Case 2-1, three typical weekend days in January, April and October were chosen to represent winter, spring and

autumn. All the other case settings were the same as those of Case 2-1, except that those related to seasonal factors were derived by the CREST model. For example, the PV generation and some power usage would vary with seasons. The performance of the three mechanisms as well as the reference (Ref.) conventional paradigm in different seasons is presented in Table 5.

In Table 5, it is observed that although the index values varied with seasons for all the mechanisms, the amount of variation was not significant. More importantly, the basic conclusion still held in the typical days for all seasons. That is, the SDR mechanism performed the best in all the three indexes, followed by the MMR mechanism, and the performance of the BS mechanism and the conventional paradigm were roughly at the same level.

Customers' behaviours vary between weekdays and weekends, so the impact of day types were examined as well. A typical weekday in July was chosen, and the corresponding data were derived from the CREST model and EV database. All the other settings kept the same as those in Case 2-1. The results are presented in Table 6.

Form Table 6, it is observed that the results under different day types did not differ from each other prominently. The conclusions on the performance of the three mechanisms still held both for weekdays and weekends.

5.3.4. Case 2-4: results of different retail price schemes

In Case 2-1 and all the other previous cases, a flat retail price was assumed throughout the horizon. In this case, it was replaced by two of the most common time-of-use retail price schemes in GB, i.e. Economy 7 and Economy 10. The rate settings of Economy 7 and Economy 10 were described in Table 7, and the evaluation results were presented in Table 8.

The results in Table 8 show that the conclusions derived in Case 2-1 still held, although the performance indexes values would vary with the retail price adopted.

5.4. Remarks on the choices of cases and parameters that were evaluated in this paper

The cases were divided as two sets. The first set of cases are methodology-oriented, focusing on demonstrating the effectiveness of all the methods proposed in this paper, including the multiagent-based simulation, evaluation indexes, step length control technique and learning process involvement technique. Specifically, in Case 1-1, the proposed multiagent-based simulation and evaluation indexes were demonstrated and verified, by showing the detailed results (including power curves, income distribution and internal price evolution) and evaluation scores (including the scores from individual index level to the overall index level) with detailed analysis. In Case 1-2, the step length control technique was validated, while in Case 1-3 the learning process involvement technique was validated. In Case 1-2, 1-3, 1-4 and 1-5, four parameters (i.e. the ramping rate, learning rate, initial values

PV Penetration											
100%	0.69	0.69	0.70	0.72	0.72	0.75	0.70	0.67	0.62	0.56	0.55
90%	0.68	0.70	0.70	0.72	0.69	0.75	0.70	0.69	0.64	0.69	0.68
80%	0.66	0.68	0.68	0.70	0.66	0.69	0.69	0.68	0.69	0.67	0.61
70%	0.65	0.68	0.69	0.70	0.66	0.68	0.68	0.66	0.68	0.68	0.71
60%	0.67	0.68	0.68	0.73	0.71	0.72	0.74	0.72	0.72	0.72	0.69
50%	0.63	0.70	0.72	0.73	0.72	0.72	0.71	0.71	0.70	0.72	0.70
40%	0.65	0.67	0.70	0.72	0.66	0.72	0.73	0.71	0.71	0.73	0.69
30%	0.64	0.68	0.69	0.73	0.71	0.67	0.68	0.68	0.66	0.73	0.65
20%	0.66	0.73	0.70	0.72	0.71	0.67	0.75	0.71	0.72	0.68	0.65
10%	0.71	0.74	0.76	0.76	0.73	0.71	0.67	0.67	0.68	0.68	0.64
0%	0.32	0.32	0.27	0.30	0.30	0.23	0.15	0.14	0.12	0.12	0.15
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%

(a) SDR mechanism

PV Penetration											
100%	0.65	0.50	0.47	0.46	0.39	0.28	0.17	0.01	-0.13	-0.35	-0.96
90%	0.66	0.54	0.50	0.50	0.44	0.36	0.31	0.20	0.13	0.29	0.31
80%	0.65	0.54	0.50	0.49	0.44	0.37	0.31	0.33	0.43	0.41	0.41
70%	0.67	0.57	0.53	0.53	0.49	0.44	0.42	0.35	0.44	0.49	0.53
60%	0.69	0.59	0.58	0.62	0.56	0.59	0.57	0.61	0.60	0.60	0.59
50%	0.67	0.60	0.59	0.61	0.60	0.57	0.59	0.57	0.62	0.64	0.62
40%	0.66	0.59	0.60	0.63	0.56	0.64	0.62	0.65	0.65	0.65	0.65
30%	0.65	0.57	0.60	0.63	0.59	0.63	0.65	0.62	0.63	0.65	0.65
20%	0.67	0.63	0.63	0.66	0.64	0.65	0.67	0.68	0.64	0.62	0.60
10%	0.71	0.65	0.68	0.71	0.63	0.71	0.69	0.57	0.63	0.59	0.60
0%	0.32	0.30	0.30	0.33	0.32	0.28	0.20	0.18	0.16	0.15	0.19
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%

(b) MMR mechanism

PV Penetration											
100%	0.72	0.56	0.56	0.57	0.57	0.57	0.56	0.57	0.56	0.55	0.56
90%	0.71	0.58	0.57	0.58	0.58	0.59	0.60	0.61	0.61	0.61	0.59
80%	0.69	0.58	0.57	0.57	0.58	0.59	0.59	0.60	0.54	0.55	0.54
70%	0.64	0.56	0.57	0.58	0.58	0.59	0.61	0.60	0.57	0.57	0.55
60%	0.60	0.54	0.53	0.52	0.52	0.52	0.53	0.54	0.51	0.53	0.54
50%	0.60	0.52	0.53	0.53	0.54	0.53	0.57	0.56	0.54	0.55	0.56
40%	0.58	0.53	0.53	0.53	0.57	0.54	0.57	0.52	0.53	0.53	0.53
30%	0.59	0.56	0.57	0.57	0.57	0.58	0.54	0.55	0.52	0.53	0.52
20%	0.62	0.56	0.57	0.58	0.57	0.55	0.54	0.52	0.49	0.49	0.48
10%	0.68	0.55	0.59	0.58	0.47	0.50	0.50	0.37	0.43	0.35	0.38
0%	0.28	0.36	0.23	0.23	0.24	0.17	0.11	0.09	0.12	0.13	0.12
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%

(c) BS mechanism

PV Penetration											
100%	0.56	0.57	0.58	0.59	0.60	0.61	0.62	0.62	0.63	0.64	0.64
90%	0.55	0.56	0.57	0.58	0.59	0.60	0.61	0.61	0.62	0.63	0.63
80%	0.53	0.54	0.55	0.56	0.58	0.58	0.60	0.61	0.60	0.60	0.61
70%	0.52	0.53	0.55	0.55	0.56	0.57	0.59	0.59	0.60	0.59	0.58
60%	0.52	0.53	0.53	0.54	0.55	0.55	0.56	0.58	0.56	0.57	0.58
50%	0.50	0.52	0.53	0.54	0.55	0.54	0.57	0.56	0.56	0.57	0.58
40%	0.50	0.52	0.52	0.52	0.55	0.52	0.55	0.52	0.53	0.52	0.53
30%	0.50	0.53	0.54	0.54	0.54	0.55	0.51	0.53	0.50	0.51	0.50
20%	0.51	0.52	0.53	0.53	0.53	0.51	0.48	0.48	0.44	0.44	0.42
10%	0.55	0.47	0.50	0.45	0.39	0.40	0.40	0.27	0.31	0.22	0.24
0%	0.40	0.41	0.36	0.38	0.36	0.32	0.24	0.23	0.21	0.20	0.22
	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%

(d) Conventional Paradigm



Fig. 17. The overall performance scores of the three mechanisms in scenarios with different PV and EV penetration levels.

and maximum number of iterations) were tested respectively, because they are key parameters regarding the proposed methods and may affect the simulation results and performance of P2P energy sharing mechanisms significantly.

It is worth noting that the first set of cases were all evaluated in only one scenario or several typical scenarios with only one P2P energy sharing mechanism (SDR), one possibility of PV installation and EV ownership (half customers own PV panels but no EVs, and the other half

Table 5
Evaluation index values under different seasons for Case 2–3.

Index	Spring (April)				Summer (July)				Autumn (October)				Winter (January)			
	SDR	MMR	BS	Ref	SDR	MMR	BS	Ref	SDR	MMR	BS	Ref	SDR	MMR	BS	Ref
Economic Performance Index (<i>EP_I</i>)	0.79	0.68	0.46	0.51	0.80	0.71	0.46	0.52	0.83	0.71	0.52	0.58	0.86	0.76	0.54	0.57
Technical Performance Index (<i>TP_I</i>)	0.68	0.49	0.43	0.41	0.69	0.51	0.44	0.44	0.69	0.49	0.43	0.42	0.76	0.49	0.40	0.40
Overall Performance Index (<i>OP_I</i>)	0.73	0.58	0.44	0.46	0.74	0.61	0.45	0.48	0.76	0.60	0.48	0.50	0.81	0.62	0.47	0.49

own EVs but no PV panels) and one retail price scheme (flat price). The scenario chosen is just a small set of the large numbers of scenarios, because the focus of the first set of cases is to verify the effectiveness of the proposed methodology, rather than give a thorough evaluation and sensitivity analysis, which is in contrast the focus of the second set of cases.

The motivation behind the second set of cases is twofold: one is to compare and evaluate the P2P energy sharing mechanisms in existing studies (specifically, SDR, MMR and BS mechanisms), and the other is to provide some practical implications on applying P2P energy sharing in current and future scenarios of GB. Due to the former aspect of motivation, the three existing P2P energy sharing mechanisms were evaluated and compared from Case 2-1 through 2-4. Because of the latter aspect of motivation, various scenarios of GB were examined and a number of sensitivity analysis was conducted. A base case was first provided in Case 2-1, and then the scenarios characterized with different factors were assessed. The factors include PV and EV penetration levels (Case 2-2), seasons (Case 2-3), day types (Case 2-3) and retail price schemes (Case 2-4). These factors were considered because they are all important practical factors that may affect the performance of P2P energy sharing mechanisms.

The cases and parameters that were evaluated in this paper have effectively verified the proposed methodology, and provided good evaluation for existing P2P energy sharing mechanisms in the GB background. In spite of this, we also note that the evaluation will never be totally complete because there will be more and more P2P energy sharing mechanisms designed in the future and more factors may need to be considered in the future or in other countries. We hope that the work presented in this paper provides useful methodology and good foundation for the followers to work with.

6. Conclusions and future work

A multiagent-based simulation framework and a systematic index system were developed for the simulation and evaluation of P2P energy sharing mechanisms. The multiagent-based simulation framework are composed of three types of agents and three corresponding models. Two techniques, i.e. step length control and learning process involvement, were proposed to facilitate the convergence of simulation, and a last-defence mechanism was described to deal with divergence. The evaluation index system is a hierarchical system composed of three economic indexes and three technical indexes. The indexes were normalised and synthesized to reflect the overall performance.

The proposed simulation framework and evaluation indexes were validated in current and future scenarios of GB, and some practical implications were obtained. The following conclusions were derived

Table 6
Evaluation index values with different day types for Case 2–3.

Index	SDR Mechanism		MMR Mechanism		BS Mechanism		Conventional Mechanism	
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend
Economic Performance Index (<i>EP_I</i>)	0.78	0.80	0.70	0.71	0.46	0.46	0.52	0.52
Technical Performance Index (<i>TP_I</i>)	0.63	0.69	0.50	0.51	0.43	0.44	0.44	0.44
Overall Performance Index (<i>OP_I</i>)	0.70	0.74	0.60	0.61	0.44	0.45	0.48	0.48

Table 7
Tariff Structure for Economy 7 and Economy 10 in GB.

Tariff Type	Standard Rate (pence/kWh)	Off-Peak Rate (pence/kWh)	Standard Period	Off-Peak Period
Economy 7	18.30	7.88	7:00–24:00	0:00–7:00
Economy 10	18.68	10.07	5:00–13:00 16:00–20:00 22:00–24:00	0:00–5:00 13:00–16:00 20:00–22:00

based on the numerical results:

- (1) The proposed techniques, both step length control and learning process involvement, are able to facilitate convergence of simulation and thus improve the performance of P2P energy sharing mechanisms. The effects depend on the values of ramping rate and learning rate. At proper values, the improvement brought by the two techniques is at the same level.
- (2) Generally, P2P energy sharing among residential customers has the potential to bring many economic and technical benefits to GB in the future, compared to the conventional paradigm. The two exceptions are the scenario where the PV penetration in the region is close to zero, and the scenario where almost each customer owns PV and EV simultaneously.
- (3) Overall, the SDR mechanism outperforms all the other mechanisms and the MMR mechanism is well performed in most scenarios, although with some slight reduction in a few individual indexes compared to the conventional paradigm. The BS mechanism generally reaps no more benefit compared to the conventional non-P2P paradigm. This conclusion is not sensitive to season factors, day types and retail price schemes adopted.

Based on the work in this paper, the following directions are identified for further exploration:

- (1) The communication among agents was considered perfect without any delay or error. The imperfect communication may undermine the performance of P2P energy sharing, and is worth further study.
- (2) It was assumed that all the agents made decisions with perfect forecast for the future. In fact, there may be significant uncertainties in renewable generation and human behaviours, which may undermine the performance of P2P energy sharing. This issue is to be studied in the future.
- (3) The energy sharing coordinator was considered as a market operator that only took care of energy trading. Further research is to

Table 8
Evaluation index values for Case 2–4.

Index	SDR Mechanism			MMR Mechanism			BS Mechanism			Conventional Mechanism		
	Flat	E7	E10	Flat	E7	E10	Flat	E7	E10	Flat	E7	E10
Economic Performance Index (<i>EP_I</i>)	0.80	0.78	0.79	0.71	0.58	0.72	0.46	0.46	0.45	0.52	0.51	0.51
Technical Performance Index (<i>TP_I</i>)	0.69	0.68	0.69	0.51	0.53	0.54	0.44	0.45	0.44	0.44	0.47	0.44
Overall Performance Index (<i>OP_I</i>)	0.74	0.73	0.74	0.61	0.55	0.63	0.45	0.45	0.44	0.48	0.49	0.50

- analyse and tackle the physical problems (e.g. over voltage and congestion) in the power networks along with P2P energy sharing.
- (4) The case studies in this paper did not consider household energy storage in residential houses of GB. We note that in the future the price of household energy storage may decrease dramatically, given which household energy storage cannot be ignored and should be considered in the evaluation. If household energy storage is considered, the proposed simulation and evaluation methodology is still applicable, but the results of evaluation on existing P2P energy sharing mechanisms may be different.
 - (5) The demand data used in this paper was randomly sampled from GREST model, which just reflects the average situation of GB. Data with more details on the geographical distribution of local generation and demand across GB is needed to conduct more comprehensive evaluation of the impact of P2P energy sharing on GB. Moreover, how the customers are grouped, which is affected by market competition, policies and physical network constraints, may have great effects, and worth being studied in the future.

P2P energy sharing is an emerging direction that has the potential to reshape the paradigm of power systems and bring various benefits for both customers and power systems. This paper established basic simulation and evaluation framework for P2P energy sharing, based on which a number of further work can be further conducted. In terms of the decision model of customers, the impact of various uncertainties

can be considered. Moreover, more devices, such as energy storage systems, and more types of customers, such as commercial and industrial customers, can be involved. In terms of the implementation model, the impact of imperfect communication and the corresponding solutions need to be studied. Furthermore, improved pricing models that are able to mitigate power network problems can be developed for the coordinators. As for the evaluation index system, more indexes can be added according to practical needs in other scenarios in the future. In addition, more detailed evaluation could be conducted for specific countries/areas by having local generation and demand data with geographical information and considering the grouping of customers.

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Appendix A

When evaluating the supply and demand ratio (SDR), mid-market rate (MMR) and bill sharing (BS) mechanisms for residential customers in the GB scenarios, the abstract agents and models in the multiagent-based simulation framework described in Section 3 are realised as follows.

A.1. Prosumer agent and decision-making model

The decision-making model in a prosumer agent, as abstractly shown in Formula (3), is realised as in this sub-section, in which the objective function is to minimise the net cost (i.e. maximise the net income) while satisfying a set of constraints on physical device limits, human comfort and flexibility of different types of appliances. The specific form of the objective function varies with the P2P energy sharing mechanism adopted because different billing rules are specified in different mechanisms. For the SDR mechanism and BS mechanism, the objective function is as follows:

$$\min \sum_{t=1}^T p_t^{\text{internal}} \left(\left(\sum_{\delta \in A_f} x_{\delta,t} \right) + \left(\frac{x_t^{\text{ch}}}{\eta^{\text{ch}}} + x_t^{\text{dis}} \eta^{\text{dis}} \right) + P_t^{\text{must-run}} - P_{\text{PV},t} \right) \Delta t \tag{A1}$$

where T is the total time steps considered for scheduling; A_f refers to the set of flexible appliances which include noninterruptible and thermal appliances (denoted as $A_f = A_{\text{NL}} \cup A_{\text{TCL}}$); x_{δ} represents the power of the flexible appliance; x^{ch} and x^{dis} are the charging and discharging power of the electric vehicle, and η^{ch} and η^{dis} denote the charging and discharging efficiency; $P^{\text{must-run}}$ represents the sum of inflexible demand; P_{PV} denotes the power output of PV panels; Δt is the length of each time step. p_t^{internal} denotes the internal price issued by the coordinator agent in the P2P energy sharing mechanism, which is composed of buying and selling prices:

$$p_t^{\text{internal}} = \begin{cases} P_t^{\text{buy}} \left(\sum_{\delta \in A_f} x_{\delta,t} \right) + \left(\frac{x_t^{\text{ch}}}{\eta^{\text{ch}}} + x_t^{\text{dis}} \eta^{\text{dis}} \right) + P_t^{\text{must-run}} - P_{\text{PV},t} \geq 0 \\ P_t^{\text{sell}} \left(\sum_{\delta \in A_f} x_{\delta,t} \right) + \left(\frac{x_t^{\text{ch}}}{\eta^{\text{ch}}} + x_t^{\text{dis}} \eta^{\text{dis}} \right) + P_t^{\text{must-run}} - P_{\text{PV},t} < 0 \end{cases} \tag{A2}$$

In contrast, for the MMR mechanism, the objective function is in another form:

$$\min \sum_{t=1}^T p_t^{\text{buy}} \left(\sum_{\delta \in A_f} x_{\delta,t} + \frac{x_t^{\text{ch}}}{\eta^{\text{ch}}} + P_t^{\text{must-run}} \right) \Delta t - p_t^{\text{sell}} (x_t^{\text{dis}} \eta^{\text{dis}} + P_{PV,t}) \Delta t \tag{A3}$$

The constraints under different mechanisms are the same, as presented as follows.

(1) The constraints for non-interruptible appliances (i.e. $\delta \in A_{\text{NL}}$) include

$$x_{\delta,t} = 0 \quad \forall t \in [1,b) \cup (e,T], \delta \in A_{\text{NL}}, \tag{A4}$$

$$\sum_{t=b}^e x_{\delta,t} = L_{\delta} P_{\delta}, \tag{A5}$$

$$\sum_{s=t}^{t+L_{\delta}-1} x_{\delta,s} \geq (x_{\delta,t} - x_{\delta,t-1}) \cdot L_{\delta} \quad \forall t \in (b, e - L_{\delta} + 1], \tag{A6}$$

$$x_{\delta,t} = \{0, P_{\delta}\} \quad \forall t \in T. \tag{A7}$$

In Formulas (A4)–(A7), b and e are the allowed start time and required end time of the task respectively; L_{δ} is the time duration of the task (note that $e - b \geq L_{\delta}$); P_{δ} is the rate power of the appliance. Formula (A4) regulates that the appliance is not allowed to work outside the permissioned time interval. Formula (A5) guarantees that the task needs to be finished before deadline. Formula (A6) requires that the task cannot be interrupted. Finally, Formula (A7) specifies that the possible power status of the appliance.

(2) The constraints for thermostatically controlled appliances (i.e. $\delta \in A_{\text{TCL}}$) include:

$$\sum_{s=1}^t x_{\delta,s} \cdot \Delta t + \rho \cdot M \cdot c_{\text{water}} \cdot (\theta_0 - \theta_{\text{low}}) \geq \sum_{s=1}^t C_s \quad \forall t \in [1, T], \tag{A8}$$

$$\sum_{s=1}^t x_{\delta,s} \cdot \Delta t \leq \rho \cdot M \cdot c_{\text{water}} \cdot (\theta_{\text{up}} - \theta_0) + \sum_{s=1}^t C_s \quad \forall t \in [1, T], \tag{A9}$$

$$C_t = \rho \cdot d_t \cdot c_{\text{water}} \cdot (\theta_{\text{req}} - \theta_{\text{en},t}) \quad \forall t \in [1, T], \tag{A10}$$

$$x_{\delta,t} = [0, P_{\delta}] \quad \forall t \in T. \tag{A11}$$

In Formulas (A8)–(A11), ρ is a constant coefficient for unit conversion between J and kWh; M is the mass of water in full storage; c_{water} is the specific heat of water; θ_0 , θ_{req} and θ_{en} represent the initial water temperature, required water temperature and cold water temperature respectively; θ_{low} and θ_{up} represent the lower and upper limits of water temperature; C represents the heat energy demand for hot water use; d represents the amount of hot water drawn. Formula (A8) specifies that the total heat energy gained from the heater plus the initial heat energy stored in the tank till the t th time step should be no less than the total heat demand till the same time step. Similarly, Formula (A9) guarantees that the total heat stored in the tank cannot exceed the upper limit. Formula (A10) calculates the heat energy demand due to hot water use. Formula (A11) shows that the heating power should be within a range.

(3) The constraints for the electric vehicle include:

$$SOC_t = SOC_0 + \frac{1}{E} \sum_{s=1}^t (x_s^{\text{ch}} + x_s^{\text{dis}}) \Delta t \quad \forall t \in [1, t_{\text{out}}] \cup (t_{\text{in}}, T], \tag{A12}$$

$$SOC_{t_{\text{in}}} = SOC_{t_{\text{out}}} - \Delta SOC, \tag{A13}$$

$$SOC_{\text{min}} \leq SOC_t \leq SOC_{\text{max}} \quad \forall t \in [1, t_{\text{out}}] \cup [t_{\text{in}}, T], \tag{A14}$$

$$SOC_0 = SOC_T, \tag{A15}$$

$$0 \leq x_t^{\text{ch}} \leq P_{\text{max}}^{\text{ch}}, \tag{A16}$$

$$P_{\text{max}}^{\text{dis}} \leq x_t^{\text{dis}} \leq 0. \tag{A17}$$

In Formulas (A12)–(A17), SOC represents the state of charge (SOC) of the battery on the electric vehicle; SOC_0 is the initial SOC; E is the rated capacity of the battery; t_{in} and t_{out} are the time steps at which the electric vehicle plugs in and out (i.e. return and leave home); ΔSOC is the energy consumption of the electric vehicle during the travel, measured by SOC; SOC_{min} and SOC_{max} are the lower and upper limits of SOC; $P_{\text{max}}^{\text{ch}}$ and $P_{\text{max}}^{\text{dis}}$ are the upper limits of charging and discharging power. Formula (A12) calculates the SOC of EV battery at any time step t . Formula (A13) describes the relationship between the SOC at plug-in time and plug-out time. Formula (A14) requires that the SOC at any time step should be kept within a pre-defined range. Formula (A15) requires that the SOC at the end of the scheduling horizon should be equal to that at the very beginning, ensuring that the scheduling can keep going beyond the current scheduling horizon. Formulas (A16) and (A17) specify the upper limits of charging and discharging power, in which the charging power is denoted as positive while the discharging power is negative. It is worth noting that in the situation described by Formulas (A12)–(A17), the electric vehicle just leaves home once. But this will not lose any generality, because it is straightforward to model the situations where the electric vehicle leaves/returns home several times, by adding more formulas that are similar to Formula (A13). It is also worth noting that in (A12)–(A17), it is assumed that $t_{\text{out}} < t_{\text{in}}$, but it is straightforward how to formulate the situations where $t_{\text{out}} > t_{\text{in}}$, so it is not presented here.

So far, the decision-making model in a prosumer agent is formulated in detail. Note that the decision variables are denoted by x which are the

power consumption level of appliances and charging/discharging power of the electric vehicle. The formulated decision-making model consists of the objective function (A1)–(A3) and constraints (A4)–(A17), which is in nature a mixed integer linear programming problem that is able to be solved by mature solution tools.

A.2. Coordinator agent and pricing models

As stated in the beginning of Appendix A, three existing P2P energy sharing mechanisms, i.e. SDR, MMR and BS, are chosen to be evaluated. They specify different pricing models in the coordinator agent.

A.2.1. Supply and demand ratio mechanism

In the SDR mechanism, prosumers are required to provide energy bids for the coordinator at every iteration. Specifically, based on the results of the decision-making model presented in Section A.1, the energy bid of a prosumer is given by

$$e^{\text{bid}} = \left\{ e_t^{\text{bid}} | e_t^{\text{bid}} = \left(\sum_{\delta \in A_t} x_{\delta,t}^* \right) + \left(\frac{x_t^{\text{ch}*}}{\eta^{\text{ch}}} + x_t^{\text{dis}*} \eta^{\text{dis}} \right) + P_t^{\text{must-run}} - P_{\text{PV},t}, t \in T \right\} \quad (\text{A18})$$

in which $x^* = \{x_{\delta,t}^*, x_t^{\text{ch}*}, x_t^{\text{dis}*}\}, \delta \in A_t, t \in T$ are the optimal solution of the decision-making model consisting of Formulas (A1)–(A17). With the energy bids from all the prosumers, the coordinator calculates the internal selling price by

$$p_t^{\text{sell}} = \begin{cases} \frac{r_t^{\text{export}} \cdot r_t^{\text{retail}}}{(r_t^{\text{retail}} - r_t^{\text{export}}) \cdot \text{SDR}_t + r_t^{\text{export}}}, & 0 \leq \text{SDR}_t \leq 1 \\ r_t^{\text{export}}, & \text{SDR}_t > 1 \end{cases} \quad (\text{A19})$$

and the internal buying price by

$$p_t^{\text{buy}} = \begin{cases} p_t^{\text{sell}} \cdot \text{SDR}_t + r_t^{\text{retail}} (1 - \text{SDR}_t), & 0 \leq \text{SDR}_t \leq 1 \\ r_t^{\text{export}}, & \text{SDR}_t > 1 \end{cases} \quad (\text{A20})$$

in which

$$\text{SDR}_t = \frac{\sum_{n \in \mathcal{PA}^-} |e_{n,t}^{\text{bid}}|}{\sum_{n \in \mathcal{PA}^+} e_{n,t}^{\text{bid}}} \quad (\text{A21})$$

where

$$\mathcal{PA}^- = \{n | e_{n,t}^{\text{bid}} < 0, n \in \mathcal{PA}\} \quad (\text{A22})$$

and

$$\mathcal{PA}^+ = \{n | e_{n,t}^{\text{bid}} \geq 0, n \in \mathcal{PA}\}. \quad (\text{A23})$$

In Formulas (A19)–(A23), r_t^{export} and r_t^{retail} are the export and retail price between the coordinator and the retailer as illustrated in Fig. 2; SDR represents the supply and demand ratio of the whole P2P energy sharing region. Formulas (A19)–(A23) establish the pricing model in the coordinator agent under the SDR mechanism. It can be seen that the internal price reflects the supply and demand relationship within the energy sharing region, thus encouraging energy sharing and energy balance in the region.

A.2.2. Mid-market rate mechanism

The basic logic behind the MMR mechanism is that the internal price should be always set at the middle of the export price and retail price so that all the prosumers, for both producers and consumers, benefit fairly from the internal energy sharing. The MMR mechanism requires each prosumer to provide the energy bid that contains both generation and demand at each time step separately rather than an overall net demand as that in the SDR mechanism:

$$e^{\text{bid}} = e_{\text{gen}}^{\text{bid}} \cup e_{\text{dem}}^{\text{bid}} \\ = \{e_{\text{gen},t}^{\text{bid}} | e_{\text{gen},t}^{\text{bid}} = (x_t^{\text{dis}*} \eta^{\text{dis}}) - P_{\text{PV},t}, t \in T\} \\ \cup \left\{ e_{\text{dem},t}^{\text{bid}} | e_{\text{dem},t}^{\text{bid}} = \left(\sum_{\delta \in A_t} x_{\delta,t}^* \right) + \left(\frac{x_t^{\text{ch}*}}{\eta^{\text{ch}}} \right) + P_t^{\text{must-run}}, t \in T \right\} \quad (\text{A24})$$

With the energy bids of all the prosumers, the coordinator calculates the internal price in different ways according to the relationship between total generation and demand in the energy sharing region. If the generation is equal to demand, the internal buying and selling price are equal, taking the average of the export and retail price:

$$p_t^{\text{buy}} = p_t^{\text{sell}} = r_t^{\text{average}} = \frac{(r_t^{\text{export}} + r_t^{\text{retail}})}{2}, \quad \text{if } \sum_{n \in \mathcal{PA}} |e_{\text{gen},n,t}^{\text{bid}}| = \sum_{n \in \mathcal{PA}} e_{\text{dem},n,t}^{\text{bid}} \quad (\text{A25})$$

If the generation is less than demand, the deficit generation has to be supplied by the power imported from the retailer at the retail price, and the cost of this import should be covered. Therefore, in this situation, the internal selling price keeps the same as that in Formula (A25), but the buying price is modified:

$$\begin{cases} p_t^{\text{buy}} = \frac{\sum_{n \in \mathcal{P}, \mathcal{A}} |e_{\text{gen},n,t}^{\text{bid}}| \cdot r_t^{\text{average}} + \left(\sum_{n \in \mathcal{P}, \mathcal{A}} e_{\text{dem},n,t}^{\text{bid}} - \sum_{n \in \mathcal{P}, \mathcal{A}} |e_{\text{gen},n,t}^{\text{bid}}| \right) \cdot r_t^{\text{retail}}}{\sum_{n \in \mathcal{P}, \mathcal{A}} e_{\text{dem},n,t}^{\text{bid}}}, \\ p_t^{\text{sell}} = r_t^{\text{average}} \\ \text{if } \sum_{n \in \mathcal{P}, \mathcal{A}} |e_{\text{gen},n,t}^{\text{bid}}| < \sum_{n \in \mathcal{P}, \mathcal{A}} e_{\text{dem},n,t}^{\text{bid}}. \end{cases} \tag{A26}$$

Similarly, if the generation is higher than demand, the surplus generation needs to be sold to the retailer at the export price, and this part of income needs to be distributed among all the prosumers who provide electricity by generation or EV discharging. The internal price is calculated as follows:

$$\begin{cases} p_t^{\text{buy}} = r_t^{\text{average}} \\ p_t^{\text{sell}} = \frac{\sum_{n \in \mathcal{P}, \mathcal{A}} e_{\text{dem},n,t}^{\text{bid}} \cdot r_t^{\text{average}} + \left(\sum_{n \in \mathcal{P}, \mathcal{A}} |e_{\text{gen},n,t}^{\text{bid}}| - \sum_{n \in \mathcal{P}, \mathcal{A}} e_{\text{dem},n,t}^{\text{bid}} \right) \cdot r_t^{\text{export}}}{\sum_{n \in \mathcal{P}, \mathcal{A}} |e_{\text{gen},n,t}^{\text{bid}}|}, \\ \text{if } \sum_{n \in \mathcal{P}, \mathcal{A}} |e_{\text{gen},n,t}^{\text{bid}}| > \sum_{n \in \mathcal{P}, \mathcal{A}} e_{\text{dem},n,t}^{\text{bid}}. \end{cases} \tag{A27}$$

Formulas (A25)–(A27) compose the pricing model in the coordinator agent under mid-market rate mechanism.

A.2.3. Bill sharing mechanism

Bill sharing is a mechanism in which all the prosumers share the energy cost and income evenly throughout the time horizon. The energy bids required by the BS mechanism are the same as those in the SDR mechanism as described by Formula (A18). The internal price is calculated by

$$\begin{cases} p_t^{\text{buy}} = r_t^{\text{retail}} \cdot \frac{\sum_{t \in T_u^+} \sum_{n \in \mathcal{P}, \mathcal{A}} e_{n,t}^{\text{bid}}}{\sum_{n \in \mathcal{P}, \mathcal{A}} \sum_{t \in T_u^+} e_{n,t}^{\text{bid}}}, \quad T_u^+ = \left\{ t \mid \sum_{n \in \mathcal{P}, \mathcal{A}} e_{n,t}^{\text{bid}} > 0, t \in T \right\}, T_l^+ = \{ t \mid |e_{n,t}^{\text{bid}}| > 0, t \in T \} \\ p_t^{\text{sell}} = r_t^{\text{export}} \cdot \frac{\sum_{t \in T_u^-} \sum_{n \in \mathcal{P}, \mathcal{A}} |e_{n,t}^{\text{bid}}|}{\sum_{n \in \mathcal{P}, \mathcal{A}} \sum_{t \in T_l^-} |e_{n,t}^{\text{bid}}|}, \quad T_u^- = \left\{ t \mid \sum_{n \in \mathcal{P}, \mathcal{A}} e_{n,t}^{\text{bid}} < 0, t \in T \right\}, T_l^- = \{ t \mid |e_{n,t}^{\text{bid}}| < 0, t \in T \} \end{cases} \tag{A28}$$

Formula (A28) actually distributes the total energy cost and income of the whole energy sharing region among the prosumers according the amount of energy they consume and generate. Taking the buying price part as an example, $r_t^{\text{retail}} \cdot \sum_{t \in T_u^+} \sum_{n \in \mathcal{P}, \mathcal{A}} e_{n,t}^{\text{bid}}$ is the total energy cost of the whole region for importing electricity from the retailer throughout the time horizon, which is divided by $\sum_{n \in \mathcal{P}, \mathcal{A}} \sum_{t \in T_l^+} e_{n,t}^{\text{bid}}$, the sum of each individual prosumer's total positive net energy consumption throughout the time horizon.

A.3. Implementation model

The SDR mechanism specifies the implementation model clearly. An iterative bidding and pricing process is adopted, and the contents of bid are specified in detail as described in Formula (A18). The other two mechanisms, MMR and BS, specify the contents of bid as well, as described in Formula (A24) and (A18) respectively, but do not specify if they are implemented in a one-shot or iterative way. In this paper, they are assumed to be implemented in an iterative way that is the same as that in the SDR mechanism. The reason is twofold: one is to make it convenient to compare the three mechanisms; the other is that the iterative process can also be seen as the procedure to work out the equilibrium that is used in the one-shot implementation.

A.4. Retailer agent

Three retail price schemes are considered to be offered by the retailer agent, i.e. flat rate, Economy 7 and Economy 10. Economy 7 and Economy 10 are time-of-use pricing schemes, in which a day is divided as standard periods with a standard rate and off-peak periods with a lower off-peak rate. The main difference between Economy 7 and Economy 10 lies in that the duration of off-peak hours is 7 h and 10 h respectively. The distribution of off-peak hours and the values of standard and off-peak rates are also different.

The export price offered by the retailer agent is considered as the export rate specified in the feed-in tariff scheme of Great Britain, being a fixed value throughout a day.

Appendix B

This section analyses why the proposed step length control and learning process involvement techniques can enhance the convergence of the multiagent-based simulation for P2P energy sharing.

Before proposing techniques for enhancing convergence, the mechanism behind divergence needs to be revealed first. Similar to the reason for solution infeasibility (as presented in Ref. [48]) which focused on decentralized participation of flexible demand in a bulk power system with large thermal generators, the divergence of the simulation for P2P energy sharing is in nature due to the non-(strict)convexity of the objective function of a prosumer's decision making model (e.g. Formulae (A1) and (A2) in Appendix A) and the reschedulable capability of some flexible loads between different time slots (e.g. the electric water heaters (EWHs) and electric vehicles in Appendix A), which result in the discontinuity of a prosumer's demand function. This issue will be clarified by a simple numerical example as below.

Assume that a Prosumer A only owns an electric water heater with storage that needs to consume 6 kWh in total within 2 h to prepare enough hot water for later use. Also assume that the heating power of the water heater ranges from 0 to 4 kW. Denote $p_{t=1}$ and $p_{t=2}$ as the electricity prices of the

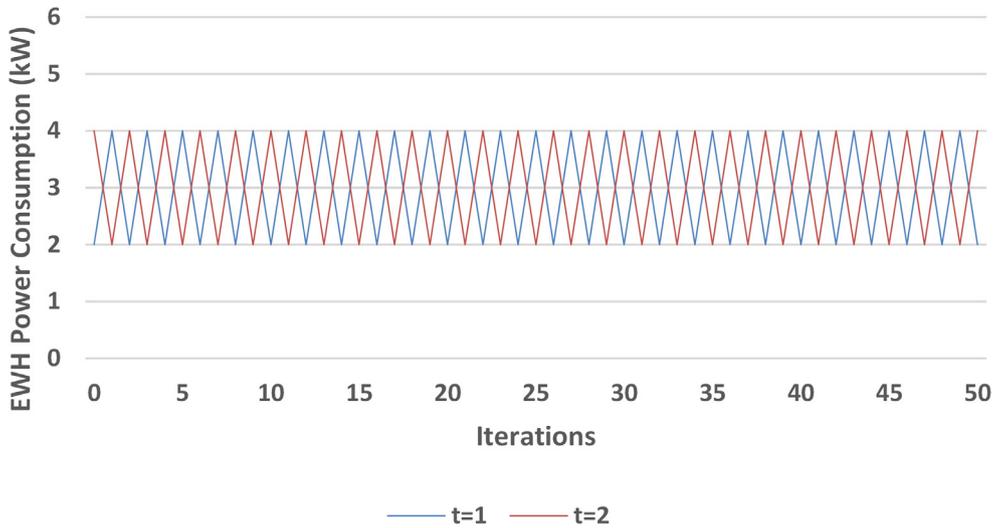


Fig. B1. The power schedules of Prosumer A without any techniques for convergence.

two hours respectively. The demand functions of Prosumer A are expressed as

$$d_{t=1}^* = \begin{cases} 2(\text{kW}) & \text{if } p_{t=1} > p_{t=2} \\ 4(\text{kW}) & \text{if } p_{t=1} < p_{t=2} \end{cases}$$

$$d_{t=2}^* = \begin{cases} 4(\text{kW}) & \text{if } p_{t=1} > p_{t=2} \\ 2(\text{kW}) & \text{if } p_{t=1} < p_{t=2} \end{cases} \tag{B1}$$

in which $d_{t=1}^*$ and $d_{t=2}^*$ consist the optimal heating schedule of Prosumer A given the electricity prices. The demand function of Prosumer A exhibits a discontinuity when $p_{t=1} = p_{t=2}$. That is, the price response ($d_{t=1}^*$ and $d_{t=2}^*$) will jump between 2 kW and 4 kW when the sign of the correlation of the respective prices changes, and at $p_{t=1} = p_{t=2}$, the price response becomes singular because the total electricity cost of Prosumer A is always the same whatever the heating schedule is. This discontinuity may result in divergence of the simulation. Assume that there is another prosumer, Prosumer B, who only owns PV panels and the PV power outputs of the two hours are $P_{t=1}^{PV} = 3(\text{kW})$ and $P_{t=2}^{PV} = 3(\text{kW})$ respectively. The PV power outputs are assumed as uncontrollable. Prosumer A and Prosumer B form a P2P energy sharing community and supply and demand ratio (SDR) mechanism (detailed in Section A.2.1 of Appendix A) is assumed to be adopted. Assume that the retail price and export price offered by the retailer are 14.57 pence/kWh and 5.03 pence/kWh respectively. If the initial schedule of Prosumer A is assumed to be

$$P_{t=1, \text{iter}=0}^{\text{EWH}} = 2(\text{kW}) \text{ and } P_{t=2, \text{iter}=0}^{\text{EWH}} = 4(\text{kW}), \tag{B2}$$

then at 1st iteration, according to Formulae (A18)–(A23) in Appendix A, the internal buying prices will be

$$p_{t=1, \text{iter}=1}^{\text{buying}} = 5.03(\text{pence/kWh}) \text{ and } p_{t=2, \text{iter}=1}^{\text{buying}} = 8.15(\text{pence/kWh}). \tag{B3}$$

Due to the fact that $p_{t=1}^{\text{buying}} < p_{t=2}^{\text{buying}}$, according to Formula (B1), Prosumer A will reschedule the heater as

$$P_{t=1, \text{iter}=1}^{\text{EWH}} = 4(\text{kW}) \text{ and } P_{t=2, \text{iter}=1}^{\text{EWH}} = 2(\text{kW}), \tag{B4}$$

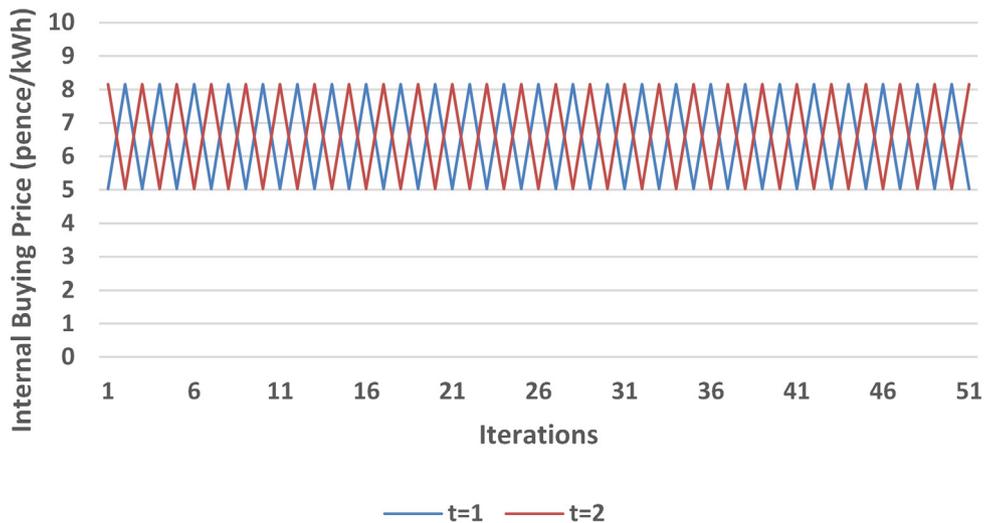


Fig. B2. The internal buying prices without any techniques for convergence.

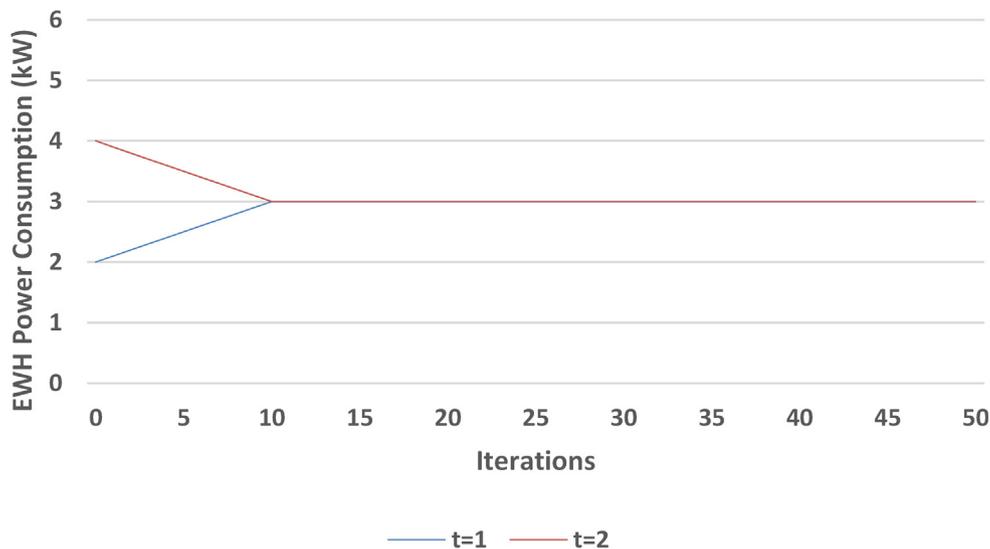


Fig. B3. The power schedules of Prosumer A with a limitation for its power change (± 0.1 kW).

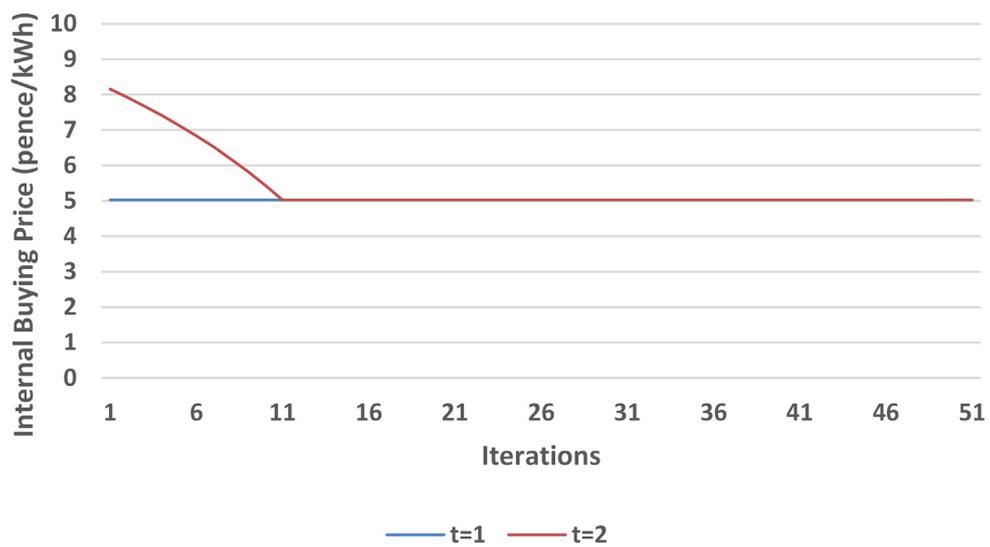


Fig. B4. Internal buying prices with a limitation for Prosumer A's power change (± 0.1 kW).

and send the schedule to the P2P energy sharing coordinator. Then 2nd iteration begins. The coordinator issues the new internal prices based on the schedule made at 1st iteration, being

$$p_{t=1,iter=2}^{buying} = 8.15(\text{pence/kWh}) \text{ and } p_{t=2,iter=2}^{buying} = 5.03(\text{pence/kWh}). \tag{B5}$$

Now $p_{t=1}^{buying} > p_{t=2}^{buying}$, so Prosumer A reschedules the heater as

$$P_{t=1,iter=2}^{EWH} = 2(\text{kW}) \text{ and } P_{t=2,iter=2}^{EWH} = 4(\text{kW}). \tag{B6}$$

Note that the schedule becomes exactly the same as the initial schedule. Therefore, the mode in 1st and 2nd iteration will keep repeating in later iterations, and the simulation will never end (i.e. the simulation diverges), as illustrated in Figs. B1 and B2.

The above numerical example showcases how the discontinuity of the demand functions of prosumers finally result in divergence in P2P energy sharing. Note that as pointed in Ref. [48], little theory exists to guarantee 100% convergence for this type of problems, so heuristic techniques have to be used to help improve convergence.

Observing the iterative process of the above example (as showcased by Formulae (B2)–(B6) and illustrated in Figs. B1 and B2), it is seen that actually the SDR mechanism gave the right incentive signal every time (i.e. the internal prices motivated Prosumer A to change the schedule to use excess local PV generation from Prosumer B), but due to the discontinuity of the demand function, Prosumer A over-adjusted its power consumption every time, resulting in the oscillation-like divergence. Considering this fact, it is natural to be proposed to limit the change of power consumption of each prosumer for avoiding divergence. Therefore, now assume that at each iteration, Prosumer A is only allowed to at most make a ± 0.1 kW change to its schedule for each time slot. Also assume that Prosumer A will not change its schedule if no more cost can be saved. Keep all the other settings the same, and then run the simulation again. The results are shown in Figs. B3 and B4.

From Figs. B3 and B4, it can be seen that gradually guided by the internal prices, the simulation converges after 10th iteration. Thanks to the limitation for the allowable power change at each iteration, Prosumer A does not over-adjust its power any longer, so oscillation does not happen and convergence is finally achieved. At the convergence, the power consumption of Prosumer A is completely supplied by the local PV generation of Prosumer B at both hours, resulting in perfect local energy balance and the least electricity cost of the whole P2P energy sharing community.

The above example showcases how the limitation of power consumption change for each prosumer can contribute to better convergence. The ramping rate specified in the step length technique (as presented in Section 3.3.1) is a direct application of this idea. As for the learning process involvement (as presented in Section 3.3.2), the involvement of Formula (11) combines the past experience with current decision, making the decisions more stable, i.e. making the change of bids less severe throughout iterations. Therefore, the learning process involvement technique can somehow be seen as an indirect way to limit the change of prosumers' decision at each iteration.

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