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Peer-to-Peer energy trading in a Microgrid☆

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HIGHLIGHTS

- P2P energy trading refers to direct energy trading among prosumers and consumers.
- A P2P system architecture was developed.
- A P2P energy trading platform, Elecbay, was designed.
- P2P energy trading was simulated based on game theory.
- Results prove that P2P energy trading facilitates local power and energy balance.

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ABSTRACT

Peer-to-Peer (P2P) energy trading represents direct energy trading between peers, where energy from small-scale Distributed Energy Resources (DERs) in dwellings, offices, factories, etc, is traded among local energy prosumers and consumers. A hierarchical system architecture model was proposed to identify and categorize the key elements and technologies involved in P2P energy trading. A P2P energy trading platform was designed and P2P energy trading was simulated using game theory. Test results in a LV grid-connected Microgrid show that P2P energy trading is able to improve the local balance of energy generation and consumption. Moreover, the increased diversity of generation and load profiles of peers is able to further facilitate the balance.

1. Introduction

With the increasing connection of Distributed Energy Resources (DERs), traditional energy consumers are becoming prosumers, who can both consume and generate energy [1]. Electricity generation of DERs is usually intermittent and difficult to predict. When prosumers have surplus electricity, they can curtail it, store it with energy storage devices, export it back to the power grid, or sell it to other energy consumers. The direct energy trading among consumers and prosumers is called Peer-to-Peer (P2P) energy trading, which is developed based on the "P2P economy" concept (also known as sharing economy) [2], and is usually implemented within a local electricity distribution system.

A peer in the P2P energy trading refers to one or a group of local energy customers, including generators, consumers and prosumers. The peers buy or sell energy directly with each other without intermediation by conventional energy suppliers [3]. P2P energy trading is usually enabled by Information and Communication Technologies (ICT) -based online services [2].

Conventional energy trading is mainly unidirectional. Electricity is usually transmitted from large-scale generators to consumers over long distances, while the cash flow goes the opposite way. In contrast, the P2P energy trading encourages multidirectional trading within a local geographical area. Trials of energy trading based on the "P2P economy" concept have already been carried out across the globe, for example, Piclo in the UK [4], Vandebron in Netherlands [5], and sonnenCommunity in Germany [6]. These trials mainly focused on providing incentive tariffs to electricity customers from the energy suppliers' perspective.

Piclo is an online platform that performs peer-to-peer energy trading for generators and business consumers. It uses a matching algorithm to match local generation and consumption. Data visualizations and analytics are provided to customers. The meter data, generator pricing and consumer preference information are used to match electricity demand and supply every half hour. Generators have control and visibility over who buys electricity from them. Consumers can select and prioritize from which generators to buy electricity [4].

Vandebron is an online platform in Netherland where energy

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consumers can buy electricity directly from independent producers, such as farmers with wind turbines. Similar to Piclo, Vandebron acts as an energy supplier who provides incentive tariffs for consumers and generators to exchange energy. Prosumers who inject surplus energy to Vandebron are able to purchase energy from Vandebron at a lower price compared with other suppliers [5].

SonnenCommunity was developed by SonnenBatterie, which is a battery storage manufacturer in Germany. It is a community of SonnenBatterie owners who share self-produced energy with others with a low-priced tariff provided by SonnenCommunity. With a SonnenBatterie system and photovoltaic panels, members can completely cover their own energy needs on sunny days, and even have surplus energy. This surplus energy is not fed into the power grid, but into battery energy storage that serves the community when they cannot produce sufficient energy due to bad weather [6]. The idea is very similar to those of Piclo and Vandebron, but sonnenCommunity highlights the importance of the storage system.

In recent years, P2P energy trading has also been investigated at the distribution network level. In [7], a paradigm of P2P energy sharing among neighboring Microgrids was proposed for improving the utilization of local DERs and saving the energy bills for all Microgrids. Alam et al. [8] integrated a demand side management system coordinated with P2P energy trading among the households in the smart grid in order to minimize energy cost. In [9], an energy sharing model with price-based demand response was proposed. In [10], a non-cooperative game-theoretical model of the competition between demand response aggregators for selling energy stored in energy storage was illustrated.

The operation of Microgrids and multi-agent energy management systems in liberalized electricity has been widely discussed in recent years. Roche et al. [11] provided a review of several multi-agent systems which were used for grid energy management. A number of concepts and experiments were compared and analysed. In [12], a selection of available models for distributed generation planning and design was presented and analysed in the perspective of gathering their capabilities in an optimization framework to support a paradigm shift in urban energy systems. In [13], a retailing spot market of electric energy was proposed. Its interoperability with other stakeholders in the electric power infrastructure, which was modelled as a cooperating multi-agent system was elaborated. Mashhour et al. [14] presented a novel hourly-ahead profit model for an active distribution company, which had high capacity level of connected Distributed Generators (DGs) that could make selling proposals for the markets in a pool-based system. Besides, a profit-based network reconfiguration methodology for a multi-substation multi-feeder distribution company was also introduced and analysed. Vergados et al. [15] studied the problem of orchestrating the energy prosumers into virtual clusters, in order to participate in the market as a single entity and to reduce the total energy cost through the reduction of the total relative forecasting inaccuracies. In [16], a general framework for implementing a retail energy market based on the Nikaido-Isoda relaxation algorithm was proposed as an electricity market structure with large DERs penetration and demand side management of consumers. By considering the related uncertainties, the DERs were able to maximise their expected payoff or profit by undertaking strategies through the price bidding strategy considering Nash equilibrium. Coelho et al. [17] discussed the major issues and challenges in multi-agent system and smart Microgrids, presented a review of state-of-the-art applications and trends, and suggested future applications with attention to renewable energy resources integration in emerging scenarios, which would be able to decentralise the high complex energy system, allowing users to participate in the system more actively.

The work presented in this paper contains prominent novelty and contributions compared to the above listed literature. First of all, although many of the above listed papers (including [11,13,15–17]) considered liberalized markets in the forms of bilateral contracts, auctions or energy pools, the entities in the markets were all modelled as either generators or consumers. However, prosumers who are able to both generate and consume electricity are an important type of market entities, and they are not supposed to be modelled as pure generators or pure consumers. In this paper, the prosumers were modelled as entities that are able to shift their roles between generators and consumers. As a result, the ways of dealing with the energy trading among the market entities are changed as well. Secondly, in some of the studies mentioned in [17], the multi-agent systems were used for supporting Microgrid operation and management, or for improving supply reliability and stability. Those are different from the P2P energy trading discussed in this paper, in which the major objective of each peer is to maximise its own economic benefits. Thirdly, this paper establishes a four-layer system architecture model for P2P energy trading and proposes an associated bidding system for the P2P energy trading among consumers and prosumers in a grid-connected Microgrid for the first time, both of which were not addressed in existing studies. Last but not the least, this paper also provides more results on the benefits of P2P energy trading, which were not fully investigated in existing literature.

The structure of this paper is summarized as follows. In Section 2, a four-layer system architecture of the P2P energy trading is proposed. Section 3 discusses a business model and the design of an online trading platform 'Elecbay'. It is an example of the possible implementations in the business layer, based on which a P2P energy trading is carried out. In Section 4, game theory and Nash Equilibrium are used to validate how energy is traded among peers within a Microgrid during the bidding process. Case study is presented in Section 5, in which the benefits of using the P2P energy trading are demonstrated. Section 6 concludes the whole paper.

2. Four-layer system architecture of Peer-to-Peer energy trading

A four-layer system architecture is proposed for P2P energy trading, as shown in Fig. 1, to identify and categorize the key elements and technologies involved in P2P energy trading based on the roles they play.

There are three dimensions in the system architecture.

In the first dimension, the key functions involved in P2P energy trading are categorized into four interoperable layers. Each layer is introduced as follows.

The power grid layer consists of all physical components of the power system, including feeders, transformers, smart meters, loads, DERs, etc. These components form the physical electricity distribution network where P2P energy trading is implemented.

The ICT layer consists of communication devices, protocols, applications and information flow. Communication devices refer to sensors, wired/wireless communication connections, routers, switches, servers and various types of computers. Protocols include TCP/IP (Transmission Control Protocol/Internet Protocol), PPP (Point-to-Point Protocol), X2.5, etc. Communication applications can be various, such as information transfer and file exchange. The information flow refers to the senders, the receivers, and the content of each message transferred among communication devices.

The control layer mainly consists of the control functions of the electricity distribution system. Different control strategies are defined in this layer for preserving the quality and reliability of power supply and control the power flow. Voltage control, frequency control and active power control are examples of possible control functions in the control layer.

Business layer determines how electricity is traded among peers and with the third parties. It mainly involves peers, suppliers, distribution system operators (DSOs) and energy market regulators. Various kinds of business models could be developed in this layer to implement different forms of P2P energy trading.

The second dimension of the system architecture is categorized based on the size of the peers participating in P2P energy trading, i.e. premises, Microgrids, Cells, and regions (consisting of multi-Cells).

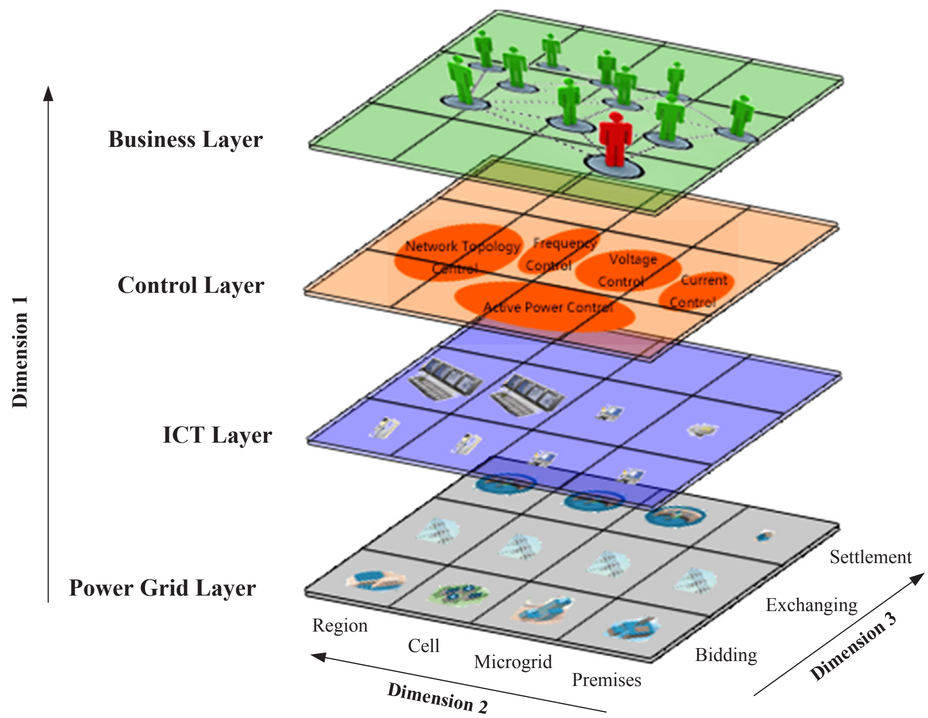

Fig. 1. A four-layer system architecture of Peer-to-Peer energy trading.

Individual premise refers to one single house connected to the electricity distribution system. Microgrids are electricity distribution systems containing loads and DERs, which operate in a controlled and coordinated way either connected to the main power network or islanded. A Microgrid normally consists of a collection of individual premises and DERs in a local geographical area that share the same medium-voltage/low-voltage (MV/LV) transformer. Similarly, Cell is a concept proposed in studies [18,19], and is an entity that consists of a number of Microgrids. It is used to define a wider area of network in which a collection of DERs can be controlled in response to a number of objectives [20]. A Cell may contain several Microgrids, and may also operate in either grid-connected or islanded mode. A region can be as large as a city or a metropolitan area which consists of multiple Cells. A Microgrid, a Cell or a region can all be considered as a peer and trade with each other.

The third dimension shows the time sequence of the P2P energy trading process. Bidding is the first process of P2P energy trading when energy customers (generators, consumers and prosumers) reach trading agreements with each other prior to the energy exchange. During the bidding process, energy customers interact with each other and agree on the price and amount of energy to be traded. Energy exchanging is the second process, during which energy is generated, transmitted and consumed. Settlement is the final process when bills and transactions are finally settled via settlement arrangements and payment. Considering the physical network constraints and uncertainty of DERs, a seller who has promised to sell a certain amount of electricity sometimes is unable to generate that exact amount as listed in the orders. The similar situation also applies to a buyer. The difference between the promised and actual electricity generation or consumption quantity needs to be calculated and charged during the settlement.

There are various types of elements and technologies which are suitable for the implementation of P2P energy trading. Identification is the process of finding or defining the key elements or technologies for P2P energy trading. Categorization is the process of grouping those key elements and technologies into different layers and sections as introduced in Fig. 1 for a better presentation and implementation. The categorization is mainly based on their functionality, size of peers and timescale in P2P energy trading.

This paper focuses on the business layer during the bidding process in a grid-connected LV Microgrid. The business layer presents the fundamental differences of P2P energy trading compared with traditional energy trading. Investigation of the business layer is also the basis of research in other layers.

3. Platform for Peer-to-Peer energy trading

Different energy trading arrangements for local distribution networks have been investigated, for example, the local pool concept was used to aggregates the distributed generation from a local area (pooling) to supply the local consumers without using additional wholesale market intermediaries [21]. The objective of the local pool is to balance the local energy generation and demand with minimum generation costs [22].

"P2P economy", also known as "sharing economy", was recently proposed for the energy trading arrangements in local distribution networks. P2P energy trading allows each peer (a consumer, a prosumer, a generator, or even a supplier) to decide with which peer to trade (buy from or sell to) energy according to its own objective, e.g. minimum costs, maximum profits, minimum pollution, most reliable energy supply, etc.

P2P energy trading cannot be applied without a software platform, which enables the information exchange among peers, and also assists the system operators (e.g. DSOs) to monitor and control the distribution network. In addition, different trading rules defined by the platform also have significant influences on the decisions made by peers when trading with other peers.

Various software platforms can be designed to facilitate P2P energy trading. The "Elecbay" proposed in this paper is used for the P2P energy trading in a grid-connected Microgrid. The key players of P2P energy trading include buyers, sellers, suppliers (suppliers can act as buyers or sellers), DSOs and the "Elecbay". The interactions of the key players during P2P energy trading are illustrated by Fig. 2.

"Elecbay" in Fig. 2 is a software platform on which peers (either energy sellers or buyers) trade energy with others. Energy sellers list the items, i.e. their surplus energy over half an hour, for sale. Energy buyers browse all the listed items and then place orders. Each order contains

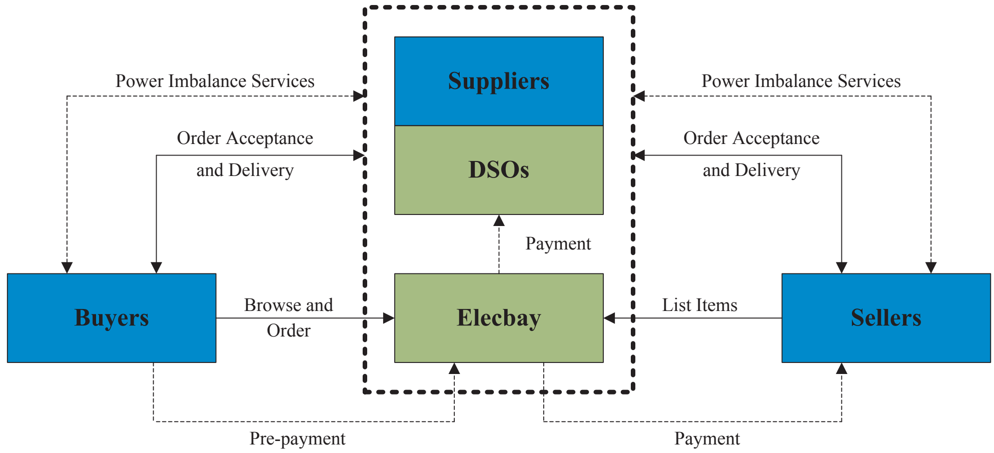

Fig. 2. Interactions of key players during P2P energy trading.

the information including the time period for the energy exchange, the amount of energy to be exchanged, the price of the energy to be exchanged and the details about the seller and buyer, e.g. the identities, the ratings of energy supply reliability, etc. Alternatively, energy sellers can also browse the items listed by energy buyers, i.e. the required energy over half an hour, and then place orders.

After the orders are placed by peers, they are either accepted or rejected by Elecbay, DSOs, and energy suppliers as shown in Fig. 2. The acceptance or rejection of each order is determined based on the network constraints, e.g. voltage excursion, thermal overloading, etc.

After the order acceptance or rejection, each peer generates/consumes the amount of energy as promised in the accepted orders. Energy is delivered through the distribution network. The energy balancing services are provided by Elecbay. The actual energy generation and consumption of each peer is recorded by smart meters.

However, as it is electrical energy traded on Elecbay, there can possibly be a disparity between the promised amount of energy in the placed orders and the actual energy consumption or generation recorded by smart meters. For peers who fail to generate/consume the promised amount of energy, they are required to trade with suppliers with less beneficial (selling or buying) prices and even charged with penalty. In this paper the selling and buying prices with suppliers and penalty are calculated based on the existing methods that are currently used in the GB (Great Britain) electricity wholesale market [23]. Payments are all made to Elecbay. After deducting service charges, Elecbay allocates the money to suppliers, DSOs, energy sellers, and energy buyers if they contribute to the energy balancing.

The processing of each order placed in Elecbay is further demonstrated in a time sequence in Fig. 3.

The publishing and bidding time period is the first time period of order process in Elecbay, during which peers are able to list items (the surplus energy over half an hour for sale, or the required energy over half an hour for purchase) and place orders. This time period starts several days, weeks or months before the half-hourly energy exchange time period, and ends by the gate closure, which is one hour before the energy exchange time period in this paper. Orders can be placed, cancelled or modified by peers only before the gate closure. Peers list items and place orders based on the forecast of their own energy generation and consumption. They make decisions to trade with other peers by comparing the amount and prices of energy to be exchanged.

During the one hour time period between the gate closure and the energy exchange time period, the order acceptance/rejection is carried out by the DSOs. They evaluate if there is going to be a network constraint violation, e.g. voltage excursion, thermal overloading, etc, when all the placed orders are accepted. Once a network constraint violation is identified, DSOs are the only entities which have the permission to modify or cancel orders after the gate closure. The rules for order modification or cancellation are various. For example, with the last on first off principle, the orders placed at a later time (i.e. closer to the gate closure) have a higher possibility to be cancelled.

During the half-hourly energy exchange time period, Elecbay provides the energy balancing services. The cost of all the actions taken for the energy balancing is recorded for the settlement time period. Besides, the actual energy generation and consumption of each peer is also recorded by the smart meter in each premise.

In the settlement time period, Elecbay liaises with DSOs and suppliers and provides the energy bill of each peer. This settlement and billing process takes time, and therefore the bills cannot be available to peers immediately. 1–31 days is considered in this paper as the length of this time period. As mentioned previously, for peers who fail to generate/consume the promised amount of energy, they are required to trade with suppliers with less beneficial (selling or buying) prices and even be charged with penalty. Elecbay collects the payment received from energy buyers, keeps the service charges, and then sends the rest to the relevant energy sellers and suppliers.

"Elecbay" is one of the first platforms proposed for P2P energy trading in LV distribution networks, where energy consumers and prosumers are given the options to be able to not only trade energy with energy suppliers, but also trade among each other. One peer is able to be either a seller or a buyer at different time periods of a day, which is very different compared to the current GB electricity wholesale market, where generators are constantly sellers and suppliers are constantly buyers.

The publishing and bidding time period is the most unique time

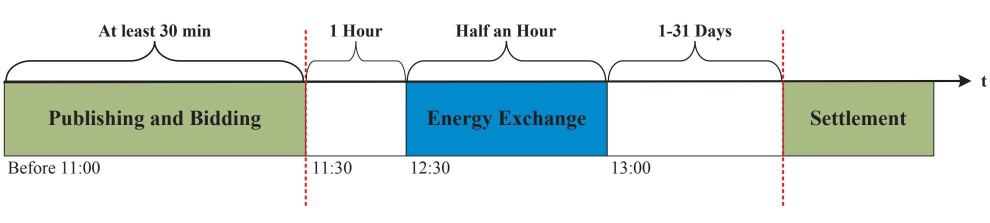

Fig. 3. An example of processing of an order in Elecbay.

period that makes P2P energy trading arrangements different from other existing energy trading arrangements in the distribution networks. Therefore it is the basis of the study on other time periods in P2P energy trading. The simulation method and case study demonstrated in Sections 4 and 5, which validate the publishing and bidding time period in a grid-connected LV Microgrid with different types of energy prosumers, are both based on the design of Elecbay proposed in this section.

4. Simulation of P2P bidding

The simulation of the bidding through the P2P energy trading platform “Elecbay” is of great importance, which could be used to:

1. demonstrate how energy consumers and prosumers within a grid-connected LV Microgrid carry out P2P energy trading with each other;
2. obtain new load profiles of energy consumers and prosumers to quantify how their energy consumption is affected by the P2P energy trading; and
3. enable analysis and control of grid-connected Microgrids and power grids under the P2P energy trading.

The simulation mimics the bidding of energy consumers and prosumers before the gate closure. Input data of the simulation, including the generation profiles of energy prosumers and the consumption profiles of energy consumers and prosumers, is based on forecast information. Besides, the following assumptions were made:

1. The P2P energy trading through “Elecbay” is competitive, which means energy consumers and prosumers are not aggregated with each other for achieving higher benefits via co-operation.
2. Energy consumers and prosumers are considered as “good citizens”, who contribute to maintaining local energy balance.
3. Energy suppliers (i.e. the electricity retailers) are passive peers in this paper. They buy energy from energy prosumers with low unit prices, and sell energy to energy consumers and prosumers with high unit prices. Energy consumers and prosumers consider energy suppliers as the last peer to trade with during the P2P bidding. This assumption is consistent with the reality in many countries such as the UK.
4. Service charges of Elecbay are neglected in this paper

4.1. Roles of flexible demand and storage in Peer-to-Peer energy trading

In Elecbay, energy consumers and prosumers sell and buy energy by scheduling the energy devices in their own premises. There are mainly three types of energy devices owned by typical small-scale residential and commercial energy consumers and prosumers, as shown in Fig. 4. Generation includes Photovoltaic (PV) panels, wind turbines, Combined Heat and Power (CHPs) units, micro-turbines, etc. Demand includes non-flexible demand and flexible demand. Electrical storage, which is able to either provide or consume energy, includes batteries, electrical vehicles (EVs), etc.

The strategic bidding behaviours of small-scale energy consumers

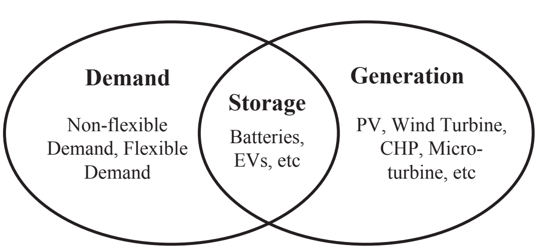

Fig. 4. Categories of energy devices in residential/commercial premises.

and prosumers in P2P energy trading mainly rely on the scheduling of flexible demand and storage systems, if the generation is considered to be from the uncontrollable renewable energy. DGs from intermittent renewable energy are able to be managed through disconnecting/reconnecting operations or derating maximum power outputs for energy trading purposes. However, those techniques are not investigated in this paper because it will be more beneficial for each individual peer to always keep its DG connected and generating maximum power, considering the zero marginal cost of renewable energy. Although energy storage systems are able to provide significant amount of flexibility for P2P energy trading, they are still generally very expensive. Therefore, this paper focuses on investigating the feasibility of P2P energy trading with flexible demand scheduling only. Specifically, electric water heaters with tanks are considered as representatives. The use of energy storage was not considered in this paper.

Note that in this paper, the flexible demand is scheduled without sacrificing any satisfaction of end users. The flexible demands considered in the case study of this paper are electric water heaters with tanks, which have thermal storage capability. This capability results in the fact that there are many different heating schedules that are all able to totally satisfy users’ demand (in this case, to prepare enough hot water with required temperature for users throughout the day), and thus brings flexibility for scheduling. For example, to prepare required amount of hot water with required temperature to be used at 5:00 p.m., the water can be pre-heated either during 3:00–4:00 p.m. or during 4:00–5:00 p.m. without any difference in terms of satisfying users’ hot water need. In other words, by limiting the minimum and maximum water temperature in tank as presented in Section 4.2.1, the scheduling of water heaters will not cause any dissatisfaction for end users. This way of dealing with flexible demands is commonly used in many existing studies such as [24,25]. Beyond this way, to compromise satisfaction of end users will bring more flexibility for scheduling but involve more social cost at the same time, which is not considered in this paper.

4.2. Simulation of a single time period using game theory

This section illustrates the method used for simulating the P2P bidding within a single energy exchange time period through the P2P energy trading platform Elecbay. Game theory was used for the simulation.

There are two basic types of games in game theory: cooperative games and non-cooperative games. A cooperative game is a game where groups of players enforce cooperative behaviour, and hence the game is a competition between coalitions of players, rather than between individual players. A non-cooperative game is a game in which players make decisions independently, for example, auctions and strategic voting [26]. A Nash equilibrium is a solution of a non-cooperative game involving two or more players, in which each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing only their own strategy [27].

During the P2P bidding for a single energy exchange time period, the interaction among peers is modelled as a non-cooperative game, due to the assumptions made at the beginning of this section. The solution of the game, in which no peer is able to increase the benefit by modifying only its own placed orders, is the Nash equilibrium, which is considered as the result of P2P bidding through Elecbay.

4.2.1. The formulation of P2P bidding as a non-cooperative game

Players of the game are energy consumers and prosumers with flexible demand. Denote $N = \{1, 2, \ldots, i \ldots, n\}$, where n is the number of players in the game, and N is the set of players in the game.

Strategies of a player are the decided status of flexible demand, which directly affect the amount of electricity to be injected to (positive value) or absorbed from (negative value) the Microgrid and are denoted by $s^i_{j^i}$, $j^i = 1,2,\ldots,m_i$, where m_i stands for the number of strategies that player i can choose. S^i is denoted as the set of strategies of player i. In this paper, $m_i = 2$, which means that the flexible demand of each consumer or prosumer is scheduled either ON or OFF during the 30-min energy exchange time period.

A strategy combination is the combination of strategies chosen by the players in the game, which is denoted as $s \in \{(s_1^1, s_1^2, ..., s_1^n), ..., (s_{m_1}^1, s_{m_2}^2, ..., s_{m_n}^n)\}$. Each strategy combination consists of n elements. Denote S to be the set of all the possible strategy combinations in the game.

The total number of strategy combinations in the game is

$$M = \prod_{i=1}^{n} m_i \tag{1}$$

The payoff function is a mathematical function describing the award obtained by a single player at the outcome of a game, which motivates the player to adopt certain strategy and thus is the key to simulate the behaviour of the player [28]. The payoff function used in this paper is defined as follows:

$$u_k^i = \frac{(L + E_{out-i-k}) \times C_k^i}{|E_{mgout-k}| + \varepsilon} \tag{2}$$

in which

$$L = \begin{cases} |\min(E_{out-i-k})| & if\ \min(E_{out-i-k}) < 0 \\ 0 & if\ \min(E_{out-i-k}) \geqslant 0 \end{cases}$$

where $k \in [1, M]$. k denotes one of the strategy combinations in S; u_k^i denotes the payoff value of player i in strategy combination k; $E_{out\text{-}i\text{-}k}$ denotes the amount of electrical energy injected to (positive value) or absorbed from (negative value) the Microgrid by player i in strategy combination k; $\min(E_{out-i-k})$ is the minimum value of $E_{out\text{-}i\text{-}k}$ for all players in all strategy combinations; L is a constant that levels up the u_k^i to always be a non-negative value; Therefore, if $\min(E_{out-i-k}) \geqslant 0$, meaning that all the values of $E_{out\text{-}i\text{-}k}$ for any player in any strategy combination is above or equal to zero, hence $L = 0$ is sufficient to guarantee that u_k^i is a non-negative value; in contrast, if $\min(E_{out-i-k}) < 0$, L needs to be at least equal to the absolute value of $\min(E_{out-i-k})$ in order to guarantee that u_k^i is a non-negative value; $|E_{mgout\text{-}k}|$ denotes the absolute value of energy exchange between the Microgrid and the utility grid in strategy combination k; ε is a very small positive constant which guarantees the denominator not to be zero; C_k^i stands for the comfort index of user i in strategy combination k, which will be explained in details later in this section.

The higher the payoff value u_k^i is, the better the outcome of strategy combination k is recognized by the player i. As introduced in Eq. (2), the payoff value of player i in strategy combination k is determined by three factors, as explained below.

The first factor is $E_{out\text{-}i\text{-}k}$. The higher $E_{out\text{-}i\text{-}k}$ is, the larger amount of energy is injected to the Microgrid, or the smaller amount of energy is consumed by the player i, and the higher possibility there is that player i is able to sell more energy to, or buy less energy from other players or energy suppliers via the P2P energy trading platform. Therefore, $E_{out\text{-}i\text{-}k}$ is placed in the numerator so that the higher $E_{out\text{-}i\text{-}k}$ is, the higher u_k^i is.

The second factor is $|E_{mgout\text{-}k}|$. This factor is introduced to the payoff function in order to reflect and minimise the energy exchange between the Microgrid and the external utility grid for local energy balancing. Therefore, $|E_{mgout\text{-}k}|$ is placed in the denominator so that the lower $|E_{mgout\text{-}k}|$ is, the higher u_k^i is.

The third factor is the comfort index C_k^i. It is defined to guarantee that the scheduling of flexible demand does not worsen the customer comfort, specifically thermal comfort given that water heaters with tanks are considered in this paper. The thermal index C_k^i is placed in the numerator as a multiplier and takes a binary value (either 0 or 1) following this principle: if the strategy chosen by a player does not lead to thermal comfort violation or does alleviate the existing thermal comfort violation, C_k^i takes the value of 1 to approve the current strategy; otherwise, C_k^i denies the strategy by taking the value of 0, which results in the minimum value of the payoff function u_k^i (equal to 0). Quantitatively, the thermal comfort is measured by the temperature of water in the tank after scheduling, denoted by T_k^i [29]. The detailed logic on how C_k^i takes values is described as the following formula:

Table 1
Relationship between the comfort index of a player and the water temperature in the tank after scheduling.

	$T_k^i < T_{min}^i$	$T_{min}^i \leqslant T_k^i \leqslant T_{max}^i$	$T_k^i > T_{max}^i$
Strategy 1 (Flexible Demand ON)	$C_k^i = 1$	$C_k^i = 1$	$C_k^i = 0$
Strategy 2 (Flexible Demand OFF)	$C_k^i = 0$	$C_k^i = 1$	$C_k^i = 1$

$$C_k^i = \begin{cases} 0, & if\ T_k^i > T_{max}^i\ and\ the\ heater\ is\ ON,\ or\ if\ T_k^i < T_{min}^i \\ & and\ the\ heater\ is\ OFF \\ 1, & if\ T_k^i < T_{min}^i\ and\ the\ heater\ is\ ON,\ or\ if\ T_k^i > T_{max}^i \\ & and\ the\ heater\ is\ OFF, \\ & or\ if\ T_{min}^i \leqslant T_k^i \leqslant T_{max}^i \end{cases} \tag{3}$$

where T_{min}^i and T_{max}^i stand for the lower and the upper limits of the water temperature in the tank owned by player i.

The relationship between C_k^i and T_k^i is further explained in Table 1.

If $T_{min}^i \leqslant T_k^i \leqslant T_{max}^i$, which means the water temperature in the tank after scheduling is within the temperature limits, the comfort index C_k^i equals to 1 whenever the flexible demand is ON or OFF. In this case, both strategies are approved because the thermal comfort will always be guaranteed.

If $T_k^i < T_{min}^i$, which means the water temperature in the tank after scheduling is lower than the lower temperature limit, the value of comfort index C_k^i depends on the strategy taken. The Strategy 1 (ON) is helpful to increase the water temperature (although still lower than the lower limit), so it is approved, i.e. C_k^i equals to 1. On the other hand, the Strategy 2 (OFF) will further decrease the water temperature, which worsens the thermal comfort, so it is denied by setting C_k^i as 0. The situations where $T_k^i > T_{max}^i$ are similar to those where $T_k^i < T_{min}^i$, so the corresponding explanation will not be presented for conciseness.

With the payoff function (2), the associated payoff value of player i given a strategy combination s can be calculated, donated as $u^i(s)$.

4.2.2. The calculation of the Nash equilibrium in a non-cooperative game

This subsection describes the method used to calculate the Nash equilibrium of the non-cooperative game established in the previous sub-section.

In game theory, a player's strategy is defined as any of the options the player is able to choose in a strategy set where the outcome depends not only on its own action, but also on actions of other players. A pure strategy provides a complete definition of how a player plays the game. A mixed strategy is an assignment of a probability to each pure strategy. It allows for each player to randomly select a pure strategy. Mixed strategies are considered in the calculation in this sub-section. It is assumed that for any player i, the probability of adopting one pure strategy $s_{j^i}^i \in S^i$ is $\sigma_{j^i}^i$. The mixed strategy of player i is therefore defined as $\{\sigma_{j_i}^i | j_i = 1,2,...,m_i\}$, donated as σ^i, and the following equation holds:

$$\sum_{j_i=1}^{m_i} \sigma_{j^i}^i = 1 \tag{4}$$

A mix strategy combination of all the players is donated as $\sigma = (\sigma^{-i}, \sigma^i)$, where σ^{-i} represents the set of the mix strategies of all the players except player i. The payoff value of player i given a mix strategy combination σ is calculated by

$$u^i(\sigma) = \sum_{s \in S} [u^i(s) \cdot \prod_{i \in N} \sigma_{j^i}^i] \tag{5}$$

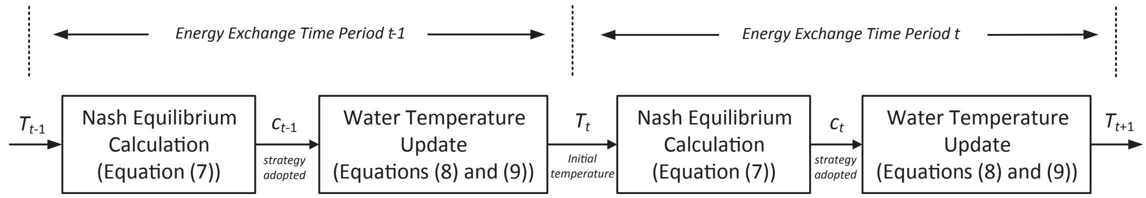

Fig. 5. The procedure of the multi-time period simulation.

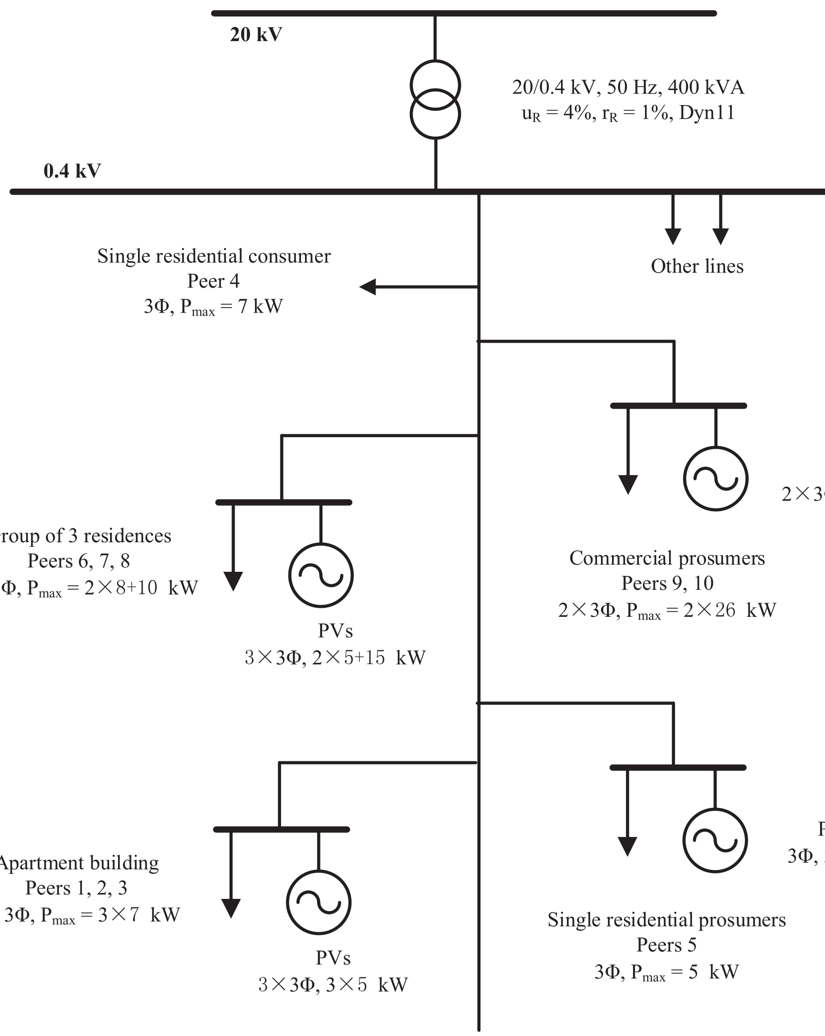

Fig. 6. The Benchmark LV Microgrid adapted from [29].

where $s = (s^1_{j^1}, s^2_{j^2}, ..., s^n_{j^n})$.

Given all the above, the definition of Nash equilibrium is able to be derived. A mixed strategy combination σ^* is a Nash equilibrium if

$$u^i(\sigma^*) \geqslant u^i(\sigma^{*-i},\sigma^i)\ , \quad \forall\ i \in N\ , \forall\ \sigma^i \in \Sigma^i \tag{6}$$

where Σ^i denotes the set of all the mixed strategies of player i.

According to [28], the calculation of this Nash equilibrium is equivalent to solving the following optimization problem:

$$\begin{aligned} &\min \sum_{i \in N} [\beta^i - u^i(\sigma)] \\ &s.\ t.\ u^i(\sigma^{-i}, s^i_{j^i}) - \beta^i \leqslant 0 \quad \forall\ j^i = 1,...,m_i\ , \forall\ i \in N \\ &\sum_{j_i=1}^{m_i} \sigma^i_{j_i} = 1 \qquad \forall\ i \in N \\ &\sigma^i_{j^i} \geqslant 0 \qquad \forall\ j^i = 1,...,m_i\ , \forall\ i \in N \end{aligned} \tag{7}$$

where β^i is an ancillary variable, which represents the highest possible payoff value of the player i. It is a decision variable that is calculated by solving the optimization problem expressed by Eq. (7), rather than a parameter that is given as input to the optimization. Considering that $u^i(\sigma)$ stands for the payoff value of player i in the strategy combination σ, the objective function of the optimization problem (7) is to minimize the sum of differences between the highest possible payoff value β^i and the payoff value $u^i(\sigma)$ in the strategy combination σ, so that after optimization, the calculated strategy combination σ is the one that makes each player have a payoff value that is close to the highest possible value as much as possible. It is proved that this strategy combination σ is just a Nash Equilibrium of the game studied. Detailed proof has been provided in [28].

By solving the optimization problem presented as Eq. (7), the Nash equilibrium of the non-cooperative game is found.

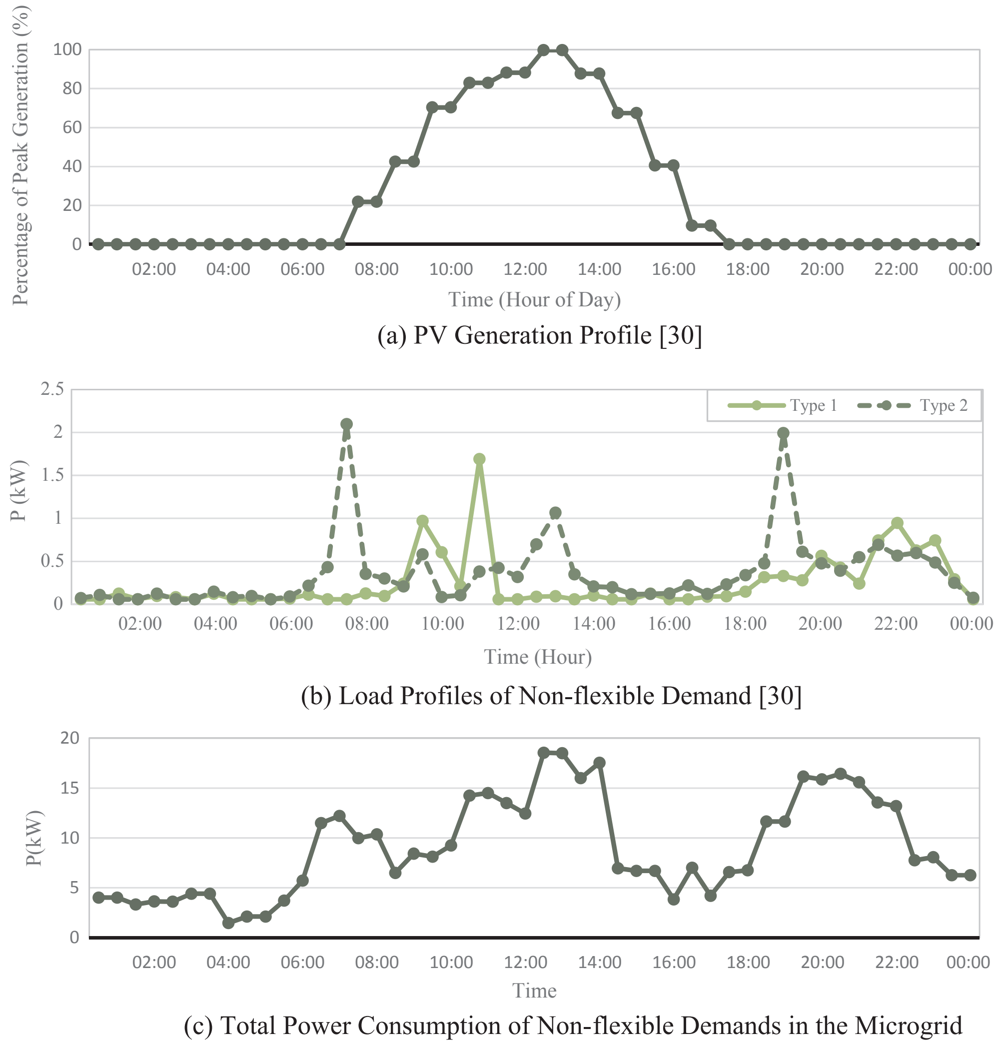

Fig. 7. Input data of Peers 1 and 2, and the total non-flexible demands of the Microgrid in Case Study 5.1.

Table 2
Key parameters of Peers 1 and 2 in Case Study 5.1.

Parameters	Peer 1	Peer 2
Maximum PV generation	5 kW	5 kW
Maximum flexible demand	3 kW	3 kW
[T_{min}, T_{max}] of flexible demand	[55, 65] (°C)	[55, 65] (°C)
Q of flexible demand	3 kW	3 kW
R of flexible demand	1.52 °C/kW	1.52 °C/kW
C of flexible demand	863.4 kWh/°C	863.4 kWh/°C
V of flexible demand	50 gallon	50 gallon
Maximum non-flexible demand	4 kW	4 kW
Non-flexible load profile	Type 1	Type 2

4.3. Simulation of multiple time periods considering time-coupled constraints of water temperature

This section illustrates the consideration for simulating the P2P bidding for multiple energy exchange time periods through the P2P energy trading platform Elecbay. In any energy exchange time period t, the initial water temperature needs to be given for each player to calculate the payoff value, based on which the control strategy is made and the Nash equilibrium is found. For a water heater of any player, the initial water temperature of time period t is determined by the initial temperature and the strategy of the previous time period $t-1$. The quantitative relationship is specified as follows:

$$T_t = \theta_{t-1} - (\theta_{t-1} - T_{t-1})e^{\left[-\frac{\Delta t}{RC}\right]} + c_{t-1}\cdot QR\left(1 - e^{\left[-\frac{\Delta t}{RC}\right]}\right) \tag{8}$$

where T_t and T_{t-1} are the initial water temperature in tank of time periods t and $t-1$; θ_{t-1} is the ambient temperature in time period $t-1$; c_{t-1} is the actual ON/OFF status of the water heater during time period $t-1$; Δt is the length of an energy exchange time period; Q, R and C are heater capacity, thermal resistance and thermal capacitance of the water heater respectively. When hot water is consumed, the water temperature changes by

$$T_t = \frac{[T_{cur,t}\cdot(V - d_{t-1}) + \theta_{t-1}\cdot d_{t-1}]}{V} \tag{9}$$

where $T_{cur,t}$ is the initial water temperature of time period t before considering the consumption during time period $t-1$; V is the mass of water in full storage; d_{t-1} is the demand of hot water drawn during time period $t-1$.

With Eqs. (8) and (9), the multiple energy exchange time periods are linked and the water temperature change is simulated throughout the time line. The procedure of the multi-time period simulation is summarized in Fig. 5.

Note that if the strategies at the calculated Nash equilibrium are pure strategies, the pure strategies can directly be taken as the adopted control strategies, c, between the Nash equilibrium calculation and water temperature update blocks in Fig. 5. However, if the strategies at the calculated Nash equilibrium are mixed strategies, the adopted

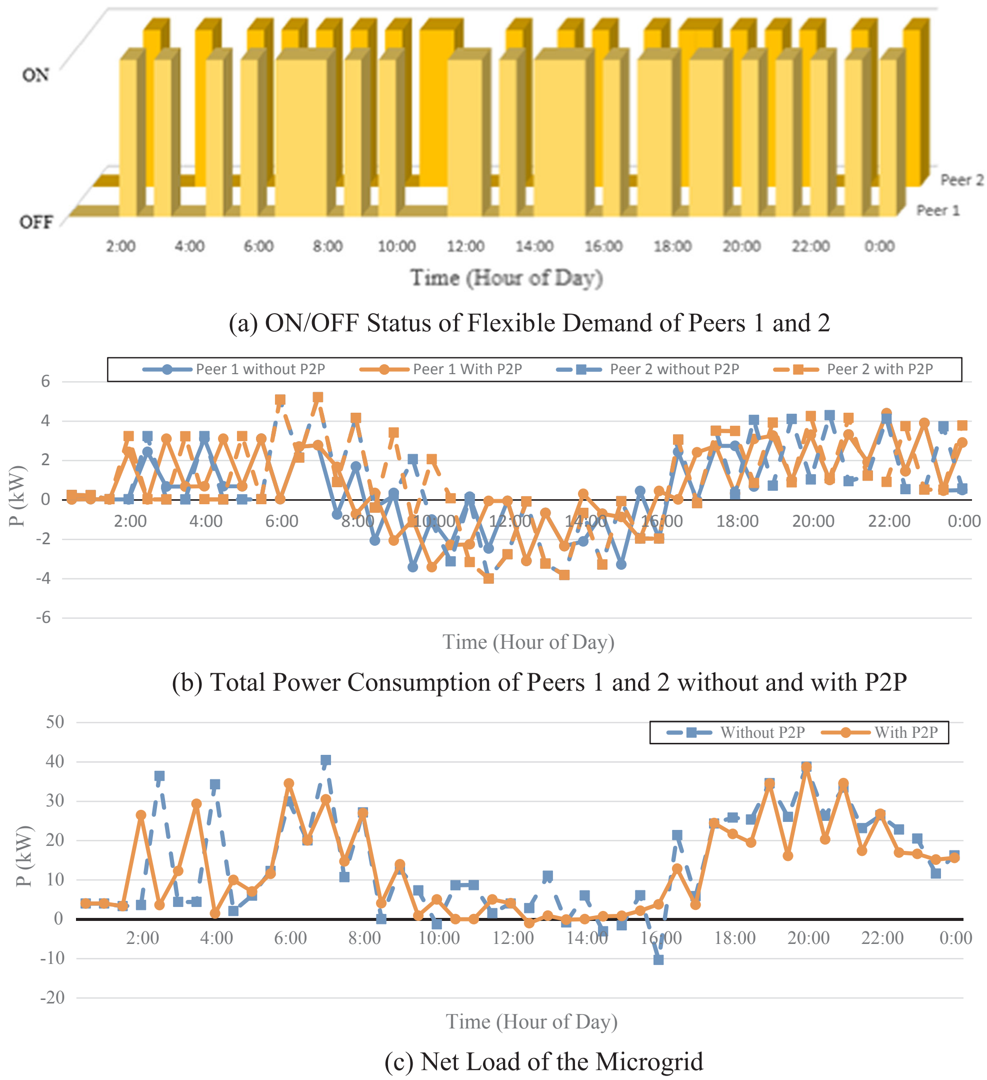

Fig. 8. Simulation results of Peers 1 and 2, and the Microgrid in Case Study 5.1.

Table 3
Comparison of energy exchange between the Microgrid and the utility grid over one day and peak load of the Microgrid in Case Study 5.1.

	Energy Exchange (kWh)	Reduction of Energy Exchange	Peak Load (kW)	Reduction of Peak Load
Without P2P	339.34	N/A	40.51	N/A
With P2P	308.15	9.19%	38.73	4.41%

control strategies need to be decided by sampling from the probability distribution in the mixed strategies, e.g. using Monte Carlo sampling, and in this case the multi-time period simulation needs to be conducted many times to get results with statistical significance.

5. Case study

5.1. Case study in a Benchmark LV Microgrid

A Benchmark LV Microgrid, as shown in Fig. 6, was used for the case study to test the bidding through the proposed P2P energy trading

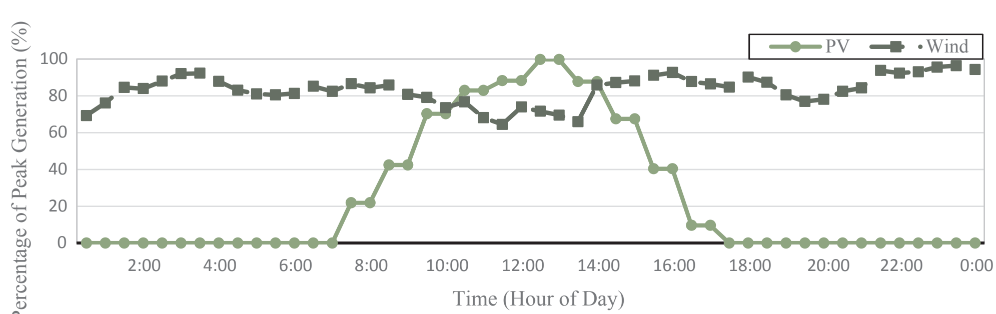

Fig. 9. PV and wind generation profiles in Case Study 5.2.

Table 4
Key parameters of Peers 1, 2 and 3 in Case Study 5.2.

Parameters	Peer 1	Peer 2	Peer 3
Maximum PV generation	5 kW	5 kW	N/A
Maximum wind generation	N/A	N/A	5 kW
Maximum flexible demand	3 kW	3 kW	3 kW
[T_{min}, T_{max}] of flexible demand	[55, 65] (°C)	[55, 65] (°C)	[55, 65] (°C)
Q of flexible demand	3 kW	3 kW	3 kW
R of flexible demand	1.52 °C/kW	1.52 °C/kW	1.52 °C/kW
C of flexible demand	863.4 kWh/°C	863.4 kWh/°C	863.4 kWh/°C
V of flexible demand	50 gallon	50 gallon	50 gallon
Maximum non-flexible demand	4 kW	4 kW	4 kW
Non-flexible load profile	Type 1	Type 2	Type 1

platform "Elecbay" [2,29].

There are 10 peers in the benchmark LV Microgrid in total. It was assumed that (1) all of the peers have both non-flexible and flexible demands in their premises; (2) all of the flexible demands are electric water heaters with tanks; (3) all of the peers except Peer 4 have DGs connected to their premises; and (4) all of the DGs are considered to be PV panels in this case study.

Table 5
Comparison of energy exchange between the Microgrid and the utility grid over one day and peak load of the Microgrid in Case Study 5.2.

	Energy Exchange (kWh)	Reduction of Energy Exchange	Peak Load (kW)	Reduction of Peak Load
Without P2P	204.31	N/A	31.87	N/A
With P2P	117.49	42.49%	26.26	17.60%

Table 6
Comparison of results in Case Study 5.1 and Case Study 5.2.

	Reduction of Energy Exchange with P2P	Reduction of Peak Load with P2P
Case Study 5.1 (Low Diversity)	9.19%	4.41%
Case Study 5.2 (High Diversity)	42.49%	17.60%

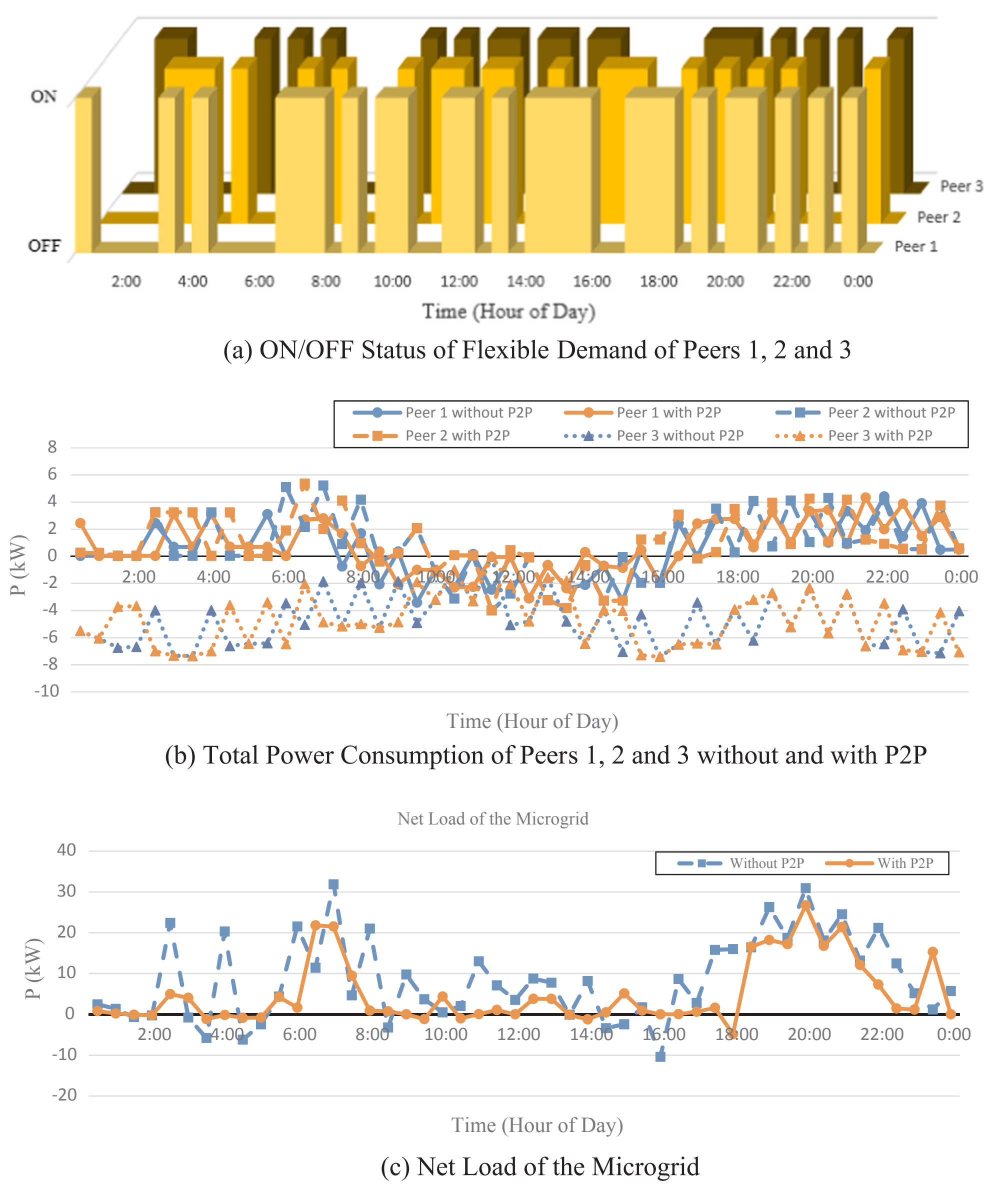

Fig. 10. Simulation results of Peers 1, 2 and 3, and the Microgrid in Case Study 5.2.

The input data, including the PV generation profiles, and the load profiles of the non-flexible demand (both Types 1, 1-person residential premise and Type 2, 2-person residential premise), were produced by the CREST (Centre for Renewable Energy Systems Technology) demand model [30]. The inputs of Peers 1 and 2 are taken as examples that are shown in Fig. 7(a) and (b) and Table 2. The overall power consumption of non-flexible demands in the Microgrid is shown in Fig. 7(c). $L = 26.00$ (kW) and $\varepsilon = 0.01$ (kW) for the payoff function Eq. (2).

As shown in Fig. 6, Peers 1 and 2 are both located in the same residential apartment building. Moreover, as listed in Table 2, their maximum PV generation, flexible demand and non-flexible demand are also the same. Therefore, they were chosen as examples throughout the case study to demonstrate and compare the impact of P2P energy trading on the residential energy prosumers of the same scale but with different power consumption patterns.

Simulation results are presented in Fig. 8 and Table 3.

Fig. 8(a) shows that with P2P energy trading, the flexible demand owned by peers of different non-flexible load profiles are scheduled to be ON during different time periods of the day. The flexible demand is less likely to be turned ON or OFF simultaneously, even given that they are assumed to have very similar types of water heater, water usage pattern and initial water temperature in tank. Fig. 8(b) further illustrates the power consumption of those peers with or without P2P energy trading over a day. The peaks of their power generation and consumption appear at different time periods of the day.

Fig. 8(c) and Table 3 show that with P2P energy trading, the overall energy exchange between the Microgrid and the utility grid is reduced. However, the local generation and demands are not well balanced due to the relatively low diversity of generation and load profiles of peers. The reduction of the peak load of the whole Microgrid after adopting P2P energy trading is only 4.41%.

5.2. Case study in a LV Microgrid with higher peer variety

Based on Case Study 5.1, another case was designed with higher peer diversity. The DGs owned by peers 3, 8 and 10 were changed to wind turbines with the same generation capacity. The generation profiles of the wind turbines were shown in Fig. 9. Other relevant inputs were illustrated in Fig. 7(b), (c) and Table 4. $L = 26.00$ (kW) and $\varepsilon = 0.01$ (kW) for the payoff function Eq. (2).

Simulation results are presented in Fig. 10 and Table 5.

Fig. 10(a) shows that with P2P energy trading, the flexible demand owned by peers of different non-flexible load profiles and different type of DGs are scheduled to be ON during different time periods of the day. The flexible demand is less likely to be turned ON or OFF simultaneously. Especially for Peer 3 whose DG is a wind turbine, its flexible demand is scheduled in a very different pattern compared with Peers 1 and 2. Fig. 10(b) illustrates the power consumption of those peers with or without P2P energy trading over a day. The peaks of their power generation and consumption appear at different time periods of the day.

Fig. 10(c) and Table 5 show that with P2P energy trading, the overall energy exchange between the Microgrid and the utility grid is significantly reduced. The local generation and demands are also more balanced compared with the simulation results in Case Study 5.1. The reduction of the peak load of the whole Microgrid has increased to 17.60%, compared with 4.41% in Case Study 5.1. This is due to the increased variety of peers in the Microgrid.

Compared the results of Case Studies 5.1 and 5.2, as shown in Table 6, it is concluded that with higher peer variety, the reduction of energy exchange between the Microgrid and the utility grid with P2P energy trading significantly increased (from 9.19% to 42.49% comparing the two cases). Besides, the reduction of peak load with P2P energy trading also rose (from 4.41% to 17.60% comparing the two cases). That is to say, P2P energy trading is able to better reduce the energy exchange between the Microgrid and the utility grid, and better balance local generation and demand.

Note that only one type of flexible demand (electric water heaters with tanks) is considered so far in the case study. With the introduction of other advanced technologies such as energy storage, flexible DG operations, etc, the benefits of P2P energy trading have the potential to become even more significant.

6. Conclusion

P2P energy trading is one of the promising paradigms of future smart grid, which enables the direct energy trading among energy consumers and prosumers in local power networks. A four-layer system architecture of P2P energy trading was proposed to identify and categorize the key elements and technologies involved in P2P energy trading. A P2P energy trading platform “Elecbay” was designed for a grid-connected LV Microgrid. The simulation of P2P bidding among energy consumers and prosumers through the energy trading platform “Elecbay” was developed using game theory.

Case studies show that P2P energy trading is able to reduce the energy exchange between the Microgrid and the utility grid and balance local generation and demand, and therefore, has the potential to facilitate a large penetration of renewable energy resources in the power grid. The increased variety of energy consumers and prosumers in the Microgrid is able to further improve the benefits of P2P energy trading.

This paper demonstrates the possibilities and potential benefits of integrating P2P energy trading in local power networks from the technical perspectives. However, a series of reforms on the current energy policy, laws and energy trading systems are still required before it becomes a reality. Besides, the introduction of P2P energy trading arrangements also has the potential to change the consumers’ and prosumers’ behaviours of energy consumption. For example, they will tend to consume more hot water when there is more electricity generated by their renewable energy sources. Those changes will further lead to conflicts between the economic performance and the social dissatisfaction. This is one of the directions for future research in this area.

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