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A decentralized peer-to-peer control scheme for heating and cooling trading in distributed energy systems

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ABSTRACT

With the increasing penetration of distributed energy resources, integrating renewable generations into energy systems is a significant trend for smart and cleaner energy systems. To this end, advanced energy management has become of great importance. Conventional control of distributed energy resources relies on a central operator, which is responsible for the energy flow from producers to consumers and regulates money transactions. As this operator or the bulk grid is a monopoly, not every user can freely connect to a distributed energy resource, and distributed energy resource s can neither compete on price and services nor decide the price of the energy they want to sell to the users. To facilitate the utilization of locally-produced energy, and balance the supply and demand, a novel decentralized competitive energy system is proposed. Through this highly automated and fully decentralized multi-energy management approach, different parties on the peer-to-peer network can conduct money transaction at the machine level without interference of the central operator. An integrated multi-layer system architecture of the competitive energy system is elaborated, including system operation mechanism, device bidding strategy, and a hardware device Energy Router. The underlying protocol for money transactions among devices is IOTA, a peer-to-peer network supporting the data and value transfer for machine economy. The proposed energy network can facilitate autonomous negotiation and execution of transactions among machines without central operator's intervention, and prevent monopolies, as well as promote easy admission of new distributed energy resources. Furthermore, a case study of a decentralized competitive heating system is presented to demonstrate the proposed architecture, and computer simulations were conducted to verify its rationality and potential value. The simulation results indicate that the peer-to-peer heating system outperforms conventional central heating systems in terms of both user cost and system efficiency, as it encourages end users to consume locally-produced energy. The proposed decentralized solution can save 61% operation cost in heating seasons.

1. Introduction

China's energy system would be dominated by fossil fuel in 2021–2025. It's worth noting that, in recent years, a series of policies were issued to develop renewable energies and make China's energy system cleaner and more sustainable. In this case, renewable energy would take the largest share in electricity generation after 2041 (Suo et al., 2020). Integrated multi-energy systems become increasingly important for the sustainability in energy system development and for promoting the application of clean energy technologies (Su et al., 2020).

Currently, traditional centralized energy systems dominate energy markets. These systems comprise large-capacity, centralized production devices, and specialized distribution facilities delivering energy to a wide range of users. Fully centralized energy supply systems lead to a series of problems: load unbalance in large-scale networks, loss through long-distance transportation, and vulnerability to natural disasters. Waste heat generated in large thermal power plants in rural areas is unavailable for use in urban areas, and renewable energy cannot be utilized in centralized systems owing to their low energy density (Long, 2016). To circumvent these problems, distributed multi-energy networks and microgrids that promote local renewable energy utilization are now gaining momentum. Distributed energy systems provide power and heat

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Nomenclature

Abbreviation

P2P	Peer-to-peer
M2M	Machine-to-machine
DERs	Distributed energy resources
PV	Photovoltaic
PE	Physical equipment
CE	Controlled entity
CE-LO	Controlled entity with local optimization
CE-GO	Controlled entity with global optimization
ICT	Information and communication technology
DLT	Distributed ledger technology
TOU	Time-of-use
MILP	Mixed integer linear programing
MINLP	Mixed integer non-linear programing
DMS	Distribution management system
TCP	Transmission control protocol
IP	Internet protocol
PPP	Point-to-point protocol
DG	Distribution generation

Sets

I	Consumers participating in P2P energy trading
J	Producers participating in P2P energy trading

Parameters

Q_i	Demand (kW)
m	The number of producers participating in the P2P trading
$\overline{M}_j$	Upper limit of production capacity (kW)
t	Time step (h)
PE	Prospective earnings (Yuan)
M_j	Production capacity (kW)
n	The number of consumers participating in the P2P trading
$\underline{M}_j$	Lower limit of production capacity (kW)
s	Time slot series
E	Heating supply capacity (kW)

Variables (continues)

P_j	P2P energy bidding price (Yuan/kW·h)
C_{ij}	Trading volume (kW)
In	Profit of producers
R	Surplus heat (kW)
EF	Energy efficiency
P_{ij}	P2P energy transaction price (Yuan/kW·h)
B	Energy bill of consumers
Px	Purchase price of energy of energy storage units (Yuan/kW·h)
V	Available capacity of energy storage (kW)

Variables (binary)

x_{ij}	1, if there is energy trading between consumer *i* and producer *j*, otherwise 0

Superscript/ subscript

i	Consumer series number
$cost$	Production marginal cost
l	Lower limit
k	The *k-th* round bidding
a	The *a-th* selling price adjustment
p	Production devices
j	Producer series number
$grid$	Bulk energy grid
h	Upper limit
ij	Consumer *i* and producer *j*
x	Energy storage devices

locally through a series of small-scale modular energy generators, which offers more flexibility. This promotes the diversification of energy sources, enabling multi-energy complementary coupling operations, and enhances energy efficiency and reliability.

Compared with centralized supply systems, distributed energy systems fulfill the objective of energy production decentralization physically. However, the energy flow management and control of a distributed energy system still rely on central utility. Energy allocation and dispatch are carried out by central controllers, and the energy trading participants (consumers or producers) have no autonomy to decide the amount or the price of the energy to be injected into the local grid. Currently, central operators of local distributed energy networks use either of the following control methods. One is conventional rule-based control, and the other is more modern model-based optimization control. The former is more common but less energy efficient, whereas the latter is more efficient but relies heavily on model and sensor accuracy. In neither control method can DERs negotiate with energy consumers and complete peer-to-peer transactions.

A large amount of research has been conducted on model-based DER control optimization, as Fig. 1. In (Sameti and Haghighat, 2018), a comprehensive mixed integer linear programming (MILP) optimization model was proposed to optimize the energy distribution network layout and obtain its optimal operating strategy. The best integrated district energy systems were presented as a set of Pareto optimal solutions, and their optimal performance (both environmentally and economically) was confirmed in the application of the model to a district energy system in Switzerland. The authors in (Wang et al., 2018) focused on the optimal scheduling problem of a real community integrated energy system in China. They performed detailed device modeling and obtained a community integrated energy system operation strategy based on a MILP model with unit commitment. The simulation results indicated that the proposed strategy resulted in economic and reliable operation by coordinating various devices. In a similar study, an optimization solution of multiple MILP problems to achieve global operational optimization of a district heating system was presented, and implemented in a case study to verify its functionality (Michał et al., 2018). A MILP model was formulated in (Tian et al., 2019) to optimize the operation strategy of multi-energy complementary energy supply.

In some studies, the dynamic and nonlinear characteristics were taken into account. For example, the authors in (Powell et al., 2016) put forward a dynamic optimization model to determine the optimal charge and discharge time in a polygeneration distributed energy system. The dynamic optimization model was solved by decomposing the problem into multiple static mixed integer nonlinear programming (MINLP) problems. Similarly, a MINLP model has been proposed to optimize the schematic process design and operation strategy of the polygeneration system from supply

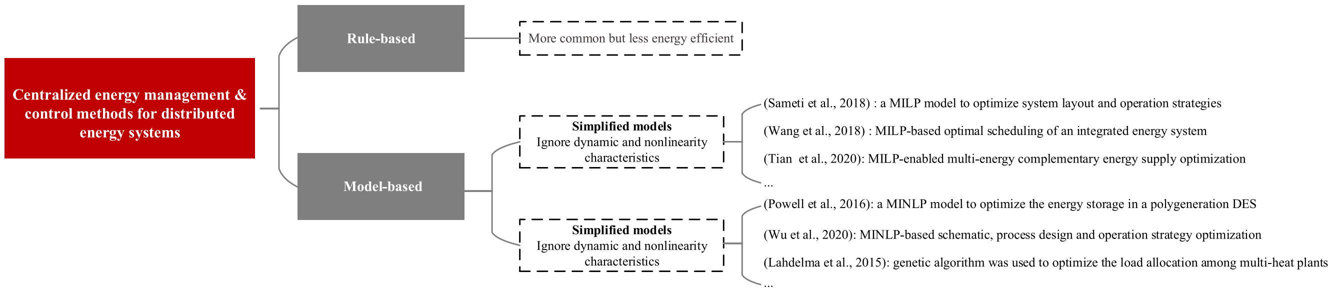

Fig. 1. Centralized energy management & control methods.

side views (Wu et al., 2020). The authors in (Schweiger et al., 2017) employed an equation-based modeling and nonlinear optimization combined framework to optimize the thermal and hydraulic behavior of a district heating and cooling system. Taking advantage of the progress in non-convex and non-smooth optimization, in (Lahdelma and Fang, 2015), they adopted a genetic algorithm to optimize the supply temperature and load allocation among multi-heat plants based on a static district heating system model.

However, even though in theory, the global optimum of economic and technical objectives can be achieved under the centralized approach, the above optimization models are not often used in practices. For example, given that the diversity and ownership complexity features of DERs, the global optimization problem suffers from dimensionality and tremendous calculation burden (Wang et al., 2020). Moreover, considering that device mathematical models are not universal and performance parameters tend to hard to access, once the system composition changes or device performance degrades over time, remodeling is needed (Dai, 2016). Therefore, the model-based optimization is rarely used in engineering practice.

With the increasing connection of DERs and the widespread use of demand-side response, traditional energy consumers are becoming prosumers who can both consume and generate energy (Luo and Davis, 2014). The top-down central paradigm exhibits poor performance in coordination of multi-energy systems, and shows less robustness dealing with the supply and demand uncertainty (Hu et al., 2018). With the expansion of energy system, the central operation optimization scheme tends to be time consuming (Luo and Davis, 2014). Therefore, a decentralized solution which allows bidirectional energy flow control, i.e., Energy Internet, has come into being (Rifkin, 2011). Energy Internet provides a platform for bilateral transactions, where each peer (energy producer and consumer) can carry out autonomous P2P energy trading, selling surplus energy to other peers or purchasing deficits from other peers equally without third-party involvement. It promotes local consumption of renewable energy and optimizes energy reconfiguration. The rapid development of Energy Internet contributes to the evolution of energy trading from a long-term central monopoly pattern to a more equitable and transparent free P2P bilateral transaction pattern. A comparison of those two patterns is presented in Table 1.

The comparative analysis between conventional unilateral energy trading and the P2P one was conducted in various studies, and the advantages and feasibility of P2P solution were explored. In (Chankook and Taeseok, 2017), the authors pointed out the similarities and differences between P2P power trading and the Internet. They compared the major P2P electricity trading cases, and reviewed potential developments and future challenges. Similarly, in (Roy et al., 2016), the potential value of P2P electricity trading in the Australian national electricity market was reviewed, and this trading mode was regarded as a potential solution to the misalignment between existing market arrangement and economic value, as it can provide a price signal for better coordination of local generation and consumption. The feasibility of P2P energy trading was analyzed by authors in (Long et al., 2017), based on cluster analysis and linear optimization of users in low-voltage power distribution networks, where solar photovoltaic (PV) power generation was considered.

Furthermore, some studies went a step further and demonstrated the overall structure of P2P power trading. In (Zhang et al., 2018), a hierarchical system architecture model of P2P energy trading was proposed, whereby the platform “Elecbay” enabling P2P energy trading in grid-connected microgrids was established. The simulation of P2P bidding among energy consumers and prosumers was developed using game theory, and the results indicated that P2P energy trading may improve the local balance of energy generation and consumption. A bi-level optimization-based energy sharing model was developed in (Fernandez et al., 2021) for coordinated resource allocation and P2P energy trading. Authors in (Werth et al., 2018) proposed and implemented a P2P framework-enabled DC microgrid with a fully decentralized control system. Its flexibility and resilience under failure circumstances of the proposed architecture were proved in practice. In (López-García et al., 2019) A decentralized control method for P2P market energy trading and grid balance was proposed to match supply and demand efficiently by splitting the energy transaction into small energy fragments. Regarding microgrids of P2P PV prosumers, an energy-sharing model with price-based demand response was

Table 1
Comparison of two energy trading patterns.

Trading controlled by central operator	P2P bilateral energy trading
Central operator controls energy trading	No central operator intervening
Central operator controls money transactions	Information is transparent bilaterally
Energy source and cost are opaque to users	Trading security can be ensured
Information is asymmetric, leading to limited user selection	Price automatically reflects dynamic performance
Energy supply and demand balance is maintained by central operator	Peer production/consumption response enthusiasm is enhanced, as all peers are energy trading participants
Information security, transaction disputes, etc.	

proposed in (Liu et al., 2017). Similarly, demand-side response was considered in (Alam et al., 2017) and (Zhou et al., 2020). In the former one, the authors addressed a demand-side management system coordinated with P2P energy trading among the households in a smart grid. In the later one, a paradigm of P2P energy trading with user-dominated demand response among smart communites was proposed. By dividing the original multi-objective optimization problem into single objective sub-problems, the mismatch problem between local demand and generation is tackled.

In P2P energy system, pricing and trading mechanisms are designed to efficiently balance the energy supply and demand within the network. An appropriate pricing scheme also can encourage prosumers to participate in trading markets (Tushar et al., 2020a, b, c). In recent years, game theory as a powerful mathematic tool, has been used extensively to develop pricing schemes, especially the Nash-type non-cooperative game model. The objective of each peer is to maximize their own economic benefit in a competitive situation. For example, in (Liu et al., 2018), a dynamic pricing methodology was presented, offering a market-oriented means to drive decentralized energy trading and to optimize financial benefits for owners of distributed energy resources. Authors in (Tang et al., 2019) optimized interaction strategies between a grid and buildings using the Stackelberg game based on their identified Nash equilibria. In (Li et al., 2019), a non-cooperative game was adopted to model the trading framework with the heterogeneity of demand flexibility associated with different types of users. While in some studies, cooperative game models were utilized, including coalition formation games (Tushar et al., 2019; 2020a, b, c). Unlike the self-interest-targeted non-cooperative game, coalition game allows participating prosumers to form suitable coalition groups to achieve stable and optimal performance. In (Tushar et al., 2020a, b, c), cooperative Stackelberg game was used by assuming the centralized power system as the leader and prosumers as followers. Numeric case studies indicate that the proposed scheme can ensure benefits to all participating energy entities in the P2P trading.

Cryptocurrency technologies, like blockchain, is a powerful tool for enabling the money transfer and consensus achievement between multiple machines. The adaptability of blockchain technologies and smart energy systems was discussed in (Ul Hassan et al., 2019) by integrating various blockchain technologies into smart energy systems. In (Eric et al., 2017), blockchains and smart contracts were utilized to develop a decentralized optimal power flow model for scheduling a mix of batteries, shapeable loads, and deferrable loads on an electricity distribution network. Furthermore, in (Thomas et al., 2019), a general smart contract form captures the elements needed for decentralize d control was presented to allow shared automatic control of energy transfer within networks in a replicable, secure, verifiable and trustworthy way.

In summary, the evolution of energy systems presented a tendency from centralization to decentralization. This includes the decentralization of not only physical energy systems but also of the control and dispatching mechanisms. The evolution of energy systems may eventually have three phases. 1) Traditional centralized form with centralized physical system and centralized control structure. 2) Semi-decentralized systems controlled by central agencies (for example, distributed energy systems with model-based global optimization). 3) Fully decentralized P2P systems in both the physical system layer and the allocation dispatching layer, supporting bilateral energy trading. A comparison of these forms is presented in Table 2.

From the literature review, the following knowledge gaps may be inferred:

1) Only electricity transactions have been studied, and no serious attempts have been made regarding cooling or heating systems. Related research on P2P energy systems is still missing.
2) Regarding electricity transactions, complete decentralization has not yet been achieved. For instance, even though a PV microgrid trading system based on blockchain technology has been proposed in (Xue, 2018), the grid company was still required as a centralized electricity service provider to facilitate money transactions. Likewise, the supply and demand management and congestion check in (Tai et al., 2016)should be carried out by the central operator. The DMS agent proposed in (Ju et al., 2018) operated as the central agent to verify whether the system safety constraints are satisfied by the scheduling strategy. Fully decentralized energy systems may never appear; however, this study represents another step toward that direction.

(PE: Physical Equipment, CE: Controlled Entity, CE-LO: Controlled Entity with Local Optimization, CE-GO: Controlled Entity with Global Optimization) (Werth et al., 2018; Beck et al., 2013; Rohbogner et al., 2012; Schollmeier, 2001; Rohbogner et al., 2013).

In this study, it is attempted to further decentralize distributed energy systems by developing a new completely decentralized and highly automated P2P competitive energy system. The novelty and contributions of this paper are: 1) Previous P2P trading studies mainly focus on electricity, the present study is primarily concerned with energy trading in cooling and heating system, which is rarely mentioned in existing studies. 2) It is the first time that a fully decentralized (no third-party intervention is required) competitive control scheme (for heating and cooling trading) based on P2P networks was proposed, as well as the concept of energy machine economy; 3) Under the technical framework of a P2P network, cryptocurrency such as IOTA is employed as the underlying money transaction structure. 4) A comparative simulation was conducted. The results show that, compared with conventional central heating systems, the P2P one can save energy bill and improve system operation efficiency, because the P2P network encourages local renewable energy generation.

2. Research scope

The scope of this study are as follows:

1) A complete multi-layer system architecture of a P2P competitive energy system is proposed, where the major objective of each peer (energy producer, customer, and prosumer) is to maximize its own economic benefits. Based on this principle, as in any open market, the amount of energy consumption and supply are determined by each individual. This process embodies global system optimization driven by economic competition, which significantly differs from distributed energy systems with model-based optimization and central operators.
2) Considering the multilateral competition of energy supply and demand, device bidding strategies are exploited. In this process, the local optimization of devices is achieved through real-time energy price adjustment. Both system-scale global optimization and device-scale local optimization are considered in this study, leading to a more efficient and reliable energy system.
3) In addition to software studies (operational strategies), a hardware implementation for this P2P energy system is discussed. By installing the Energy Router designed in this study on traditional energy devices, they can be upgraded to intelligent devices and form their own P2P network. From an engineering perspective, practical applications could benefit from this plug-

Table 2
System structure classification and comparison.

	Centralized System	Simi-decentralized System	Decentralized System
Structure			
Physical System	Centralized	Decentralized	Decentralized
Controlling & Scheduling	Centralized	Centralized	Decentralized
Energy Trading Mode	Client/Server Unilateral Trading	Client/Server mode dominates	Free bilateral energy trading without relying on central operator More transparent information
Optimization	Global Optimization	Global Optimization	Distributed optimization
Resiliency	Low Single point of failure has severe impact on global system	Medium Impact of single point of failure on global system is between that in the centralized system and that in the decentralized system	High Single point of failure has little impact on global system
Flexibility Scalability	Low Usually predetermined Reengineering is required	Low Usually predetermined Reengineering is required	High Equipped with hardware interface
Implementation difficulties	Low Straightforward implementation Easy debugging and supervision	Medium Between the centralized system and the decentralized system	High Difficult to set up Coordination may imply delays or errors Debugging is difficult
Examples	Urban central heat supply	Distributed energy system with global model-based optimization	No

and-play solution without the need to replace or retrofit existing equipment in energy system.

4) The possibility of applying IOTA technology to guide the design of the Energy Router is explored, ensuring the execution of energy transactions and the automatic transfer of money tokens between devices at the end of the transactions through smart contract technology. Thereby, an autonomous machine economy is possible, and the trust issue in energy transactions may be resolved without third-party intervention. The concept of energy machine economy has not been considered in previous studies. A case study of a P2P competitive heating system was conducted to verify the rationality of the trading mechanism of this energy system, and a comparison with traditional centralized DRE control is presented.

The rest of the paper is organized as follows. Section 3 gives a full picture of the multi-layer architecture of the proposed P2P competitive energy system. Both system-scale global optimization (bid-based P2P operation mechanism) and device-scale local optimization (devices pricing strategy), as well as the design of hardware interface are illustrated in Section 3. Section 4 presents the case study simulation, including the description of the studied energy system (a multi-energy district heating system), simulation settings and how to apply the proposed P2P solution to the studied system. The simulation results and analysis are presented in Section 5, and, the conclusion is drawn in Section 6.

3. Multi-layer architecture of P2P competitive energy system

Considering the similarity between P2P networks and energy trading in distributed systems, a five-layer architecture of a P2P competitive energy system is proposed that enables the bidirectional flow of information and energy between peers. P2P networks represent a reversal of the traditional hierarchical architecture where each peer in a distributed energy system contributes equally to the entire system, and negotiates with each other without the central operator. In the proposed P2P competitive energy system, energy transactions between peers can be carried out autonomously following the principle of maximizing one's own economic benefits. In this process, the selection of the trading parties, the amount of the traded energy, as well as the direction of the energy flow are determined by the peers themselves. This architecture, shown in Fig. 2, supports real-time dispatch of energy at each peer node through a machine-to-machine (M2M) autonomous negotiation mechanism.

The physical system layer consists of all physical components of the energy system, including energy producers (e.g., PV), energy storage devices (e.g., batteries), and end users, i.e., energy consumers. The physical layer also includes the distribution network

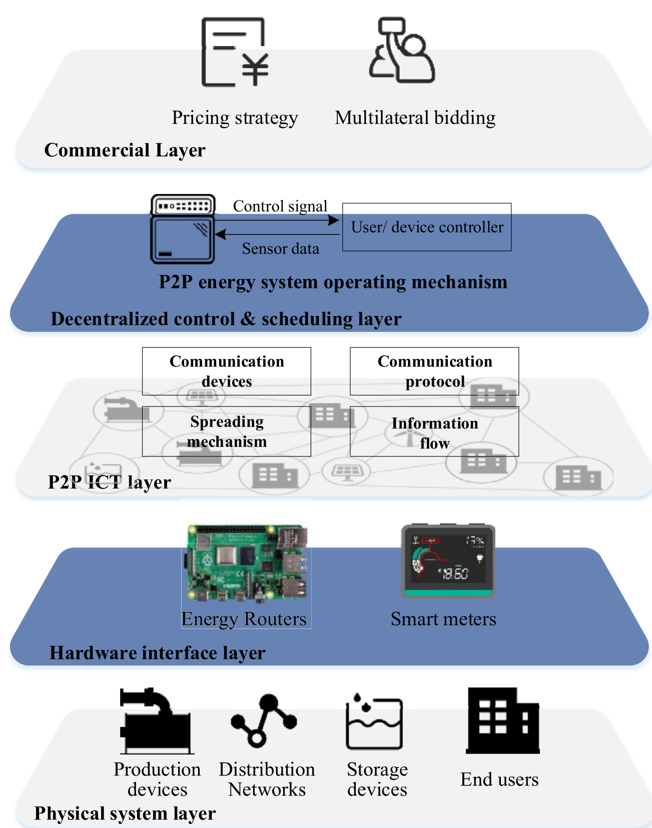

Fig. 2. Five-layer architecture of P2P competitive control for heating and cooling system (ICT: Information and Communication Technology).

connecting these components; energy transmission takes place in this layer.

The hardware interface layer comprises the Energy Routers and the smart meters. Each electromechanical device in the physical layer is equipped with Energy Routers so that the components of the physical layer are upgraded to smart devices admitted into the P2P network to participate in energy trading. The function of the smart meters is to monitor the execution of contracts and to balance the energy flow within the P2P system in real time. The major purpose of this layer is to measure and direct the flow without third-party intervention.

The information and communication technology layer consists of communication devices, communication protocols, the spreading mechanism, and the information flow. Communication devices refer to, e.g., sensors and wired/wireless communication connections. Protocols include, for instance, TCP/IP, PPP, or ×2.5. The spreading mechanism regulates the information sharing among peers in the network (Zhang et al., 2018). Information flow refers to the senders, the receivers, and the content of each message transferred.

The decentralized control and scheduling layer is the core of the proposed system. It determines the operating strategy and scheme, and specifies how P2P energy trading takes place.

The commercial layer refers to the energy selling price adjustment strategies. The major objective of this layer is to improve device competitiveness in the energy bidding market.

The P2P energy system operating mechanism, hardware interface, and pricing strategies will now be described in detail.

3.1. P2P competitive energy system operating mechanism

This diagram presents the energy flow and information flow between producers and consumers in the proposed P2P competitive system (Fig. 3).

The whole trading process is illustrated in Fig. 4.

A fixed time-step trading regulation is adopted in this P2P competitive energy system, and each time step is divided into a negotiation phase and an execution phase. The time-step length is determined by the type of energy traded. For example, if hot and cold water is traded for district heating and cooling, the time step can be 1 h. The transaction frequency should be appropriately adapted to the varying characteristics of the energy load profile.

At the beginning of the negotiation phase, consumer i ($i \in I$) predicts the energy load in this time step according to historical data and usage change. Then, the load demanded from this consumer Q_i and an inquiry request are sent to each energy producer through the P2P network, initiating the first-round bidding.

Correspondingly, energy producer j ($j \in J$)predicts its production capacity M_j in this time step according to historical data and meteorological parameters, and determines the energy selling price P_j based on its marginal cost, as well as supply and demand. Then, producers send their energy unit prices and production capacities to consumers. It is worth noting that peers participating in P2P energy trading are driven by economic benefit. To ensure peer competitiveness and reliable system operation, the upper limit P_h of the energy selling price should be lower than the centralized energy supply price P_{grid} (for example, the heating price of the district heating network), and the lower limit P_l should be higher than the production cost P_{cost}. That is, the energy selling price range is as Formulation (1).

$$P_{cost} < P_l < P_j < P_h < P_{grid} \tag{1}$$

For consumers, the major criterion in producer selection is cost, that is, priority is given to the producer with the lowest energy unit price. If the production capacity of the lowest-price producer is not adequate to meet the consumer's needs, the second lowest-price producer will serve as a supplement. This selection process continues until consumer demand is fully satisfied or demand-side load is adjusted, and it can be formulated as follows:

$$\begin{aligned} & min \ \sum_{j=1}^{m} x_{ij} P_{ij} C_{ij} \\ & s.t. \ \sum_{j=1}^{m} C_{ij} = Q_i \end{aligned}$$

$$x_{ij} = \begin{cases} 1 \text{ if producer } j \text{ made a deal with consumer } i \\ 0 \text{ else} \end{cases} \tag{2}$$

where $C_{ij}$is the trading volume stipulated in the trading contract between consumer i and producer j, $P_{ij}$is the energy unit price negotiated by consumer i and producer j, and m is the number of producers participating in the competition.

Then, consumer i sends unidirectional contracts to the producers selected, clarifying the trading volume.

Subsequently, energy producer j receives unidirectional contracts from consumers, and prioritizes them according to the

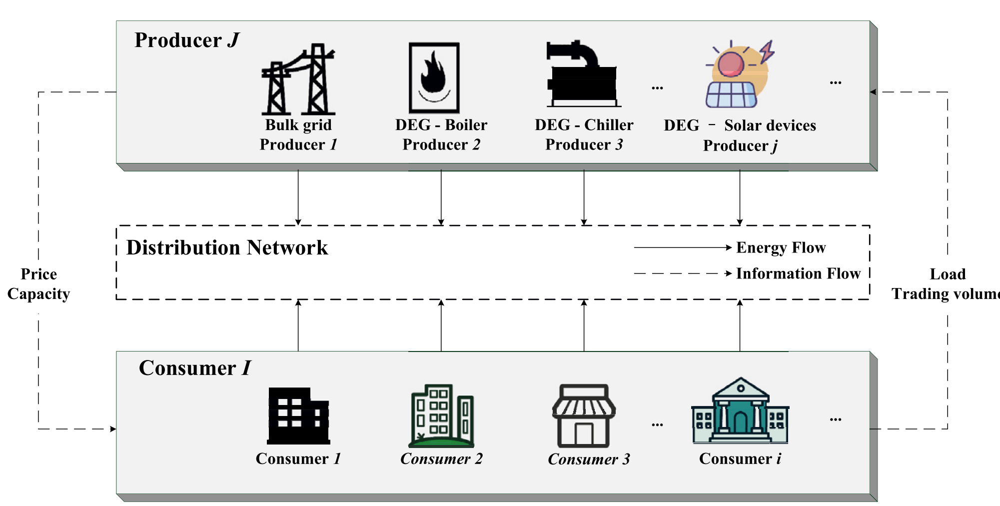

Fig. 3. Superstructure diagram of P2P energy system.

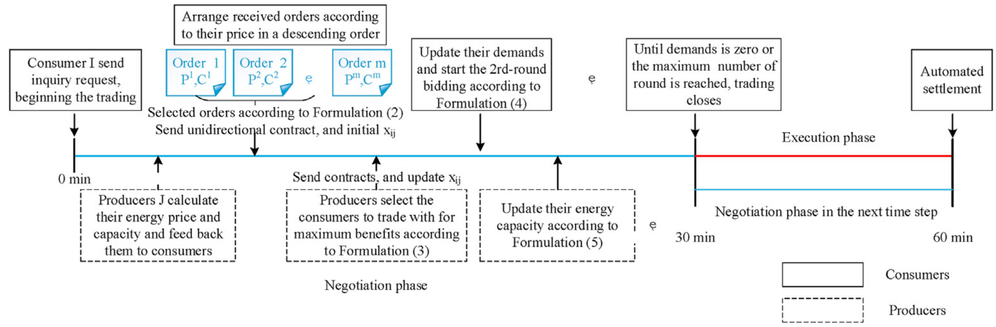

Fig. 4. Trading process of P2P control system.

principle of maximizing its own sales profit. Selecting the optimal combination of consumers is equivalent to narrowing the gap between the amount of energy produced and sold. This selection process can be formulated as follows.

$$\begin{aligned} &min\ M_j - \sum_{i=1}^{n} x_{ij}C_{ij} \\ &s.t.\ \sum_{i=1}^{n} x_{ij}C_{ij} \geq \underline{M}_j \\ &\sum_{i=1}^{n} x_{ij}C_{ij} \leq \overline{M}_j \end{aligned} \tag{3}$$

where n is the number of consumers participating, $\underline{M}_j$and $\overline{M}_j$ are the lower limit and upper limit of the production capacity of energy producer j, respectively. After that, energy producer j signs contracts with the selected consumers and updates x_{ij} to the consumers.

The first-round bidding is elaborated above. If now a consumer's demands are not fully satisfied, the second round of bidding will begin. Specifically, the predicted energy load Q_i is represented by the difference between Q_i and the trading volume for consumer i stipulated in the contract signed in the first round. Likewise, the predicted production capacity M_j is updated as well, as in. The process of consumer inquiry, producer quotation, and bidding is repeated until demand is fully satisfied or the maximum number of rounds is achieved. In the latter case, the unsatisfied demands are met by the bulk grid. One thing to note is that in each round of bidding, consumers can change their demand response in real time according to the energy selling price.

$$Q_i{}^k = Q_i{}^{k-1} - \sum_{j=1}^{m} x_{ij}{}^{k-1}C_{ij}{}^{k-1} \tag{4}$$

$$M_j{}^k = M_j{}^{k-1} - \sum_{i=1}^{n} x_{ij}{}^{k-1}C_{ij}{}^{k-1} \tag{5}$$

where k is the *k-th* round bidding.

Energy storage devices play a special role (prosumer) in energy trading, balancing the temporal and spatial differences between energy production and consumption. When charging, an energy storage device serves as a consumer, purchasing energy from producers; when discharging, a storage device switches to a producer, selling energy to consumers. To make full use of energy storage, after consumer demands have been satisfied, if there is a surplus, it will be sold to energy storage devices. Specifically, producers send the amount of excess energy to storage devices, and then, the corresponding purchase price and remaining capacity are fed back by the storage devices. When producers select storage devices for trading, the device with the highest purchase price will be given priority, followed by the devices with the second-highest price, if no sufficient capacity remains in the first-choice storage device. This process is repeated until the excess energy is sold out or there is no storage capacity available. The marginal cost of an energy storage unit is relative to the energy purchase price and energy storage loss. For producers with flexible production, an additional judgment should be made to identify whether purchase price surpasses production cost, in which case the deal is accepted; otherwise, the deal is rejected and production is adjusted accordingly.

After the negotiation phase, the execution phase begins. The energy production devices with no supply contract are turned off in this time step, whereas the others provide energy for consumers respecting the contract and transfer the surplus energy to storage devices. During the execution phase, the smart meters monitor whether the inflow and outflow energy of the seller and buyer, respectively, are consistent with the contract to maintain the energy flow balance within the system. Peers who fail to generate/consume the promised amount of energy are required to trade with producers with less beneficial (selling or buying) prices or are charged with penalties.

Transaction settlement is conducted after a deal, and the payment is rendered automatically. The energy bill of consumer i and the profits of producer j are defined by Formulation(6). The profit of storage devices is defined as the difference between sales revenue and purchase cost.

$$\begin{aligned} B_i &= \sum_{j=1}^{m} x_{ij}P_jC_{ij}t \\ In_j &= \sum_{i=1}^{n} x_{ij}P_jC_{ij}t \end{aligned} \tag{6}$$

where B_i is the energy bill of consumer i and $In_j$is the profit of producer j. t is the time step.

In accordance with the periodicity of thermal load profiles, the energy price adjustment interval is set to 24 h. Energy production devices adjust the energy price every 24 transactions according to historical data to improve market competitiveness. The adjustment strategies are presented in detail in Subsection 3.2.

3.2. Pricing strategies of devices

In this case, it is assumed that the selling price of the central grid is fixed, and the central grid serves as a backup, providing energy for consumers if the demand cannot be satisfied by other energy producers. The energy unit price for each device (bidder or receiver) is adjusted with respect to the price of the previous step, so that each peer's best economic position may be gradually achieved. The price adjustment strategies in this study concern the selling price adjustment of energy production devices, and the purchase price of storage devices is adjusted as that of production devices, when charging. Regarding the energy selling price adjustment, there are two bidding strategies, as follows.

Selling price adjustment strategy 1: Energy price is adjusted to maximize prospective earnings. Specifically, each producer sets the prospective earnings itself in the transactions between two adjacent price adjustments. If the total realized earnings from these 24 transactions are greater than the prospective earnings, the energy price will rise; otherwise, the energy price will decline. This is formulated as follows:

$$\begin{cases} If \ \sum_{a}^{a+1} In_j \geq PE_j, {P_j}^{a+1} \geq {P_j}^a \\ If \ \sum_{a}^{a+1} In_j < PE_j, {P_j}^{a+1} < {P_j}^a \end{cases} \tag{7}$$

wherePE denotes prospective earnings, $\sum_a^{a+1} In_j$is the profit of the producer j in the 24 transactions between the *a-th* price adjustment and the $(a+1)$-*th* price adjustment, and ${P_j}^{a+1}$ is the energy selling price after the *a-th* price adjustment and the $(a+1)$-*th* price adjustment, respectively.

Selling price adjustment strategy 2: Energy price is adjusted based on the earnings trend of the previous two price adjustments. Specifically, if the ratio of earnings to energy production after the last price adjustment is greater than that after the second last price adjustment, the offered energy price will rise; otherwise, it will decline, as follows:

$$\begin{cases} If \ \frac{{In_j}^a}{{M_j}^a} - \frac{{In_j}^{a-1}}{{M_j}^{a-1}} \geq 0, {P_j}^{a+1} \geq {P_j}^a \\ If \ \frac{{In_j}^a}{{M_j}^a} - \frac{{In_j}^{a-1}}{{M_j}^{a-1}} < 0, {P_j}^{a+1} < {P_j}^a \end{cases} \tag{8}$$

where${In_j}^a$ is the profit of the producer j in the 24 transactions between the *a-th* price adjustment and the $(a+1)$-*th* price adjustment (${In_j}^{a-1}$ is defined similarly), and ${M_j}^a$ is the energy production of the producer in the 24 transactions between the *a-th* price adjustment and the $(a+1)$-*th* price adjustment (${M_j}^{a-1}$ is defined similarly).

When energy storage devices discharge, providing energy for consumers, they become producers, and thus employ the selling price adjustment strategies.

3.3. Hardware interface: Energy Router

With the rise of Energy Internet and distributed ledger technology (DLT), there has been increasing interest in using cryptocurrency technologies in P2P energy trading. Cryptocurrencies like blockchain have entered the energy market enable the exploration of decentralized energy systems, and resolved trust issues in P2P money transactions and can support direct M2M money transactions in the machine economy. Today, the lack of scalability of the technology brings stakeholders to explore alternative DLTs beyond the conventional blockchain.

As an emerging type of micropayment cryptocurrency technology, IOTA is an open-source distributed ledger technology that allows connected devices to transfer data and IOTA tokens among each other for zero fees, and optimized for IoT. In contrast to blockchain technologies, a unique Tangle technology with directed acyclic graph topology is utilized by IOTA. Each node (devices in this work) in an IOTA network validates transactions, then sends them to other nodes that do the same. By this means, all valid energy transactions are agreed on by all nodes and cannot be falsified, removing the need to trust a single one in the network. Moreover, IOTA uses quantum-robust one-time signatures to stop attackers from stealing IOTA tokens, and this process makes IOTA incredibly scalable because more new transactions lead to faster validations (Serguei Popov. The Tangle, n.d.).

In this study, the underlying protocol of IOTA technology was used for the design of the hardware interface (Energy Router) of the proposed energy system. The physical structure is shown in Fig. 5.

The Energy Router consists of three parts: memory, processor and communication module. The router's functions in the P2P bidding energy system are as follows:

1) Energy Routers are attached to conventional electromechanical controllers as upper controllers, including the controllers of production devices, end user devices, and storage devices, to carry out bidirectional parameter passing. Adding routers upgrades conventional equipment to smart equipment that can then form the P2P network.
2) The standard information of the corresponding electromechanical equipment is stored in the Energy Router, which communicates with the device's own controllers to identify its operating condition, and predict the production capacity/load according to historical operational data and meteorological parameters.
3) Routers can use historical data and operational performance parameters to determine the operation efficiency of energy production devices and calculate their unit energy cost. The cost is then used by the built-in algorithm to determine the offering price.
4) Routers of different devices, both producers and consumers, communicate with each other to exchange data. In the negotiation phase, consumers send the predicted load and inquiry request to energy producers, and producers send the offered energy unit price along with energy production capacity to consumers after receiving the inquiry request. The deals are made through several rounds of bidding, where both consumers and producers select their trading party according to the principle of maximization of their own interests.
5) Routers sign a smart contract, whose essence is the program code stored in the IOTA tangle, stipulating the content in Table 3.
6) Routers verify the transactions initiated by the other peers.
7) Routers make deals under the smart contract. After the deal is made, the energy settlement is automatically performed in conjunction with the smart meter data, and the IOTA token is transferred from the buyer's account to the seller's account.

In general, Energy Routers facilitate highly automated machine negotiations and autonomous machine economy, in which payments are automatically transferred according to the negotiated contract. Given that IOTA has a unique fully decentralized verification mechanism and supports tamper-resistant data storage, it enables direct M2M transactions. This resolves certain issues commonly existing in centralized energy trading structure, such as poor information security, high operating cost, and consumer privacy breaches. Using trustless modes, IOTA also resolves the trust issue between P2P nodes resulting from the absence of other third parties. Additionally, owing to the scalability of IOTA, when the number of peers in the network increases, transaction verification speed and security will be enhanced, thus stimulating more devices to access the P2P network and form a robust system.

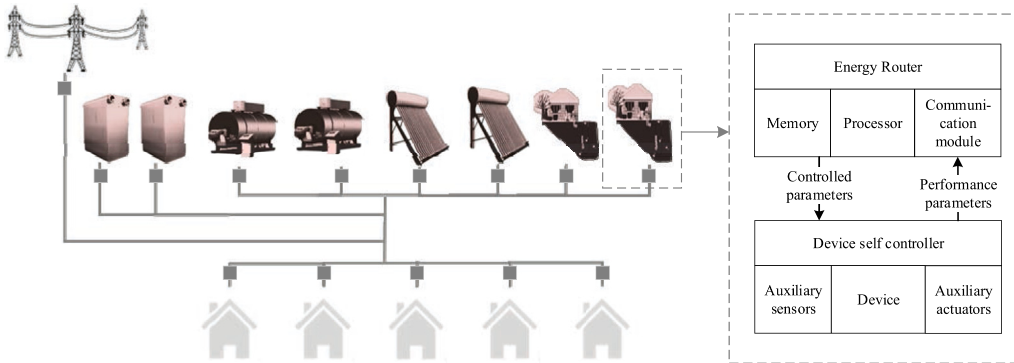

Fig. 5. Physical structure of Energy Router.

Table 3
Content of smart contracts.

Trading time	Producer	Consumer	Unit Price	Trading volume	Account address of producer	Account address of consumer

4. Case study: A P2P heating competitive system model

The proposed P2P operation mechanism and pricing strategies are applied to a multi-energy district heating system, and the system description and bidding process are demonstrated as follows. The simulation process is illustrated as Fig. 6.

4.1. Assumptions and initial settings of P2P heating system model

To demonstrate the operation mechanism of the proposed system, the architecture proposed in Section 3 was applied to a district heating system, resulting in a P2P competitive heating system model. The simplified physical system layer is shown in Fig. 7 and consists of the demand side (e.g., radiators and fan coils), the supply side (ground source heat pumps, gas boilers, central district heating, and solar hot water collectors), the energy storage devices (hot water tanks), and the distribution network. For simplicity, in this case, only space heating is taken into consideration, whereas domestic water heating is not involved; the capacity of district heating is large enough and is used as a backup source for worst-case scenarios; and no surplus heat will be injected into bulk heating grid.

In traditional district central heating systems, consumers purchase hot water from the district heating grid at a fixed price. In this monopolistic scenario, the participation of renewable energy requires the permission of the central agency, leading to limited choice for consumers. The information flow and energy flow in this centralized system are both unidirectional.

In the proposed P2P competitive heating system, the selling price of district central heating is fixed, whereas the selling price of other producers fluctuates during transactions and is adjusted in real time based on previous transactions. The marginal unit cost of other producers is higher or lower than that of district heating. For example, the marginal unit cost of solar hot water collectors is virtually zero, whereas the marginal cost of ground source heat pumps varies with electricity price over time. To prevent the energy market from being monopolized by the district heating grid, it is necessary to ensure that the selling prices of other producers are lower than the heating price of the district heating grid. Concerning

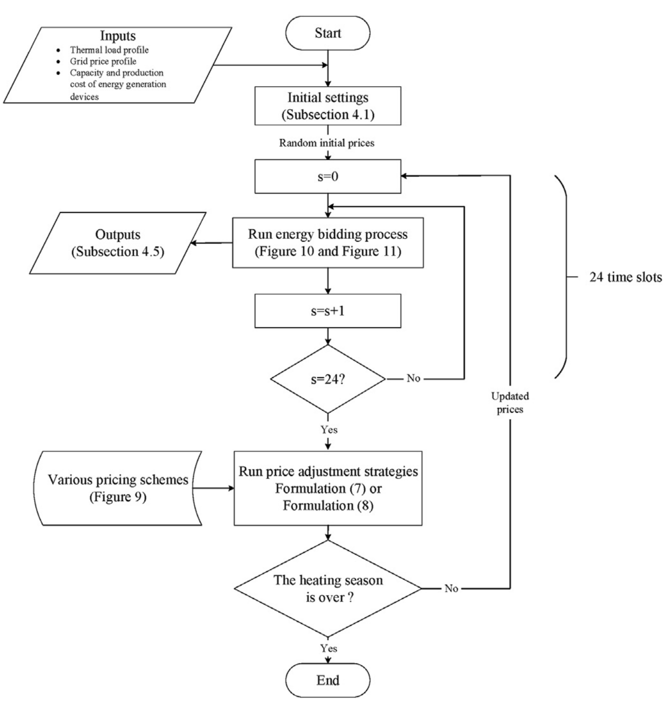

Fig. 6. Simulation process.

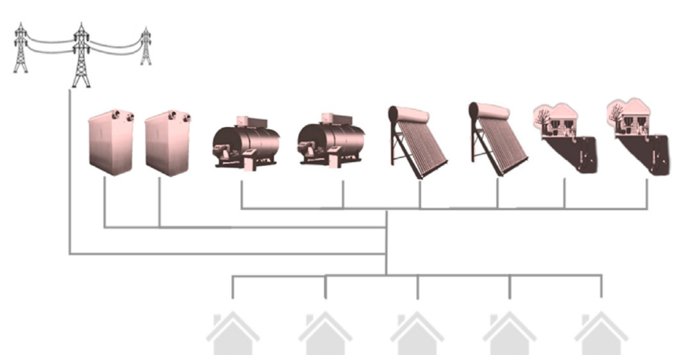

Fig. 7. Physical system layer of P2P competitive heating system.

system sustainability, the selling unit price of producers should be higher than its marginal unit cost. Naturally, if heating storage tanks are to be profitable, the unit heat selling price should be higher than the corresponding purchase price for heat storage. The constraints of the heat selling price P of producers are described in the following Formulation(9).

$$Cost < P < P_{grid} \quad (9)$$

Considering the thermal load profile, in this model, the trading time step is 1 h, and the prices are adjusted once every 24 h. The heating season of one year (120 days) is considered as a cycle, mimicking the impact of cyclical factors such as meteorological parameters on the heating load.

The simplified simulation model of the P2P heating system was constructed in MATLAB. The autonomous bidding of energy consumers and prosumers was simulated to verify the model and the trading mechanism. Furthermore, various combinations of pricing strategies were simulated to explore their impact. Finally, a comparison of system efficiency and consumer cost between the P2P heating system and a conventional central heating system was performed.

In this simulation, as the bidding price of producers is between the heat generation cost and the price of central heating, the initial bidding price was determined as a stochastic value between them, so that trading under various circumstances can take place. Regarding storage devices, the initial heat purchase price was set as the minimum bidding price of heat producers. While these initial settings in a real energy system should be determined by all stakeholders.

For devices production prediction, DOE-2 performance models were used, and the end user's space heating load as another model input profile is elaborated in Subsection 4.2.

4.2. Input profile and simulation parameters setting

On the demand side, a residential building located in Beijing China with an area of 1069 m^2 was used as a case study. The energy simulation software EnergyPlus was used to estimate the hourly space heating demand. Fig. 8 shows the user heating load during the heating season. The heating season lasted for 120 days (November 15 to March 15 of the following year). The heating load peak was 43 kW.

As to the supply side, parameters of energy generation devices and energy storage unit are shown in Table 4.

4.3. Simulation of different pricing strategies

To prevent monopolization by a small number of producers (including the heat generation devices and the discharging storage units), more than one producer is needed for each type of devices. An array of scenarios with different pricing strategies adopted by producers are simulated, as illustrated in Fig. 9. The simplest scenario where all producers employ Selling Price Adjustment Strategy 1 as the baseline scheme. Furthermore, some changes in pricing strategies of producers are made to form the other pricing schemes. Specifically, the bidding strategy of one producer is changed, while other strategy remains unchanged to identify the device-scale influence of pricing strategies. In addition to that, given that operating characteristics vary in different types of generation devices, the bidding strategy of devices is changed, and thus simulation results can be used to better understand the influence of various strategies at the system-scale.

4.4. Simulation of P2P competitive heating system operating strategies

In the heating transactions model, solar heat water, ground source heat pumps, and gas boilers can sell heat both to consumers and energy storage units, whereas central heating and storage units can sell only to consumers. The heat flow is shown in Fig. 10.

To ensure the stability of the entire system, the district heating grid always participates in transactions and provides heat to end users, which are the consumers in the energy market. By contrast, whether the ground source heat pumps and boilers operate or not depends on the bidding result in the negotiation stage, where end users are given priority, and then the excess heat production is preferentially sold to storage units. If the heat purchase price of the storage units cannot compensate for the heat generation marginal cost, producers will adjust their heat generation. Regarding solar collectors, their operating schedule heavily relies on solar radiation, and thus production cannot be adjusted. Therefore, all heat surplus from solar collectors after meeting user demands is sold to storage units. Considering the fluctuations and dynamic variation of user thermal load that may occur during two adjacent transactions, the difference between the promised and actual heat consumption can be covered by purchasing from the district heating grid or by selling to other users. The additional cost caused by dynamic load fluctuations is borne by the users.

The operating strategies of the P2P competitive heating system are shown in Fig. 11. In the first step, consumers state their thermal demand, and heat producers respond to the demand with production capacity and the unit price. Then, consumers select the producer of the lowest bidding price. That is, bids with higher unit price have a higher probability of not being responded to. Subsequently, the consumers send the proposed trading volume to the producers selected. After receiving the information from consumers, the producer selects the consumers to trade with, under the maximum profit principle. The principle is mathematically

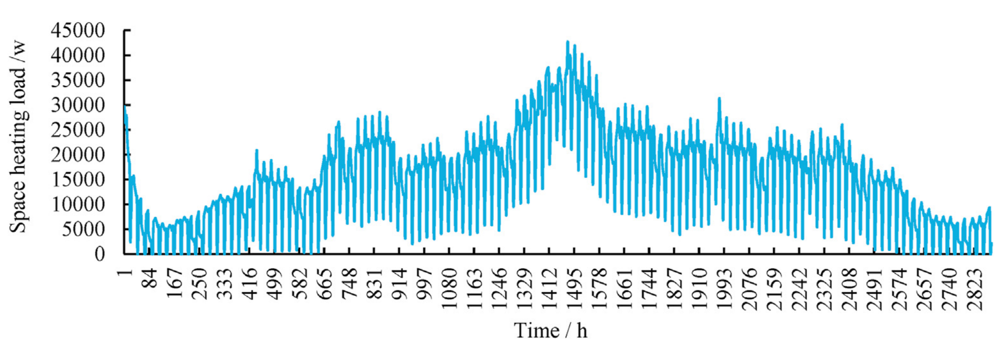

Fig. 8. Space heating user load profile during the heating season.

Table 4
Simulation parameters of energy generation devices and energy storage units.

Devices	Capacity	Cost (Yuan/kW·h) (Including initial investment and operation costs)
Central heating grid	Infinity	0.574
Gas boiler	10 kW	0.330
Ground source heat pump	20 kW	0.458
Solar hot water collectors	40 kW	0.418
Energy storage	854.1 kW·h (maximum daily heating load)	0.017

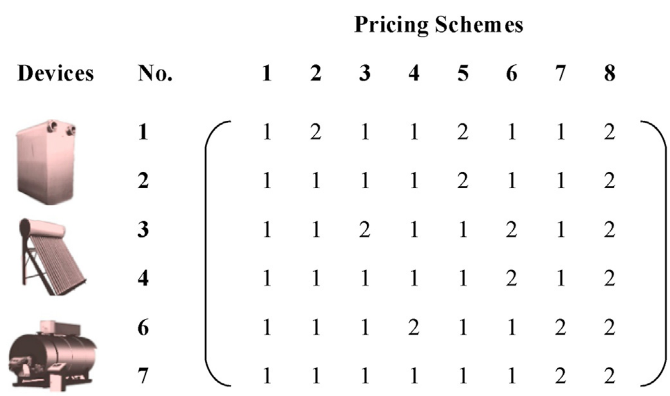

Fig. 9. Pricing schemes for producers (Elements in the matrix represent the pricing strategy adopted by the devices).

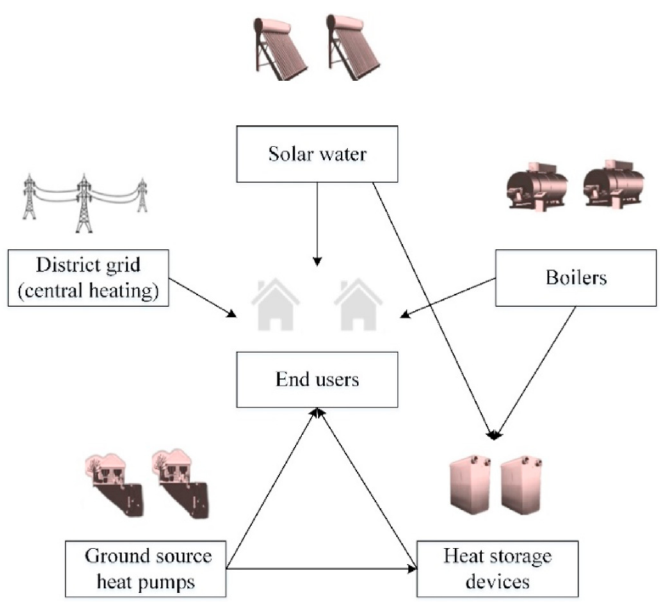

Fig. 10. Heat flow in P2P heating system.

equivalent to obtaining the optimal combination of consumers, and minimizing the difference between heat sales and heat generation. It is worth noting that the trading volume should be within the operating range of the devices. After that, the transactions between consumers and producers are concluded in the first round of bidding. At the beginning of the second round of bidding, the unsatisfied load (Q-C in Fig. 11) is broadcasted again, and the process of inquiry, quotation, the transaction is repeated until consumer demand is fully satisfied or the maximum number of rounds is reached (100 rounds in this paper, and the deficient part can be compensated by the bulk heating grid).

Heat storage devices play the role of prosumers in the heating system. That is, when discharging, they provide hot water, whereas they purchase hot water from the producers after the demands of end users are satisfied. The transaction schemes between storage units and consumers, and between producers and storage units are presented in Figs. 11 and 12, respectively. First, producers broadcast the amount of surplus heat (if any). This is responded to by storage units with the heat purchase unit price and remaining capacity. Then, the storage unit of the highest price is selected. If the capacity of that storage unit is not sufficient, the remaining amount will be acquired by the unit of the second-highest price. This continues until the surplus heat is sold out or no storage capacity remains. Heat producers with flexible production make an additional judgment as to whether the purchase price is higher than the generation marginal cost, and if not, the producer adjusts its production and rejects the order.

The profit of producer j (from consumers and prosumers) is defined as follows:

$$In_j = \sum C_j \times P_j + \sum C_{xj} \times P_x \tag{10}$$

and the heating bills of consumer i are defined as follow:

$$B_i = C_{i1} \times P_1 + C_{i2} \times P_2 + \ldots + C_{ik} \times P_k \tag{11}$$

The profit of a storage unit is the difference between sales profit and the marginal cost that is related to the heat purchase cost and the heat storage loss, where C_j and C_{xj} are the promised heat generation sales to consumers and storage units, respectively.

With 24 time steps (one day) as the cycle, producers and prosumers adjust their heat unit price based on historical transaction data to achieve gradual optimization. The price adjustment strategy is shown in Subsection 3.2.

4.5. Simulation output definition

In this work, selling unit price P, purchase price Px of storage units, trading volume C, profits I, heat storage capacity Vx, User cost B, and efficiency factor EF were simulated.

Efficiency factors of energy generation devices, energy storage devices, and the entire system are proposed here to evaluate the proportion of the heat generated by local producers that was consumed by local end users. The efficiency of producers, such as solar collectors, boilers, and ground source heat pumps, is defined as the ratio of trading volume to heat production as follows:

$$EF_p = \frac{\sum C}{\sum E} \tag{12}$$

The efficiency of heat storage devices is defined by

$$EF_x = \frac{\sum C_x}{\sum E} \times \frac{(Capacity - V_{\min})}{Capacity} \tag{13}$$

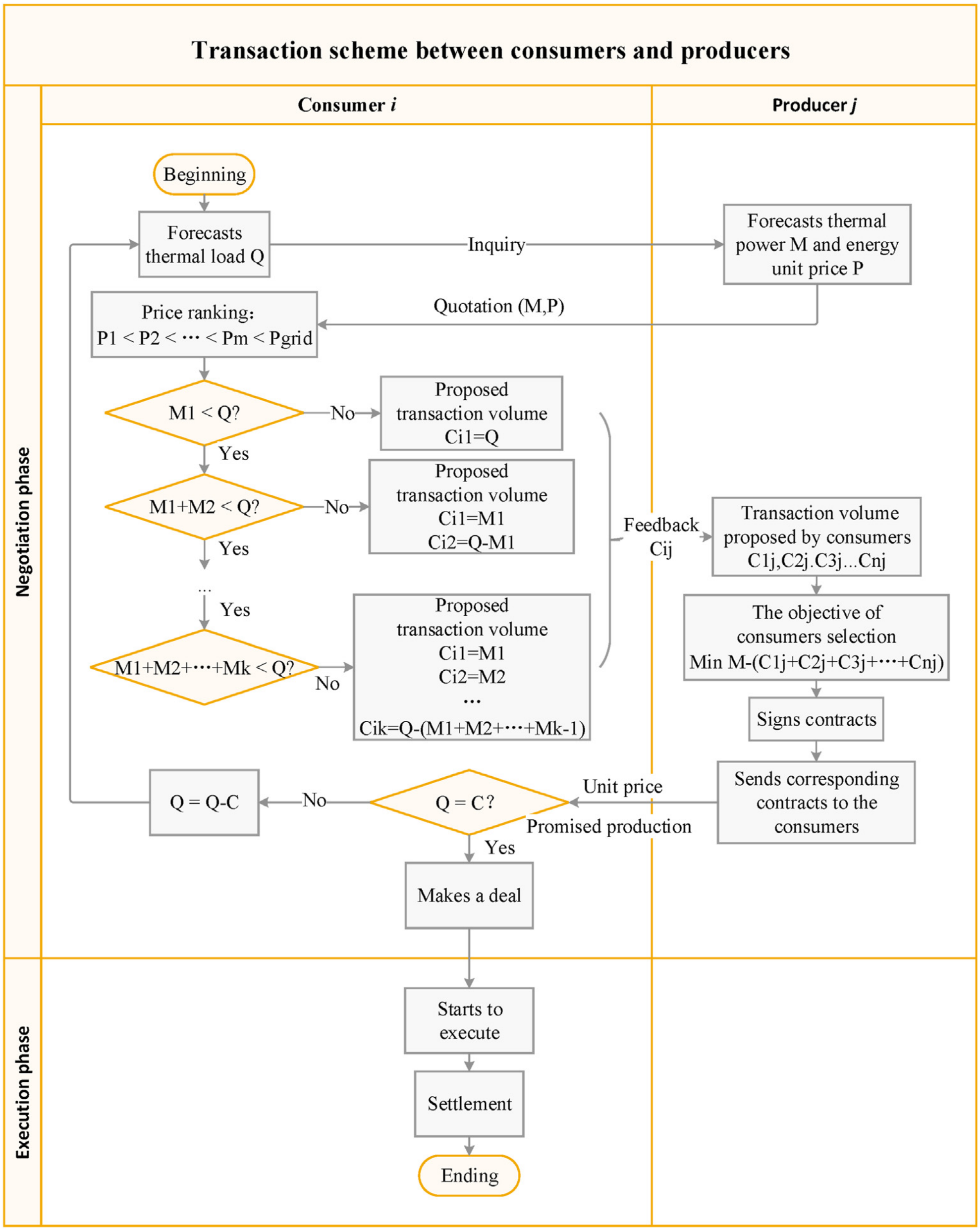

Fig. 11. Transaction scheme between consumers and producers (P refers to price, M to heating energy, and C to trading volume).

For the entire system, the comprehensive efficiency is equal to the weighted average of its components. The weights are defined to be the heat production of generation devices and the heat purchase of storage devices, as follows:

$$EF = \frac{EF_a \times \sum E + EF_b \times \sum H}{\sum E + \sum H} \tag{14}$$

where E is the heat production of generation units, $C$and C_x are the trading volume of heat generation devices and storage devices, respectively, with end users, and $\frac{(Capacity - V_{\min})}{Capacity}$ is the capacity utilization efficiency of heat storage devices.

5. Simulation results and analysis

The simulation mimics the P2P competitive trading mechanism of the heating system. The simulation results of Pricing Scheme 1 as a baseline are shown in Subsection 5.1, and the results of using other pricing schemes are presented in Subsection 5.2. Finally, the comparative simulation of the studied heating system adopting the conventional central scheme and the decentralized P2P solution respectively was conducted and the results are analyzed in Subsection 5.3. Both economic benefits and system efficiency improvement are discussed.

5.1. Simulation results of baseline pricing scheme

In this baseline scenario (see Fig. 13), all producers employ the Selling Price Adjustment Strategy 1. The simulation results indicate that except for solar hot water collectors, whose unit price is obviously high, producer prices generally tend to first increase and then decrease, as in the case of end-user heating load. The economics common sense that increasing consumer demand will lead

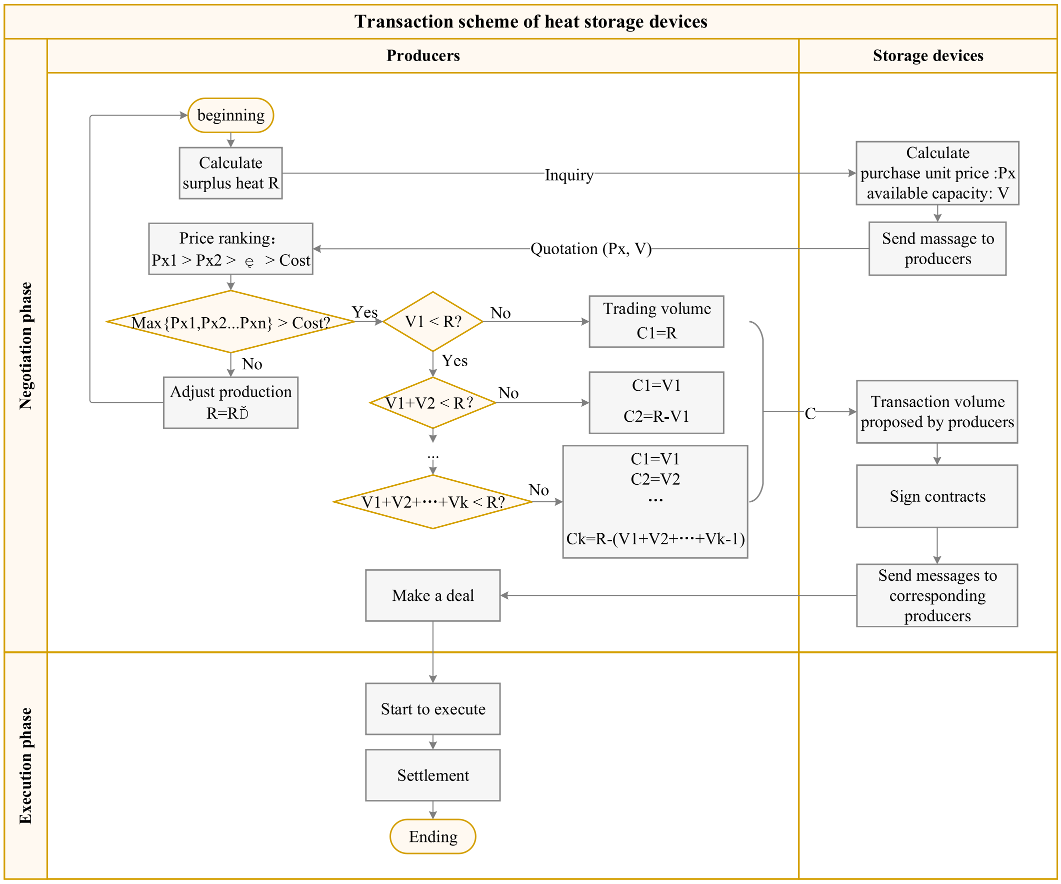

Fig. 12. Transaction scheme of heat storage devices (Px refers to the purchase unit price offered by storage devices, R to the surplus heat, V to the available capacity of storage devices, C to the trading volume, and Cost to the heat generation cost of heat producers).

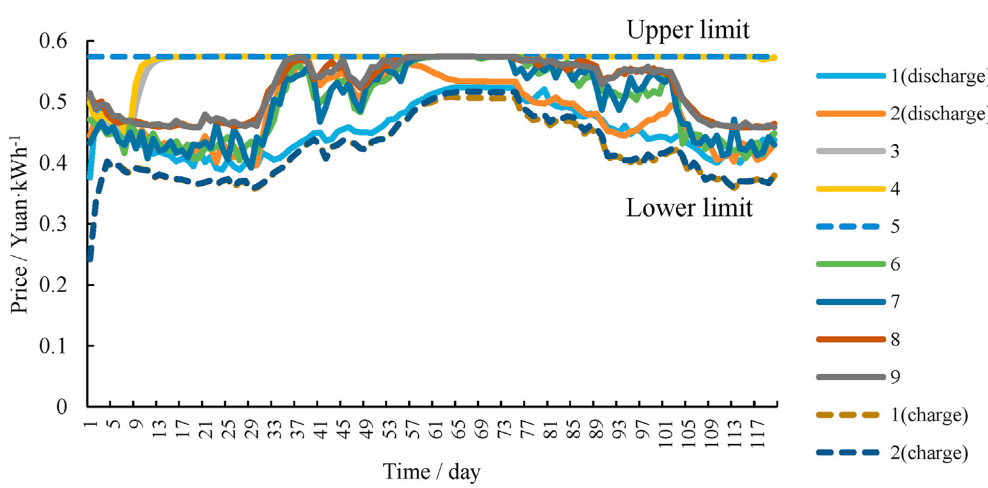

Fig. 13. Producer price profile. (Note: Nos. 1, 2 are energy storage devices, Nos. 3, 4 are solar collector, Nos. 5 is district heating grid, Nos. 6, 7 are gas boilers, and Nos. 8, 9 are ground source heat pumps).

to price rise is proved by simulation, as well as modeling reasonableness.

The simulation results of the average daily trading volume and daily average profit for each producer are shown in Fig. 14. Higher heat unit price puts solar units at a disadvantage in the energy market competition. As a result, the solar collectors sold a small amount of hot water to consumers, and the majority of solar water production was sold to storage units. This is sensible because the peak heating demand occurs at night. The amount of heat purchase varied greatly from Storage Unit 1 to Storage Unit 2, indicating that Scheme 1 leads to poor performance for storage units and forms a monopoly situation. In this case, the production capacity of local producers is not fully utilized, and the unsatisfied demand is supplemented by the district heating grid.

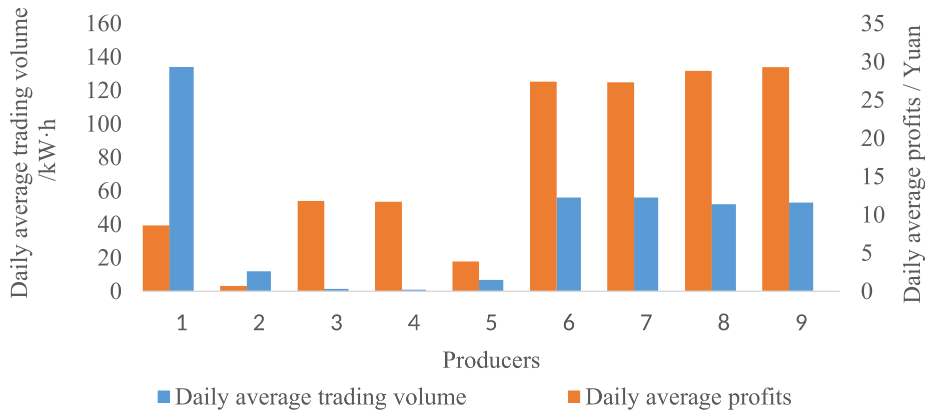

Fig. 14. Producer daily average trading volume and profits.

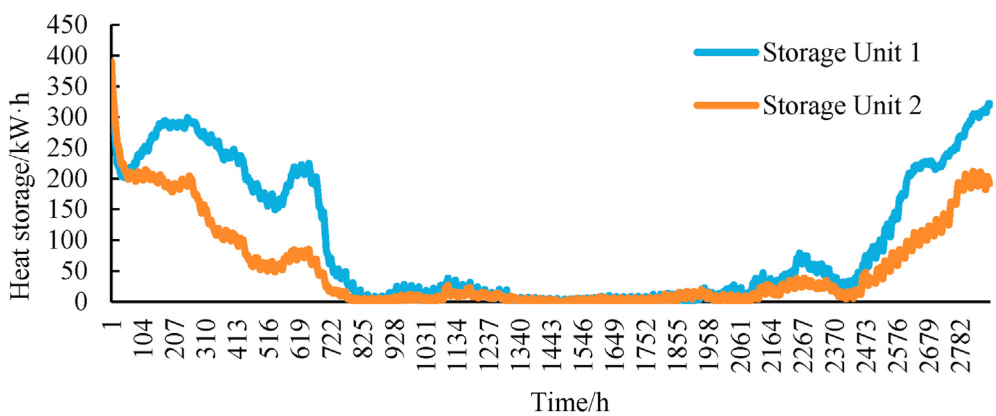

Fig. 15. Heat storage of energy storage units.

For the heat storage device performance, the simulation results indicate that the stored heat (as Fig. 15) reached its bottom at the peak of the load. This is sensible because storage devices are supposed to release all their stored heat when heating is needed most. Selling price slightly lags peak demand. Although the trading volumes of the two thermal storage devices differed greatly, a similar price trend is observed.

The daily average consumer cost for heating and its composition are shown in Fig. 16. Consumer heating bills varied with the general consensus observed in the heating load profile, indicating that the model is physically reasonable. Furthermore, the district heating grid and storage units accounted for a significant proportion of consumer bills, whereas solar water for the smallest. Scheme 1 results in poor renewable energy utilization.

As shown in Fig. 17, when Pricing Strategy 1 is used by all producers, the boilers yield the highest utilization efficiency, followed

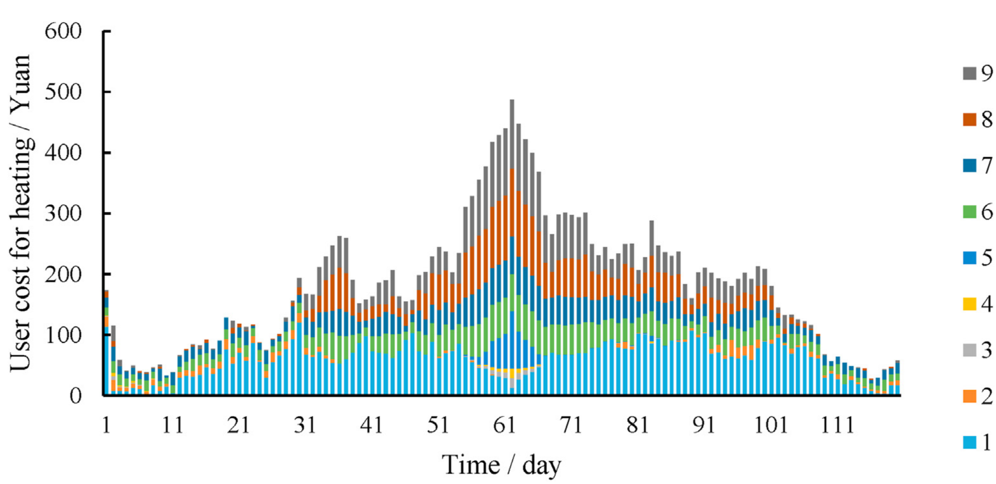

Fig. 16. Daily consumer cost for heating.

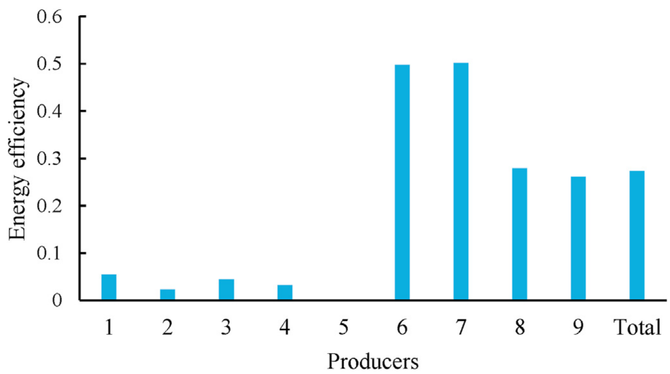

Fig. 17. Producer efficiency and comprehensive system efficiency.

by ground source heat pumps. The utilization efficiency of heat pumps is approximately half of that of boilers, and the efficiency of solar units and storage units is relatively low. The total utilization efficiency of the entire system is poor.

In general, under Scheme 1, there exists a large transaction volume difference between storage units. Moreover, most of the solar hot water was sold to storage units instead of users directly. This is not the optimal scheme for maximizing renewable energy utilization and contributing to a fair energy market. Certain factors caused relatively low total energy utilization efficiency. It can be interpreted as the prospective earnings-based pricing strategy highly relies on the value of prospective earnings. Rather than being a constant, the appropriate prospective earning ought to be time-varying, which varies with the supply and demand in energy market. Peers with appropriate prospective earnings can gain a competitive edge in the energy market, while for those who using ineffective prospective earnings, poor bidding performance is obtained. For example, it is possible that the relatively low prospective earnings make the price of solar units to rise rapidly to its upper limit and lose its appeal to end users. Consequently, the majority of solar hot water was sold to storage units and is not fully utilized.

In the second step, the Pricing Schemes 2–8 presented in Subsection 5.2 were examined to identify the influences put on system performance by pricing strategies and identify a superior one.

5.2. Simulation results of other pricing schemes

The simulation results of Scheme 2 indicate that changing the pricing strategy of one of the storage devices affects the energy storage performance, while this causes little effect on the performance of other devices as Fig. 18. It can be observed that, changing the pricing strategy of one of the storage units can reduce the difference in trading volume and earned profit among storage units. It is possible that, compared to the perspective earnings-enabled pricing strategy, Strategy 2 provides more flexibility by dynamically updating prices based on historical transactions. In this case, market signals can be better captured by all stakeholders, and the energy storage monopoly is prohibited.

Similar results are observed in Scheme 3; when the pricing strategy of Solar Collector 3 was changed, the selling price of solar water decreased compared to that in Scheme 1 due to the introduction of a smarter pricing strategy. In Scheme 3, the selling price of Solar Unit 3 exhibits a periodic variation, and the lasting high prices in Scheme 1 are avoided. The declined unit price makes Solar Unit 3 a more competitive participant in energy trading and drastically increases the amount of hot water supplied to end users, as shown in Fig. 19. Thus, both producer and system-wide efficiency is improved, as shown in Fig. 20. It clear that addition to storage units, distribute generations also benefit from a superior pricing strategy. Similar results are observed in Scheme 4. Simulation results of Scheme 4 demonstrate that altering the pricing strategy of Boiler 6 results in frequent price fluctuations, and price adjustment is more flexible, which increases its competitiveness in energy market. Specifically, the selling price of boiler 6 drops during the user demand peak period, whereas that of Boiler 7 remains constant. Accordingly, higher trading volume and profit are observed from Boiler 6.

The simulation results of Scheme 5 indicate that by altering the selling price adjustment strategy of all storage units from Strategy 1 to Strategy 2, the storage unit selling price increases compared to the baseline case. By using Strategy 2, the difference in the unit price of heat storage units is narrowed, and so does that of trading volume, as shown in Fig. 21. Accordingly, the monopoly of storage units in the baseline case is mitigated. From this perspective, Scheme 5 can facilitate system operation stability. The profits of energy storage units only take up a small portion of the whole system's earnings(see Fig. 22).

Fig. 23 and Fig. 24 illustrate the simulation results of Scheme 6. As in the case with Scheme 3, the price of solar water varies periodically, and decrease further. The trading volume of solar units apparently increases, whereas that of the other producers (except for storage units) is slightly decreased. More heat generated by solar units was sold to end users rather than storage units. In this case, from the consumer's perspective, the heating cost structure is different from that under Scheme 1. For local renewable heating sources, solar hot water accounted for a significantly increasing

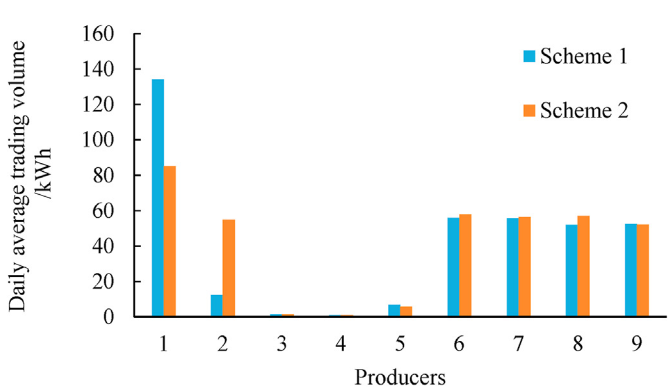

Fig. 18. Daily average trading volume.

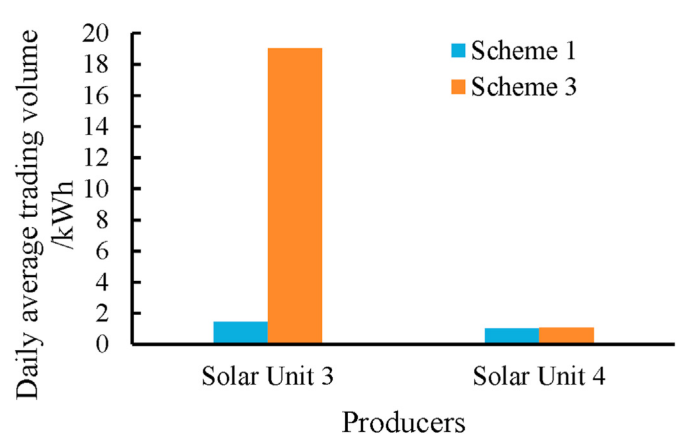

Fig. 19. Solar unit trading volume.

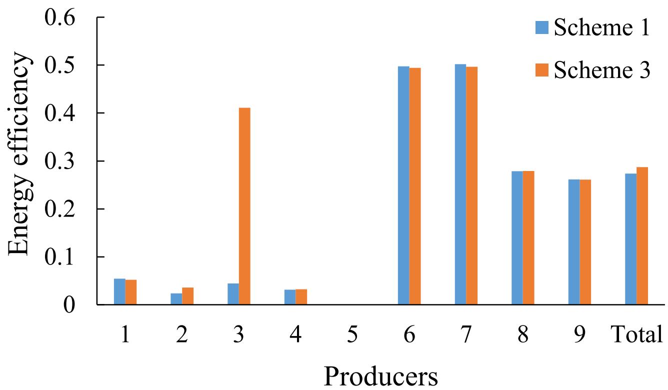

Fig. 20. Producer and system-wide efficiency.

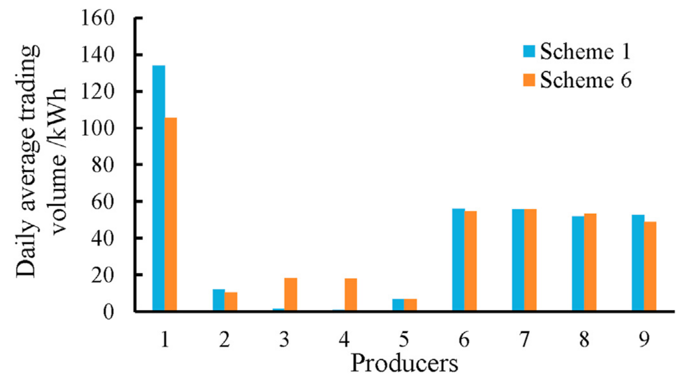

Fig. 23. Producer trading volume.

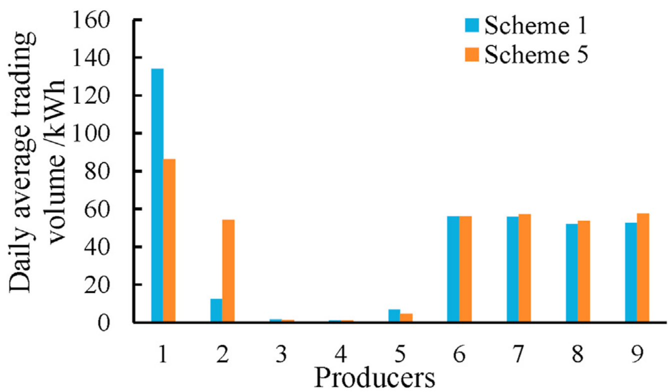

Fig. 21. Daily average trading volume.

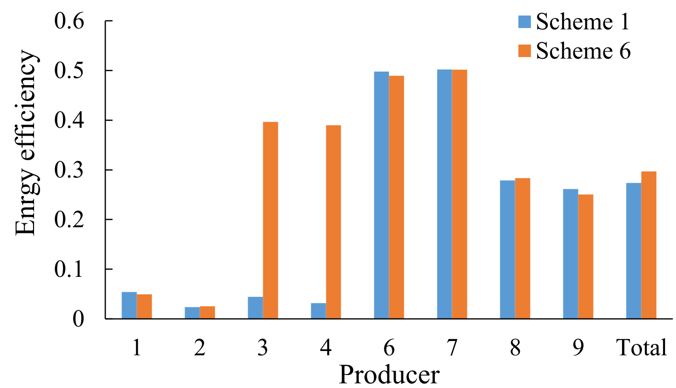

Fig. 24. Producer and system-wide efficiency.

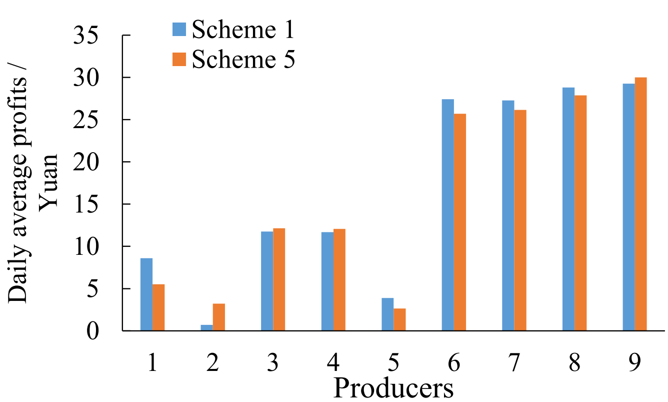

Fig. 22. Daily average profits.

proportion of the heating cost, whereas the contribution of heat storage units obviously drops. It can be concluded that compared to the Selling Price Adjustment Strategy 1, Strategy 2 is preferable for solar collectors. By employing Strategy 2, the amount of heat generated by local renewable energy sources is more likely to be consumed by local end users, and the utilization efficiency of the integrated system is improved. And it also can be concluded that, compared to energy storage units, the pricing strategy of distributed generations has more impact on the whole system.

The simulation of Scheme 7 shows similar results, demonstrating that boilers are benefitted from utilizing Pricing Strategy 2. It contributes to the increase of the boiler market share by making price variation more flexible. However, in terms of system-wide efficiency, only a slight improvement was observed due to the relatively low efficiency of boilers.

The simulation results of Scheme 8 are shown in Fig. 25 and Fig. 26. When the bidding strategies of all producers change, the trading volume of the district heating grid and storage units drops. Concurrently, the heat produced by others increases; in particular, the solar unit output increases greatly. The disproportion in the trading volume between two storage devices still exists, but the gap is dramatically narrowed. Among the producers, only the profits of solar collectors increase. Among all the schemes, Scheme 8 shows the best performance. Therefore, Pricing Strategy 2 can improve the utilization efficiency of solar energy.

As shown in Fig. 26, in general, the total user cost declines. The user can save 8.8% (1931.86 Yuan) on heating costs during the heating season. Pricing Strategy 2 contributes to consumer cost reduction. The proportion of solar water greatly rises, and more money is used for purchasing renewable energy. Pricing Strategy 2 stimulates the usage of local renewable energy.

In Scheme 8, the utilization efficiency of each producer as well as the entire system apparently increases compared to that in Scheme 1 (a 14.65% efficiency improvement is observed). The utilization efficiency of solar collectors rises the most, far higher than that of ground source heat pumps.

When all producers adopt Pricing Strategy 2, the profit of the solar units is the highest. Thereby, system-wide efficiency is improved, and the total consumer cost is reduced. Therefore, after comparative analysis, it can be observed that different pricing strategies lead to different system-wide performance, and smarter pricing strategies can improve efficiency at both individual and system levels. Pricing Strategy 2 performs better than Strategy 1.

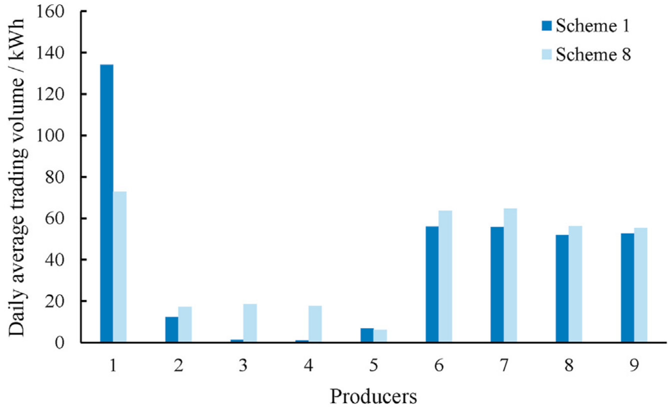

Fig. 25. Producer trading volume.

5.3. Comparison of the P2P competitive heating system and conventional heating system

To quantify the benefits of the proposed system over traditional central heating systems, a comparative analysis was conducted. The results are shown in Table 5. It should be noted that for the central heating system, a fixed heating price was adopted according to the district heating price list in Beijing in 2017. It was assumed that all end-user demand is met by the district heating grid. The simulation results of Scheme 8 were used to represent the P2P competitive heating system.

The heat generation devices in the P2P system operate more effectively than those in the conventional system because its architecture breaks the monopoly of the district heating grid, and provides more heating alternatives to end users. Thereby, the heat generated by local producers, particularly by those producers using renewable energy, can be fully utilized. From an economic perspective, by introducing the market competition mechanism to the heating system, consumers can benefit from the competition among producers. Thus, consumer cost for heating is decreased in a P2P system.

Table 5
Efficiency and user cost of two system structures.

System structure	Efficiency	User cost
Centralized	0.35	RMB 25636 Yuan
P2P	Solar units: 0.39 Boilers: 0.55 Ground source heat pumps: 0.31	RMB 9925 Yuan

6. Conclusion and discussion

With the development of DERs, centralized control and management may become the last hurdle. P2P energy trading may be a new promising paradigm for future smart energy systems. In P2P trading, no middle man is required, and consumers have direct access to multi-energy resources. No restrictions and approval are required, and thus monopoly by third-party control management can be avoided. P2P energy systems may eventually be more effective and fair to every party because all prices are set by the market.

In this study, an integrated five-layer architecture of a P2P competitive energy system was proposed, and its operating mechanism was discussed. Under this operating mechanism, each peer (producer, customer, and prosumer) determines which peers to trade energy with, as well as the amount and the price of the energy. Each peer operates so as to maximize its own economic benefits. Through this bidding process, the overall system operating efficiency is enhanced. The pricing strategies were examined in detail. Aiming to acquire their maximum economic advantages in this multilateral game of energy trading, peers autonomously adjust their energy bids in real time. This new P2P competitive energy system is more flexible, efficient, and intelligent.

In addition to developing the operating mechanism, a hardware implementation of an IOTA-enabled P2P competitive energy system was proposed. Specifically, the IOTA protocol was applied to the design of Energy Routers, which are similar to the routers of computer networks and serve as a hardware interface for the underlying physical energy devices. By attaching Energy Routers, conventional energy devices, both energy producers and consumers, can be upgraded into smart devices in a plug-and-play way without any replacemen and retrofit of existing devices. The routers communicate with each other through a P2P network to realize autonomous machine negotiation and energy dispatching; moreover, they have good scalability. Combined with the IOTA protocol and machine cryptocurrency payments, the routers are supposed to solve the trust issue in energy trading in application.

Finally, a case study of a heating system employing this P2P competitive architecture was conducted. Different pricing

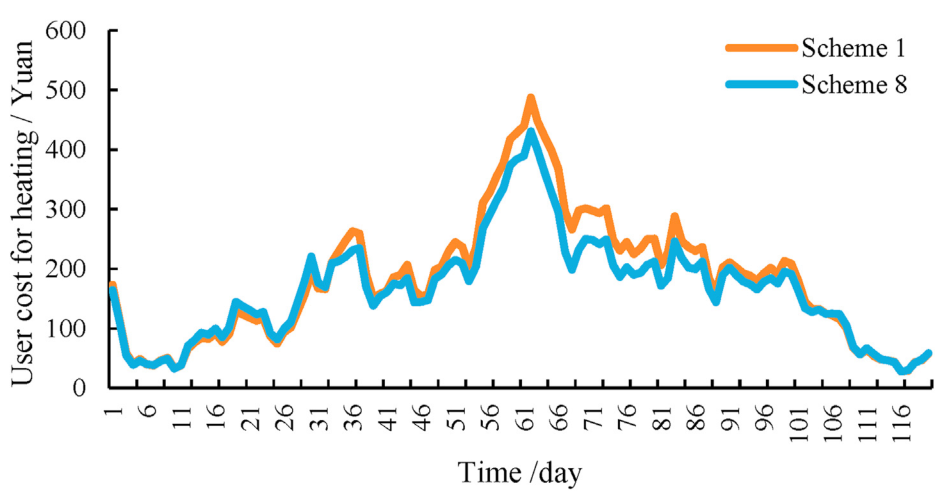

Fig. 26. Consumer cost for heating.

strategies were simulated to examine system-wide performance. The results show that pricing strategies impact system operating efficiency and Pricing Strategy 2 appears to be the best in improving the overall system performance (We observed an 8.8% increase in energy efficiency, compared to the baseline scheme). The reason may be that, as to the prospective earnings-based Pricing Strategy 1, the value of prospective earning has a great influence on devices' price updating. Irrational prospective earnings can lead to poor performance. On the contrary, Pricing Strategy 2 does not rely on any predefined static values. It updates devices' prices according to historical transaction prices and profits dynamically, and can more accurately capture the changes of energy market.

Compared with traditional central heating, the P2P heating system is more efficient at system level. The total energy cost for all consumers is reduced by 61%. On the demand side, the proposed P2P solution provides an easier access for end users to locally-produced renewable energy at lower prices. On the supply side, local producers are not forced to sell heat to the district grid at a discounted wholesale price; rather, they can sell directly to end users. In this way, at system scale, the proportion of renewable energy is increased and both economic and environmental benefits are obtained. It contributes to cleaner energy production and sustainable development of the energy system.

In some relative works, financial benefits were also mentioned. For example, in (Tushar et al., 2018), up to 53% cost savings in a single sunny day can be achieved by using a canonical coalition game-enabled P2P mechanism. In (Chen et al., 2019), the P2P network participant with storage devices improves the supply-demand matching rate by 29.04% and reduces the overall cost by 8.72% on a single day. However, all of them were conducted in power market, and no heating and cooling flows were involved. In this work, compared to central heating system, the proposed P2P competitive paradigm can reduce the user cost by 61% during a heating season. Financial benefits vary with the local time-of-use (TOU) electricity price, gas price and other energy prices, along with load profile.

6.1. Applicability to engineering application

Since no specific supply-side equipment and demand-side load mathematical models are involved in this work, the proposed P2P solution can be applied to any multi-energy systems for any energy trading (e.g. electricity, cooling and heating). Noting that, for different forms of energy flow, adjustment of the time step is needed. Although on the supply side, only solar units and ground source heat pumps were discussed in this paper, they can be easily replaced or coupled with any other source of renewable energy such as wind power by providing its corresponding parameters. Likewise, on the demand side, more types of buildings (e.g. residential buildings, commercial buildings and hotels) can participate in P2P trading by inputting its load profile.

Additionally, rather than game theory (e.g. non-cooperative Stackelberg game) and bidding models (e.g. continuous double auction), relatively simple pricing strategy and bidding scheme with less computation needs are adopted in this work. In this way, they can be easily applied to distribute controllers, which could be a Programmable Logic Controller, Raspberry Pi, Arduino or a Teensy 3 micro-controller. These controllers are cheap, easy to install. The Energy Router proposed in this paper can update existing devices to smart units participating P2P trading in a plug-and-play way. Compared to physical system renovation, it is more practical. Furthermore, underlying IOTA technology is utilized to protect user privacy and tackle the trust issue when the central operator absents.

6.2. Challenges and future work

This is a concept study of P2P control for heating and cooling systems to demonstrate P2P control for conventional heating and cooling system with multiple sources. Therefore, we simplified the simulation of the platform and energy devices. For example, a simplified distributed heating system model is adopted in this work, and the choice of pricing strategy simulated is limited to a few simple ones. In the following work, a more realistic simulation of physical systems should be built. Additionally, for an easy engineering application, relatively simple pricing strategies and bidding schemes are adopted in this paper. In the future, some comparative analyses of various trading paradigms (e.g. non-corporation game and the proposed one) should be done from both economic and practical perspective. Finally, this paper focuses on the P2P process, and pays little attention to the uncertainty of energy generation and user load. In real-world scenarios, supply and demand are dynamically coupled. Hence, to capture a more reliable result, the uncertainty of renewable energy generation and demand-side response should be integrated into the present work.

In addition to technical challenges, the development of P2P systems is also affected by policies. Currently, there is no explicit legislation to deal with the privacy concerns that P2P market may cause, as well as to balance the economic benefits of all stakeholders (existing central operators and DGs). The current policy environment restricts consumers and producers from sharing data and participating in the local energy market. However, major countries are all moving toward deregulating their energy markets. For example, with the rapid increase of distributed energy systems in China, by the end of 2019, China's distributed PV power generation capacity was about 19 times that of 2013. The multi-energy management and scheduling have become an urgent problem to be solved. Under this context, some China government deregulation efforts, such as “Internet Plus” and the "Pilot Market Trading of Distributed Generation”, were promulgated to promote the combination of Internet information technology and traditional industries. Decentralization of energy trading and cleaner production were also mentioned in these regulations. Like many other developed countries, we believe these regulations can facilitate the development of P2P solutions in China.

To sum up, several practical and technical obstacles should be overcome as well as energy policies and legal issues should be considered before the system can be realized.

CRediT authorship contribution statement

Shiyao Li: literature review, development of, Methodology, and case study implementation. 2. Second author, Professor, guides her to identify the problem and implement the proposed, Methodology, She also verifies the accuracy of the result and guides him in writing the paper. 3. Third Author, Professor. **Yiqun Pan:** Supervision, is the supervisor of. **Peng Xu:** contributed to, Methodology, and simulation guide.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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