Applied Energy 279 (2020) 115866

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Adaptive bidding strategy for real-time energy management in multi-energy market enhanced by blockchain

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HIGHLIGHTS

- Real-time energy management mode for multi-energy market is proposed.
- An adaptive learning bidding strategy with reserve price adjustment and dynamic compensation mechanism is developed.
- The optimized energy trading mode improves economy and renewable energy utilization.
- Efficient and trustable multi-energy operation is implemented with blockchain.

ARTICLE INFO

Keywords:
Bidding strategy
Multi-energy market
Real-time energy management
Blockchain
Adaptive learning
Dynamic compensation

ABSTRACT

Energy trading in the multi-energy market is affected by many uncertainties, especially the fluctuation of renewable energy sources and intermittent demand behavior of customers. The real-time energy management can effectively solve the impact of various uncertainties, ensure the instantaneous balance of energy and improve trading returns. A bidding strategy for multi-energy market is presented, in which reserve price adjustment and dynamic compensation mechanism is innovatively integrated into adaptive learning process. All energy trading participants conduct adaptive learning bidding adjustment based on real-time information in order to obtain higher transaction rate and transaction income. Meanwhile, adding dynamic compensation to the quoted price of fossil energy increases the consumption rate of renewable energy and reduces the emissions of pollutants. Furthermore, blockchain technology can ensure the seamless and effective performance of the presented bidding strategy. In the case study, the results show that our bidding strategy has an obvious advantage in social welfare and allocation efficiency than existing bidding strategies. Moreover, the problem of environmental pollution can be solved to a certain extent through flexible dynamic compensation. Finally, a decentralized application of blockchain is developed to demonstrate how the system could realize real-time energy management and dynamic trading in practice.

1. Introduction

Integrated energy utilization is an effective way to improve energy efficiency [1], reduce CO_2 emissions, and increase renewable energy penetration [2], which are among the most important energy issues in the world. Thus, integrated energy systems (IESs) which are coupled with electricity, heat, cold, gas and other energy sources [3], are under rapid development [4]. The multi-energy market is the mode of energy transaction and transfer in the IES [5], and its main objective is to ensure the balance between supply and demand for energy sources [6], and to increase the proportion of renewable energy consumption [7]. Energy trading in the multi-energy market is affected by many uncertainties, especially intermittent behavior of renewable energy sources and fluctuation in demand of customers [8]. The real-time energy management can effectively solve the impact of various uncertainties on the multi-energy market and ensure the instantaneous balance of energy [9]. Meanwhile, compared with fixed energy prices, real-time energy prices

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https://doi.org/10.1016/j.apenergy.2020.115866
Received 27 June 2020; Received in revised form 13 August 2020; Accepted 11 September 2020
Available online 24 September 2020

Nomenclature

Abbreviations

IES	integrated energy system
PV	photovoltaic
WPP	wind power plant
CCHP	combined cooling, heating and power
DN	distribution networks
GB	gas boilers
DE	demand of electricity
DH	demand of heat
DC	demand of cold
EH	electrical heating equipment
EC	electric refrigerating equipment
ZI	zero-intelligence
ZI-C	zero-intelligence with constraints
ZI-P	zero-intelligence with second-price
AA	adaptive aggressiveness
PA	positively self-adaptive
ARC	adaptive learning strategy with reserve price adjustment and dynamic compensation
API	application programming interface
AB	absorption refrigerator
DApp	decentralized application
UI	user interface
EVM	Ethereum virtual machine

Variable

SW	social welfare
AE	allocation efficiency
SWM	social welfare maximization
B_{DH}^{E}	bidding price of the heating load buyers to the electric load market
Q_{DH}^{E}	bidding amount of energy to be purchased the heating load buyers to the electric load market
B_{DC}^{E}	bidding price of the cold load buyers to the electric load market
Q_{DC}^{E}	bidding amount of energy to be purchased the cold load buyers to the electric load market
Q_{DN}^{E}	amount of energy supplied by distribution network
Q_{WPP}^{E}	amount of energy supplied by wind power plant
Q_{PV}^{E}	amount of energy supplied by photovoltaic
Q_{CCHP}^{E}	amount of energy supplied by combined cooling, heating and power
Q_{DE}^{E}	bidding amount of energy to be purchased the electric load buyers to the electric load market
$B_{i,t}^{PA}$	buyer's bidding price in PA strategy
$S_{i,t}^{PA}$	seller's bidding price in PA strategy
$RB_{i,t}$	reserve price of buyer i in t transactions
$RS_{j,t}$	reserve price of sellers j in t transactions
α_t	lowest revenue rate of a buyer
β_t	lowest revenue rate of a seller
D_j	dynamic bidding compensation
$B_{i,t}$	buyers' bidding price
$S_{i,t}$	sellers' bidding price
P'	equilibrium price
γ_t	rational choice function

Parameter

B_{DH}^{H}	bidding price of the heating load buyers to the heat load market
Q_{DH}^{H}	bidding amount of energy to be purchased of the heating load buyers to the heat load market
η_{EH}	conversion efficiency of electric heating
μ_{DH}	distribution coefficient of demand of heat
B_{DC}^{C}	bidding price of the cold load buyers to the cold load market
Q_{DC}^{C}	bidding amount of energy to be purchased of the cold load buyers to the cold load market
η_{EC}	the conversion efficiency of electric to cold
μ_{DC}	distribution coefficient of demand of cold
Q_{CCHP}^{C}	amount of energy supplied by combined cooling, heating and power to the cold load market
Q_{CCHP}^{H}	amount of energy supplied by combined cooling, heating and power to the heat load market
Q_{GB}^{H}	amount of energy supplied by the gas boilers to the heat load market
$W_{CCHP,min}^{E}$	minimum generation power constraints of the combined cooling, heating and power
$W_{CCHP,t}^{E}$	generation power of the combined cooling, heating and power at time t
$W_{CCHP,max}^{E}$	maximum generation power constraints of the combined cooling, heating and power
M_{CCHP}^{E}	power generation climbing speed constraint of the combined cooling, heating and power
$Q_{CCHP,t}^{E}$	amount of electricity generated by the combined cooling, heating and power at time t
$W_{CCHP,min}^{H}$	minimum heating power constraints of the combined cooling, heating and power
$W_{CCHP,t}^{H}$	heating power of the combined cooling, heating and power at time t
$W_{CCHP,max}^{H}$	maximum heating power constraints of the combined cooling, heating and power
M_{CCHP}^{H}	heat generation climbing speed constraint of the combined cooling, heating and power
$Q_{CCHP,t}^{H}$	amount of heat generated by the combined cooling, heating and power at time t
$W_{AB,t}^{C}$	cold power of the absorption refrigerator at time t
$W_{AB,max}^{C}$	maximum cold power constraints of the absorption refrigerator
M_{AB}^{C}	cold generation climbing speed constraint of the absorption refrigerator
$Q_{CCHP,t}^{C}$	amount of cold generated by the absorption refrigerator at time t
$W_{GB,t}^{H}$	heating power of the gas boilers at time t
$W_{GB,max}^{H}$	maximum heating power constraints of the gas boilers
M_{GB}^{H}	heat generation climbing speed constraint of the gas boilers
$Q_{GB,t}^{H}$	amount of heat generated by the gas boilers at time t
$W_{EH,t}^{H}$	heating power of the electrical heating equipment at time t
$W_{EH,max}^{H}$	maximum heating power constraints of the electrical heating equipment
M_{EH}^{H}	heat generation climbing speed constraint of the electrical heating equipment
$Q_{EH,t}^{H}$	amount of heat generated by the electrical heating equipment at time t
$W_{EC,t}^{C}$	cold power of the electric refrigerating equipment at time t
$W_{EC,max}^{C}$	maximum cold power constraints of the electric refrigerating equipment
M_{EC}^{C}	cold generation climbing speed constraint of the electric refrigerating equipment
$Q_{EC,t}^{C}$	amount of cold generated by electric refrigerating equipment at time t
P_t	trading price in t transactions

Q_t	trading amount in t transactions
ω_t	weight in t transactions
Q_{max}	total amount of energy that all sellers can provide
Q_{t-1}	total amount of energy that has been traded
SP_t	transaction price sequence up to round t
SB_t	buyer's bidding price sequence up to round t
SS_t	seller's bidding price sequence up to round t
V_i	buyer's reserve price
C_j	seller's reserve price
e_n	pollutant quantity of per unit energy supply n emitted
f_n	environmental treatment cost of unit quantity n emitted

are more conducive to play the role of market mechanisms [10], and maximizing the profit incurred while considering customer participation [11].

There has been increasing research interest and publications on the real-time energy management, where diverse approaches have been pursued, e.g. particle swarm optimization [12], ant colony optimization [13], mixed-integer linear programming [14], multi-objective operation optimization [15] and game theoretical agent-based approaches [16,17]. These methods all involve a center that manages transactions in the multi-energy market [18], as the participating units upload information to the center, which then determines the energy management strategy and sends it to each unit [19]. However, the data information increases geometrically with the increase of participants, which improves the difficulty of scheduling resources in real-time energy management [20]. Meanwhile, the data of these methods is controlled by a central institution, which makes it difficult for participating units to adjust their bidding strategies based on real-time information [8], and reduce transaction rates and overall profit [11]. Therefore, several scholars have presented double auction mechanism that can be used for distributed energy management [21], in order to achieve real-time utilization of energy supply side and active participation of energy demand side [22]. The double auction is a kind of market mechanism which confirms the transaction price and completes the resource allocation on the premise of market trader bid [23], and the bidding strategy determines whether this mode is suitable for the multi-energy market.

Bidding strategies can be divided into two categories: learning ability and non-learning ability. Zero-intelligence (ZI) strategy does not have learning ability. In this strategy buyers and sellers do not consider other information in the market when making a bid. In the actual auction mechanism, Zero-intelligence with constraints (ZI-C) strategy is usually adopted in order to avoid random bidding to disturb the trading order [24]. The ZI with second-Price (ZI-P) strategy is the earliest bidding strategy to adopt a learning mechanism, in which buyers or sellers set their expected profit margins according to the historical successful transaction price and failed transaction price in the market, and then adjust their bidding prices [25]. The Adaptive Aggressiveness (AA) strategy takes the frequent price fluctuations into account in the continuous auction market, which enables the trader to adjust the price in time according to the market changes [26]. Yang et al. [27] proposed a positively self-adaptive (PA) strategy with learning ability that make bidding price based on all the historical transaction information.

In the field of electricity and energy systems, more and more studies focus on the double auction mechanism and bidding strategies of the energy market [28]. Li et al. [29] showed that the auction scheme and bidding strategy can not only ensure the privacy of participants but also effectively facilitate demand response in the smart grid, with respect to social welfare, satisfaction ratio and computational overhead. Yu et al. [30] adopted the integrated two-stage market clearing algorithm as the bidding strategy, and took the two-way electricity market in Yunnan, China as the actual scene to verify the market superiority of the adaptive bidding strategy. Lin et al. [31] analyzed several auction mechanisms and bidding strategies, and proved the best-offer game theoretic strategy which have a higher economic efficiency than discriminatory and uniform bidding strategies. Wang et al. [26] used AA strategy in the decentralized electricity transaction and divided bidders into three rigid categories which limit its flexibility in the market. Zhao et al. [32] proposed a double auction mode for integrated energy transactions, although he did not study a corresponding bidding strategy. Previous studies have demonstrated the advantages of bidding strategies with learning ability in energy markets. It is worth noting that these studies do not consider the problems of the multi-energy market, such as real-time price fluctuations, dynamically adjusted power consumption plan and frequent electricity fees settlement [33]. On the other hand, bidding strategies with learning ability require each energy trader to master real-time information about the system.

Meanwhile, to facilitate efficient transaction in the multi-energy market, a more flexible and stable energy trading system is required [34]. The blockchain-enhanced energy trading stands out to be a suitable solution for the following reasons: Firstly, the distributed network based on blockchain avoids the trading center through the bottom-up energy management mode [35]. This mode can not only ensure the privacy of participants but also effectively facilitate demand response in the energy system [36]. Secondly, the threshold for energy producers has been lowered by blockchain, prompting more energy sellers to join the multi-energy market [37]. Thirdly, energy buyers can freely choose the mode of energy use through this trading system, and promote the reduction of energy consumption cost [38]. Fourth, the chain data structure of blockchain can automatically record the previously reached transaction agreement according to the transaction time, and solve the problem of information inconsistency through a unique consensus mechanism. Finally, the decentralized trust method of blockchain can eliminate the central institution or third-party intermediary, which helps the IES to save operating costs, avoid energy monopoly and reduce the risks of data security [39].

Motivated by all the potential advantages, active attempts have been made in the design and implementation of blockchain enabled energy trading market [2,40]. The first energy blockchain trading system has been set up in Brooklyn, New York, which sell rooftop solar power from five households to another five households directly. This study had set a precedent of adopting blockchain technology in the energy sector [41]. In the field of chemical industry, blockchain technology can be used to construct smart contracts under the machine-to-machine mode for power generation and power consumption equipment. This study explored blockchain technology in relation to Industry 4.0 [42]. Similarly, blockchain can solve the fraud problem in carbon emissions transaction and improve the management efficiency in industry 4.0 mode [43]. In terms of energy demand side management, smart contracts and decentralized identifier guaranteed by blockchain network can create a seamless, secured and efficient distributed energy system [44]. In [45], a method based on blockchain is presented to manage the energy demand and realized the independent maintenance of the transaction information though smart contracts. Despite the rapid development of energy blockchain technology, active work is still needed to develop feasible systematic protocols for blockchain enabled the real-time energy management in multi-energy market.

In general, the double auction mechanism and the adaptive learning bidding strategy can improve the efficiency and income of the energy market. However, the existing energy bidding researches aimed at electricity trading, which focus on the electricity price adjustment. The bidding strategy of multi-energy market considering real-time energy management and interaction effects of electricity, cooling and heating systems have not been reported. Meanwhile, there is a research gap on the implementation of the bidding strategy based on blockchain to the multi-energy market.

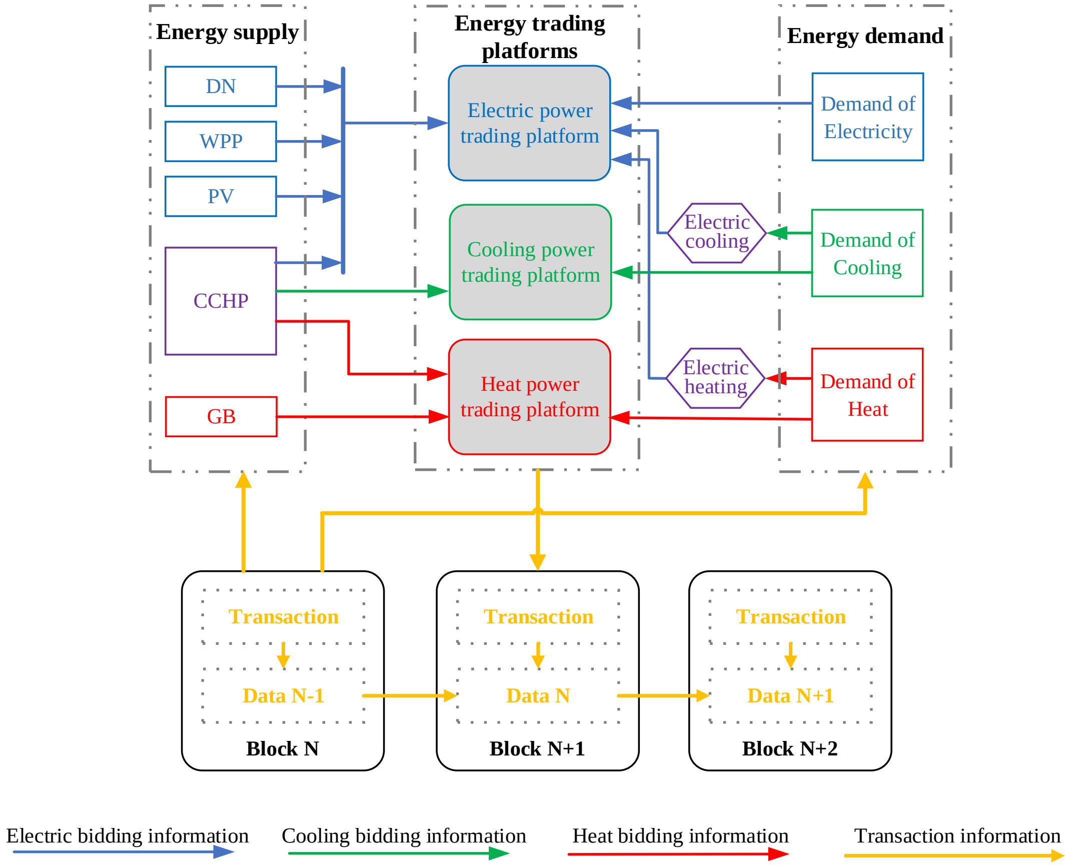


Fig. 1. Energy management mode of multi-energy market.

In this paper, we propose an optimized bidding strategy to achieve real-time energy management for multi-energy market. This adaptive learning bidding strategy with reserve price adjustment and dynamic compensation mechanism is proposed, and we call it AR-C strategy. The presented method can be developed by blockchain network to ensure the seamless and effective performance. The contributions and novelties of this work are as following:

(1) Three interactive energy trading platforms are designed to conduct double auction of electricity, heat and cold. The system facilitates comprehensive utilization of renewable energy through free trading and real-time price.
(2) An original bidding strategy (AR-C strategy) for multi-energy market is presented, in which reserve price adjustment and dynamic compensation mechanism is innovatively integrated into adaptive learning process. This mode improves transaction rates and trading returns, and increases the consumption rate of renewable energy in the energy system.
(3) A blockchain based network framework is designed to facilitate transaction of all users according to the proposed bidding strategy. This blockchain network ensures the theoretical model can be applied in practice.
(4) The trading mode proposed in this study takes into account multi-energy interaction, flexible and adaptive bidding strategy, real-time energy management etc. This work provides reference for comprehensive energy utilization and diversified energy market transactions.

This paper is structured as follows: Section 2 explains the system structure and energy management mode. Sections 3 and 4 show the bidding methodology presented and how blockchain can implement the real-time energy management. Section 5 demonstrates the feasibility of the method through a case study and Section 6 discusses conclusions and future work.

2. System structure and energy management model

2.1. System structure

Integrated energy utilization has broken through the technical, market and management barriers of the traditional energy system, and is a comprehensive energy system with unified planning and dispatch of electricity, gas, heat and cooling, et al [46]. CCHP is a typical energy integration system, which improves the efficiency of primary energy utilization through the cascade utilization principle [47]. Moreover, the penetration of renewable energy can further reduce the impact of IES on the environment, and the coupling of multiple energy sources can effectively alleviate the uncertainty of renewable energy [48]. Although the coupling of multiple energy sources brings difficulties to the economic and stable operation of the traditional energy system, reasonable optimization strategies can break this barrier and realize the situation of multi-energy economic and efficient utilization [49].

According to the physical properties of energy supply and demand, the modern IES can be divided into three energy types: electricity, heat and cold. Therefore, three parallel and interactive energy management platforms are constructed for these kinds of energy transaction. Energy sellers generally include distributed renewable energy sources such as photovoltaic (PV) and wind power plant (WPP), thermal power generator which combined cooling, heating and power (CCHP), distribution networks (DN), gas boilers (GB), and some energy storage devices. According to the energy demand, energy buyers can be divided into demand of electricity (DE), such as residential and commercial power users, demand of heat (DH), such as residents heating, and demand of cold (DC), such as cold storage. Buyers or sellers could conduct energy transactions respectively based on their own energy supply and demand patterns on the three platforms. Each participant could supply or demand one kind of energy, as well as supply or demand other energy sources at the same time. For example, CCHP can conduct different types energy transactions in three market platforms.

The conversion efficiency of energy conversion equipment is the ratio of output power and input power, as Eq. (1).

$$\eta = W_{out}/W_{in} \tag{1}$$

Due to the popularity of electrical heating equipment (EH) and electric refrigerating equipment (EC), heat/cold buyers can participate in the two trading platforms of electricity and heat/cold respectively, and choose directly to purchase heat/cold or to purchase electricity and use energy conversion equipment to heat or cold. After heating load buyers have determined the bidding price (B_{DH}^{H}) to a heat load market and the expected amount of energy to be purchased (Q_{DH}^{H}), the bidding price (B_{DH}^{E}) and quantity (Q_{DH}^{E}) can be calculated by Eq. (2) and (3), and the transaction can be conducted to the electric load market at the same time.

$$B_{DH}^{E} = B_{DH}^{H}\cdot\eta_{EH} \tag{2}$$

$$Q_{DH}^{E} = \mu_{DH}\cdot Q_{DH}^{H}/\eta_{EH} \tag{3}$$

where η_{EH} is the conversion efficiency of electric heating, and its value represents the amount of heat power quantity that can be generated per unit of electric quantity. μ_{DH} is the distribution coefficient of demand of heat, and represents the proportion of the total thermal load demand met through the electrical heating equipment.

Similarly, after determining the bidding price (B_{DC}^{C}) to the cold load market and the expected amount of energy to be purchased (Q_{DC}^{C}), the electricity price (B_{DC}^{E}) and electricity quantity (Q_{DC}^{E}) can be calculated by Eq. (4) and (5), and the transaction can be conducted to the electric load market at the same time. As shown in Eq. (4) and (5), where η_{EC} is the conversion efficiency of electric refrigerating equipment and μ_{DC} is the distribution coefficient of demand of cold.

$$B_{DC}^{E} = B_{DC}^{C}\cdot\eta_{EC} \tag{4}$$

$$Q_{DC}^{E} = \mu_{DC}\cdot Q_{DC}^{C}/\eta_{EC} \tag{5}$$

2.2. *Energy management model*

The energy management model designed in this study is based on the double auction mechanism and blockchain distributed network. In the double auction mechanism, buyers and sellers can adjust the quotation in real time according to the change of the market equilibrium price, which ensures the efficient distribution of energy. The combination of double auction mechanism and blockchain technology can effectively solve the problems of privacy and resource allocation, and ensure the maximum benefit of buyers and sellers. The double auction scheme can not only ensure the privacy of participants [50] but also effectively facilitate demand response in the smart grid, with respect to social welfare, satisfaction ratio, social efficiency, and computational overhead [29].

The energy management mode of multi-energy market as shown in Fig. 1. A double auction is conducted with a fixed time slot during the operation of the system. At time *t*, each participant can publish the energy transaction information of the $t+1$ time slot through its network node, and upload the information to the blockchain network. Energy information includes types of energy supply and demand, energy quantity, bidding price, etc. The system is classified according to different energy types, and each energy trading platform ranks the bidding information of energy buyers and sellers according to the expected price. In every energy trading platform, transaction occurs when the highest bidding price of buyers is equal to or lesser than the lowest bidding price of sellers. During the matching process, the highest bidding price of buyers is matched with the lowest bidding price of sellers, and the transaction price is the average of their bidding prices. This matching process is called round of transaction and continues until the highest bidding price of buyers is lower than the lowest bidding price of sellers [51].

The double auction proposed in this study is not continuous double auction, which means that if an energy buyer does not reach a transaction at an auction, the energy will be provided by the external distribution networks. And if an energy seller fails to reach a deal, the bidding strategy will be adjusted according to the market information in order to reach a deal agreement in the next auction. This mode effectively shortens the time of matching transactions and adapts to the real-time energy management. It improves the computational and operational efficiency for the multi-energy market. In particular, the modern IES is connected to the distribution networks. When the energy buyer fails to match the suitable seller in the system, it is easy to obtain the corresponding energy from the distribution networks and conduct energy transmission and transaction settlement with it. After the end of the matching transaction at time *t*, the energy dispatching and transmission will be carried out according to the reached energy transaction agreement between time *t* and time $t+1$. At time $t+1$, the system matches the bidding price of the next transaction, and records the energy transmission quantity from time t to time $t+1$ through metering equipment which is connected to the blockchain network and automatically settles energy transaction fees based on the agreed transaction price.

The basic principle of double auction and market clearing in traditional electricity markets is the matching of high bid price and low selling price. The lower price offered by the generator, the easier it is to conclude a deal, which makes it easier to sell low-cost but highly polluting fossil energy. In order to solve this problem, we propose a dynamic compensation to increase the price advantage of renewable energy. This compensation mechanism will be discussed in the Section 3.3 later.

In addition, the traditional transaction model relies on third-party agencies. But the transaction model proposed in this paper realizes the peer-to-peer transaction between users and energy suppliers. The agencies in the transaction model only handle disputes between buyers and sellers, and the decentralized properties have not changed. In the traditional transaction model, the transaction data is stored in a centralized server, and it is not transparent. Therefore, it faces the risk of tampering and cannot be traced back. Blockchain technology integrates asymmetric encryption technology, data signatures and consensus mechanisms to ensure that transaction data is transparent, tamper proof, and traceable, which solves the above problems well. The market clearing based on the unique consensus mechanism of blockchain can resolve the problem of information inconsistencies [52], especially for the heat or cooling demand load that sends the transaction request to two trading platforms.

2.3. *Constraint condition*

During the operation of the multi-energy market, the energy conservation and equipment safety must be considered. In the electric power trading platform, the supply of electricity quantity is equal to the demand of electricity quantity at time t, as shown in Eq. (6).

$$Q_{DN}^{E} + Q_{WPP}^{E} + Q_{PV}^{E} + Q_{CCHP}^{E} = Q_{DE}^{E} + Q_{DC}^{E} + Q_{DH}^{E} \tag{6}$$

The energy conservation constraint of the cooling and heat power trading platform can be calculated by Eq. (7) and (8)

$$Q_{CCHP}^{C} = Q_{DC}^{C} \tag{7}$$

$$Q_{CCHP}^{H} + Q_{GB}^{H} = Q_{DH}^{H} \tag{8}$$

In general, every participant in a long-lived multi-energy market is

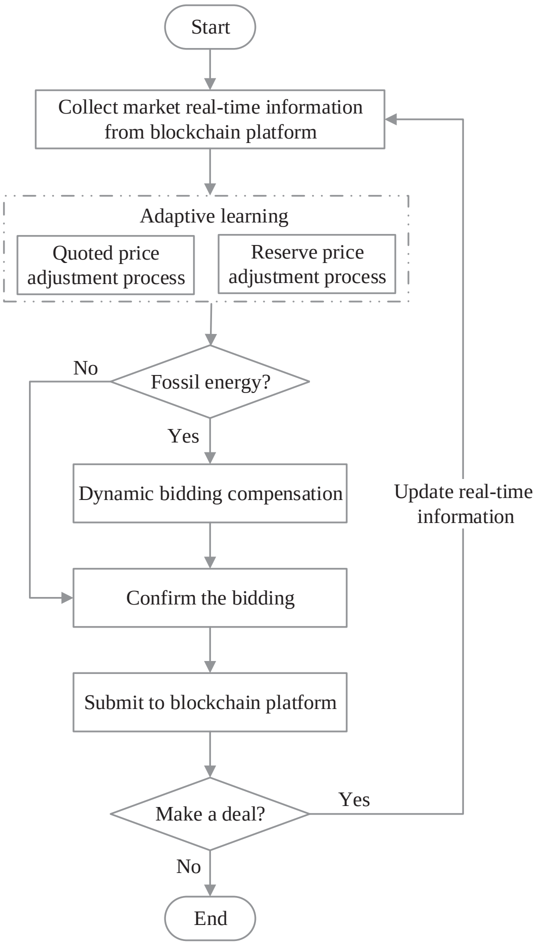


Fig. 2. Schematic of the AR-C bidding strategy.

rational. Therefore, we assume that the amount of these energy sellers and buyers submit to trading platforms is reasonably predicted. There is no possibility of repeat transactions for participants who only trade on one energy trading platform. However, constraint conditions are required to limit repeat transactions for units that submit trading requests to both energy trading platforms, such as the demand of cooling and the demand of heat. The limiting condition of a cooling buyer that contains an electrical cooling device can be calculated by Eq. (9). Similarly, the limiting condition of thermal load buyer can be calculated by Eq. (10).

$$Q_{EC}^{C}+Q_{platform}^{C}=Q_{DC}^{C} \tag{9}$$

$$Q_{EH}^{H}+Q_{platform}^{H}=Q_{DH}^{H} \tag{10}$$

where Q_{EC}^{C} is cooling load of electrical cooling equipment, and Q_{EH}^{H} is heat load of electrical heating equipment. $Q_{platform}^{C}$ and $Q_{platform}^{H}$ are represent the amount of energy that buyers purchase directly from the cooling power or heat power trading platform.

The main operation constraints of equipment safety are the upper and lower limits of power and climbing speed of various energy equipment. This paper mainly discusses the constraints of CCHP, absorption refrigerator, GB, electrical heating equipment and electric refrigerating equipment. The constraint conditions of CCHP are mainly studied from the aspects of electricity quantity, heat quantity and cooling power. And the constraint condition of CCHP to generate cooling power is mainly affected by the absorption refrigerating machine. The lower limit constraint of absorption refrigerator and GB is 0, and the lower limit of other equipment depends on the unit condition. Therefore, the constraint conditions and energy conversion formula of the above equipment can be summarized as shown in Eq. (11)–(13).

$$W_{m,min}^{n}\leq W_{m,t}^{n}\leq W_{m,max}^{n} \tag{11}$$

$$W_{m,t+1}^{n}-W_{m,t}^{n}\leq M_{m}^{n} \tag{12}$$

$$Q_{m,t}^{n}=W_{m,t}^{n}\cdot T \tag{13}$$

where m can take CCHP, absorption refrigerator, GB, electrical heating equipment and electric refrigerating equipment. And n can take E, C, and H.

According to whether it is connected to the distribution network, IESs can be divided into two types: off grid and grid connected. At present, except in remote areas such as islands, almost all IESs are grid connected. There are several advantages in joining the distribution network to energy trading in the multi-energy market. Firstly, the distribution network provides more sufficient power to ensure the security of energy supply. Secondly, the trading price of distribution network in most countries fluctuate within one day, which helps the energy demand side to actively adjust the energy consumption habit according to the price fluctuation. Finally, the addition of distribution network can provide sufficient power for electrical heating equipment and electric refrigerating equipment, and improve flexibility of multi-energy market. Therefore, we are adding distribution networks to the multi-energy market transactions to ensure that all types of energy needs can be satisfied in real time.

3. AR-C strategy in multi-energy market

The AR-C strategy is a bidding strategy with adaptive learning mode and dynamic compensation mechanism. The schematic of AR-C strategy is shown in Fig. 2. According to the real-time information of the multi-energy market, it conducts adaptive learning which includes two process of quoted price adjustment and reserve price adjustment. If energy sellers use fossil energy, environment cost is considered to get a dynamic compensation revised quoted price. The real-time information is updated by the trading system immediately after each double auction.

3.1. *Evaluation indexes*

There are many definitions and evaluation indicators for the auction process and auction results in the energy double auction. This study selects social welfare (*SW*) as one of the economic indicators to evaluate the bidding strategy. It is made by double auction transaction to create the revenue scale of the whole society, that is, sum of the total revenue of buyers and sellers in the auction. Earnings from a single transaction are usually expressed as the product of the difference between the transaction price and the reserve price and the number of transactions. The *SW* can be generally expressed as Eq. (14).

$$SW=\sum_{t=0}^{T}\left\{\sum_{i=1}^{I}\left[RB_{i,t}-P_{i,t}\right]\cdot Q_{i,t}+\sum_{j=1}^{J}\left[P_{j,t}-RS_{j,t}\right]\cdot Q_{j,t}\right\} \tag{14}$$

where $RB_{i,t}$ and $RB_{j,t}$ represent the reserve price of buyer i and seller j in t transactions, P_t represents the transaction price, and Q_t represents the amount of energy for the transaction.

In addition, allocation efficiency (*AE*) is also one of the important performance evaluation indicators of double auctions. It is the ratio of the actual total revenue of trading parties to the competitive equilibrium total revenue. Competitive equilibrium is an ideal state in which *SW* is maximized. Therefore, *AE* can be expressed as the ratio of actual *SW* to social welfare maximization (*SWM*) [53], as indicated by Eq. (15).

$$AE=SW/SWM \tag{15}$$

Market competition equilibrium refers to the balance between buyers and sellers in the market or economy, which has the characteristics of perfect competition. It is a market structure without any obstruction and interference, which means that the existence of the market is not enough to affect the prices of enterprises or consumers [25]. In a distributed energy market, every participant is equal and no one has a dominant position. The equilibrium price *P'* cannot be obtained in advance but can be estimated by calculating the weighted moving average of the transaction prices of the recent *T* historical transactions, as shown in Eq. (16). The total return of competitive equilibrium is the total amount of each transaction at the market equilibrium price, namely *SWM* [54].

$$P' = \sum_{t=0}^{T}[\omega_t \cdot P_t] \tag{16}$$

3.2. Adaptive learning mode

3.2.1. Quoted price adjustment process

The trading information is not uniformly in each double auction conducted by the system. In the initial stage of the transaction, participants are more inclined to gain more benefits instead of paying much attention to the probability of the transaction so that the adjustment of the quoted price is slow. But some participants will become more aggressive after several rounds of auctions have failed to reach a deal, and then they will speed up the adjustment of the quoted price in order to obtain a higher probability of transaction. Through the analysis of quote adjustment rules, the rate of quoted price adjustment is a nonlinear concave line. Therefore, the rational choice function γ_t is presented to realize the adaptive learning of participants. The value of γ_t determines the adjustment range of quoted price by judging the ideal degree of market environment. For the energy buyers, the value of γ_t is 1 in the most ideal case, which means that they expect to complete the transaction at the lowest price within the acceptable range to maximize the revenue. In the least ideal case the value is 0, which means that the transaction is expected to be completed at the highest price within the acceptable range to maximize the probability of the transaction. Meanwhile for the energy sellers, γ_t is the opposite. It can vary with market conditions from 0 to 1 to change the proportion of historical quoted price maximum and minimum in the bidding strategy. It is related to the number of transactions in the previous *t*-1 and the amount of energy *Q* given in Eq. (17).

$$\gamma_t = 1 - Q_{t-1}^2 / Q_{max}^2 \tag{17}$$

With the promotion of the transaction rounds, the quoted price of buyers will change from the minimum value of the historical quoted price to the maximum value, in order to get a greater probability of transaction. The sellers' quoted price changes from the maximum to the minimum value of the historical quoted price. For each bidding transaction in the market, all buyers and sellers need to adaptive amend quoted price according to the relationship between the return and the probability.

Up to round *t*, the transaction price sequence of each participant in the multi-energy market is SP_t, and the corresponding buyer's quoted price sequence of the successful transaction is SB_t, and the seller's quoted price sequence is SS_t. According to the order of the successful transaction, the participant can obtain historical information from the blockchain network. The bidding strategy that only considers adaptive learning by oneself process is known as PA strategy [55]. Assuming that all participants are rational, honest and credible, their quoted price will not be lower than their respective reserve price. Therefore, the quoted price is corresponding to PA strategy is given by Eq. (18) and (19).

$$B_{i,t}^{PA} = min\{min(SB_{t-1}) \cdot \gamma_t + max(SB_{t-1}) \cdot (1 - \gamma_t), V_i\} \tag{18}$$

$$S_{i,t}^{PA} = max\{max(SS_{t-1}) \cdot \gamma_t + min(SS_{t-1}) \cdot (1 - \gamma_t), C_j\} \tag{19}$$

where V_i is the buyer's reserve price that represents the valuation of the energy to be purchased, and C_j is the seller's reserve price that represents the cost of energy supplying.

3.2.2. Reserve price adjustment process

In the existing bidding strategies, the reserve price is regarded as a fixed value, and its influence on the bidding is not considered. However, setting different reserve prices in the actual auction will have an impact on the market [56]. Therefore, we not only consider the quote adjustment in the bidding strategy, but also adjust the reserve prices of all participants according to the real-time information adaptively. The cost or valuation of each participant in the double auction market is private and not public, so that each participant cannot get the accurate revenue of others. However, participants can estimate the revenue of other participants based on the market information, which is called a presumptive revenue rate. This study used the parameter to adjust the reserve price in the bidding strategy. The lowest revenue rate of a buyer or seller is α_t or β_t, which is obtained respectively based on the buyers' quote sequence SB_t and sellers' quote sequence SS_t in the successful transactions, as shown in Eq. (20) and (21).

$$\alpha_t = min[(SB_{t-1} - P_{t-1}) / SB_{t-1}] \tag{20}$$

$$\beta_t = min[(P_{t-1} - SS_{t-1}) / SS_{t-1}] \tag{21}$$

According to the presumptive revenue rate, reserve price V_i or C_j can be adjusted adaptively and make the constraints of the bidding strategy acceptable soft in real time. The modified reserve prices for buyers and sellers are $RB_{i,t}$ and $RS_{j,t}$ given in Eq. (22) and (23).

$$RB_{i,t} = V_i \cdot (1 - \alpha_t) \tag{22}$$

$$RS_{j,t} = C_j \cdot (1 - \beta_t) \tag{23}$$

3.3. Dynamic compensation mechanism

Although the cost of generating electricity from renewable energy sources such as WPP and PV has been reduced gradually in recent years, its cost is higher than fossil energy such as thermal power generation. Under the completely free market competition mechanism, the quoted price of renewable energy seller is likely to be higher than the quoted price of fossil energy seller. The obvious price disadvantage reduces the utilization ratio of renewable energy, such as WPP and PV. On the other hand, fossil energy will produce pollutant emissions such as carbon dioxide, sulfur dioxide, which will cause damage to the surrounding environment.

This study adds dynamic compensation mechanism for fossil energy sellers in a fully liberalized multi-energy market, which is directly added to their quoted prices in order to reduce the price advantage. When fossil energy sellers reach a transaction through the compensation, the product of the energy unit price corresponding to the compensation and the supply amount is regarded as the environmental impact cost. This cost can be delivered to the environmental management department and used for environmental governance. The dynamic compensation is D_j given by Eq. (24). The determination of dynamic compensation is based on the pollutant emissions of the fossil energy and the environmental treatment cost of the pollutant.

$$D_j = \sum_{n=1}^{N}(e_1 \cdot f_1 + e_2 \cdot f_2 + \cdots + e_n \cdot f_n) \tag{24}$$

The parameter e_n represents the pollutant quantity of per unit energy supply *n* emitted from the fossil energy seller *j*. And f_n represents the environmental treatment cost corresponding to the unit quantity of pollutants *n*. The values of e_n and f_n are determined according to the actual situation of the area.

3.4. Pricing strategy

As mentioned above, the target price of participants is their ideal

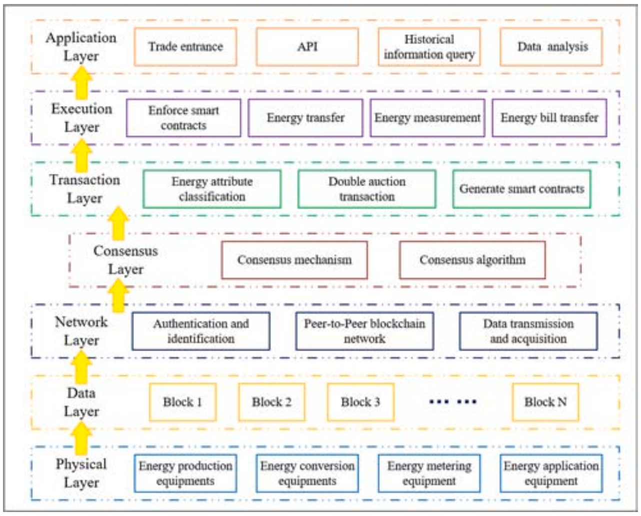


Fig. 3. Blockchain network structure of the multi-energy market.

price. If participants follow their target price as a bidding strategy, the deal may never be completed. Therefore, before each round of double auction, energy buyers can calculate the final quote and reserve price with adaptive learning mechanism. The bidding price of a buyer is indicated by Eq. (25).

$$B_{i,t} = min[min(SB_{t-1})\cdot\gamma_t + max(SB_{t-1})\cdot(1-\gamma_t), RB_i] \tag{25}$$

For energy sellers in multi-energy market, the corresponding dynamic compensation needs to be added. Therefore, the sellers' bidding price is depicted by Eq. (26).

$$S_{i,t} = max\left[max(SS_{t-1})\cdot\gamma_t + min(SS_{t-1})\cdot(1-\gamma_t), RB_j\right] + D_j \tag{26}$$

where D_j of one fossil energy seller is calculated according to Eq. (24). And since no pollutants are emitted during the renewable energy operation, D_j of a renewable energy seller can be taken as zero.

3.5. Balance mechanism

Since both energy buyers and sellers predict the energy quantity of the next time slot in advance, the energy transaction of each double auction is conducted accordingly. However, there are errors in the prediction of energy supply power, especially for renewable energy sellers such as WPP and PV, there will be the problem of intermittency and uncertainty due to the influence of weather. Therefore, when the energy seller in the transaction is unable to provide enough energy, the energy buyer will switch to electricity supplied by the distribution networks. The buyers of heating load and cold load can also use the power of the distribution networks to meet their own energy requirements through electrical heating equipment and electric refrigerating equipment, such as air conditioners. In particular, the transmission of electricity is faster than heating and cold. Real-time electricity dispatching can ensure the energy demand timely.

In the multi-energy market, every participant is equipped with metering equipment such as smart meters, calorimeters, and flow meters. The double auction could determine the energy trading parties and the unit price of the transaction. The final energy supply quantity is determined actual measurement data and settle the expenses according to the agreed transaction price. The trading information and energy transmission data in the system are uploaded to the network, and energy management and expense settlement are conducted in the network platform based on blockchain technology.

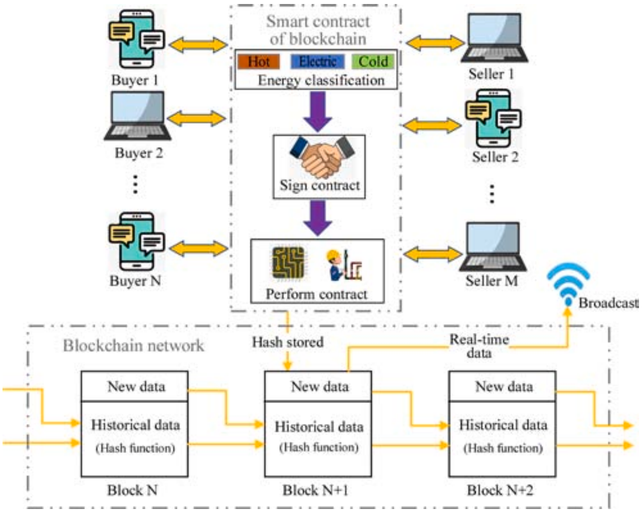


Fig. 4. Energy management process of the multi-energy market based on blockchain.

4. Blockchain implementation of energy management

The seamless and effective performance of AR-C strategy require the real-time information to be available to every participant in the multi-energy market. Blockchain has an ideal energy management functions in the real-time market. This technology provides a decentralized transaction network for a variety of energy systems. Data is stored on each participating node in a distributed mode and updated in real-time to help participants adjust bidding information. Smart contracts on the blockchain adopt "code is contract, code is law" for the fair energy transactions and dispatching. Finally, the traceability and non-tampering ensure the security of data in the energy system.

The multi-energy market transaction architecture based on blockchain can be divided into seven layers, as shown in Fig. 3. It includes the physical layer, the data layer, the network layer, the consensus layer, the transaction layer, the execution layer, and the application layer. The lower layer provides an interface to the upper layer that realize the real-time dissemination of information in these seven architecture levels.

(1) The physical layer includes energy production equipment, energy conversion equipment, energy metering equipment, and energy application equipment in a multi-energy market. These devices are the physical basis of IES and a requirement for energy supply, use and transmission.
(2) The data layer is a chain database with time-stamp, which backs up all the historical transaction data and stores it in the participating nodes of the system, forming a distributed ledger structure. All historical information can be traced back and cannot be tampered.
(3) The network layer is used for the authentication and identification. It provides Peer-to-Peer network protocols and data transmission. There is no central node, and the failure of individual nodes will not affect the whole network, which bring higher security and fault tolerance.
(4) The consensus layer is used to encapsulate the consensus mechanism and consensus algorithm of the blockchain, and provides an application programming interface (API) to the transaction layer.
(5) The transaction layer makes the power matching and agreement among the energy buyers and sellers. It classifies according to the energy attributes, uses a double auction mechanism and the AR-C bidding strategy to match the energy transactions, and then form the smart contract.

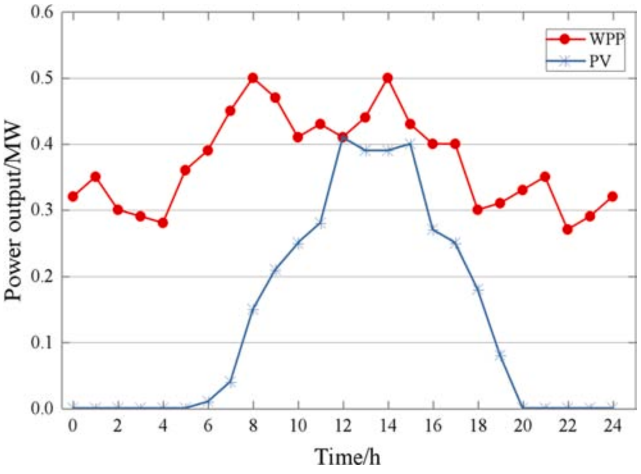


Fig. 5. Prediction values of WPP and PV output.

(6) The executive layer is used to execute the transaction layer's smart contracts as well as perform energy transfers and metering. It relies on the energy transmission equipment, such as transmission lines and heating pipelines.
(7) The application layer is used to provide transaction entry for participants and managers, as well as applications such as API, historical information query and data analysis.

A typical blockchain energy management process in the multi-energy market is shown as Fig. 4. Firstly, each participant in the system uploads energy supply and demand information to the blockchain network through communication devices such as computers or mobile phones at the start of each double auction transaction. Secondly, the energy classification and matching transactions are performed according to the method mentioned above after the blockchain network platform collects all the information. Thirdly, the trading information after matching is successfully converted into time-stamped data blocks and stored in the network by using the hash function. And then the blockchain network broadcasts matching transaction results to various energy trading entities through a real-time data processor, including the matching of energy buyers and sellers, and the final pricing. Finally, after the completion of the matching transaction, the completed transaction agreement shall be executed within the corresponding time slot t for the energy transfer and measurement of electricity, heat and cold. A new matching transaction and the settlement of fees are performed when the next double auction begins.

The energy settlement determines the energy transfer amount for each time slot by reading the metering equipment through the blockchain network. It assigns a unique ID to the energy transfer amount corresponding to each transaction, and add a time stamp to form a data block as a basis for real-time settlement. The settlement amount is the product of the final transaction agreement price and the data through measurement and authentication. The settlement amount is automatically deducted from the buyer's account and transferred to the seller's account. Blockchain platform will send a recharge request when the remaining funds in the account of the buyer are insufficient for paying the settlement amount. And the overdue payment buyers would be automatically removed from the energy trading network and the deposit in the account could be deducted.

5. Case study

5.1. System description

A multi-energy market scenario is constructed by taking Chinese typical grid-connected IES as an example. The scenario on an island in East China (Longitude 122.40°, 30.10° north latitude) is utilized for the energy supply system. This system contains 2×1 MW WPP, 5×0.2 MW PV and 1×1 MW gas CCHP unit [53]. In addition, in order to balance the heating load demand in the system effectively, one 0.5 MW gas-fired hot water boiler is added as GB unit to the system. The parameters of WPP are assumed to $\nu in = 3$ m/s, νrated $= 14$ m/s and $\nu out = 25$ m/s, shape bearing parameter $\phi = 2$ and scale parameter $\vartheta = 2\overline{\nu}/\sqrt{\pi}$ [57]. The PV radiation intensity parametersα and β are set as 0.3 and 8.54 respectively [58]. The output power of WPP and PV can be simulated through the prediction curves obtained by referring to the uncertainty factor scenario simulation and reduction method described in reference [59], as shown in Fig. 5.

Table 1
Basic parameters of energy conversion equipment.

Equipment	Conversion efficiency	Maximum power (MW)	Minimum power (MW/min)	Climbing speed (MW/min)
CCHP/E	0.35	1.00	0	0.03
CCHP/H	0.45	1.60	0	0.04
Electrical heating equipment	2.30	0.70	0	0.06
Electric refrigerating equipment	2.90	0.60	0	0.06
Absorption refrigerator	2.50	0.50	0	0.05
GB	0.75	0.50	0	0.04

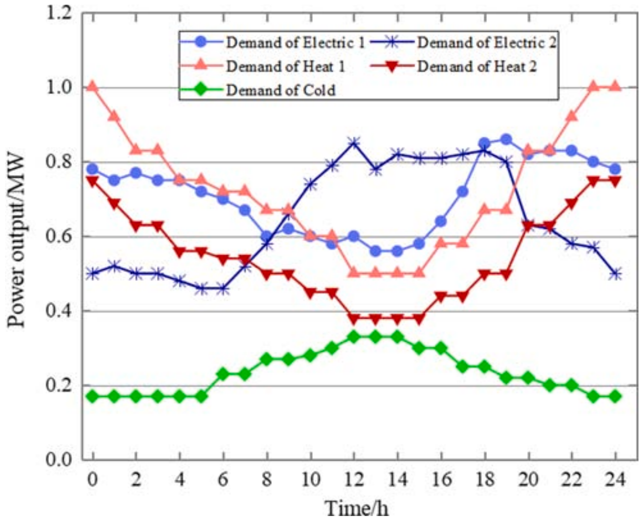


Fig. 6. Prediction values of the demand load.

The energy demand side of this system has five energy buyers include two electric demand buyers as Demand of Electric 1 and 2 two heat demand buyers as Demand of Heat 1 and 2, one cold demand buyer is Demand of Cold. The heat and cold buyers have their own EH and EC equipment such as electric heaters and air conditioners. The basic parameters of CCHP, GB and some energy conversion equipment including absorption refrigerator, electrical heating equipment and electric refrigerating equipment, are referenced in the case scenario of reference [60] as shown in Table 1. As a typical community resident in the system, the electricity consumption of Demand of Electric 1 is relatively low at daytime, and gradually increases the electricity consumption from 4 p.m. to 7 p.m. until the peak. Demand of Electric 2 is a typical commercial buyer and its electricity consumption is relatively low at night, and the electricity consumption increases from 9 a.m. and peaks at 12 a.m. Demand of Heat 1 and 2 are assumed to residents needed heating and have significantly higher demand at night than that of daytime. Demand

Table 2
Initial bidding price and reserve price.

Trading node	Energy attributes	Initial bidding price ($/MWh)	Reserve price ($/MWh)
WPP	Electricity	67.45	47.22
PV	Electricity	70.63	49.44
CCHP	Electricity	51.66	36.16
	Heat	51.66	36.16
	Cold	21.53	15.07
GB	Heat	51.66	36.16
Demand of Electric 1	Electricity	52.00	67.60
Demand of Electric 2	Electricity	50.00	65.00
Demand of Heat 1	Heat	52.00	67.60
	Electricity	119.60	155.48
Demand of Heat 2	Heat	50.00	65.00
	Electricity	115.00	149.50
Demand of Cold	Cold	24.00	31.20
	Electricity	69.60	90.48

of Cold is a typical cold storage, which needs to maintain a stable low temperature inside. When the outdoor temperature is low at night, the demand for cold load is lower than the demand during the day. The one-day load demand curves for Demand of Electric 1, Demand of Electric 2, Demand of Heat 1, Demand of Heat 2, Demand of Cold are shown in Fig. 6.

5.2. Analysis of different bidding strategies

In order to verify the feasibility of the energy management method and bidding strategy in this study, the AR-C strategy proposed in this study is compared with ZI-C strategy of random bidding strategy without learning mechanism, AA strategy [26] and PA strategy with learning mechanism [58]. This section takes the total operating period of 24 h and the operating cycle of 1 h as the time slot to conduct the double auction and conduct the simulation analysis of these bidding strategies.

5.2.1. Bidding parameters setting

The bidding at time zero is taken as the initial double auction. We assumed that all the energy buyers and sellers in the four bidding strategies have the same bidding price and reserve price in the first auction. The initial bidding price of sellers shall refer to the current selling price of electricity, heat and cold in the area where the IES is located, while the reserve price is set at a 30% reduction from the initial bidding. And the initial bidding price of buyers is set according to the average price of local energy purchase, while the reserve price is set at a 30% increase from the initial bidding. Due to the existence of the conversion equipment of electrical heating equipment, the heat buyers shall not only make a bidding price to the heat power trading platform, but also make a bidding to the electric power trading platform according to the conversion efficiency. The initial bidding data of heat buyers can be referred to in Eq. (2) and (3). For the cold buyers, the initial bidding data refers to Eq. (4) and (5) by the same way. The initial bidding prices and reserve prices of energy buyers and sellers in the multi-energy market are shown in Table 2. In addition, according to the actual situation in China, the electricity price of distribution networks fluctuates and changes regularly throughout the day can play a role of peak shaving and valley -filling. The peak power consumption is at 10: 00–14: 00 and 18: 00–20: 00, whose peak electricity price during this time period is 183.65 $/MWh. The valley electricity is at 23: 00–6: 00, whose price is 38.37 $/MWh. The rest of the day is the normal electricity period, whose electricity price is 109.22$/MWh.

It is necessary to charge additional environmental governance costs for the energy sellers of fossil energy in the AR-C strategy. The harmful substances generated during the operation of the equipment for the current energy system are mainly CO_2, SO_2 and NO_X. According to the harm grade and processing difficulty, the environmental treatment costs for CO_2, SO_2 and NO_X are set as 0.0125$/kg, 0.185$/kg and 0.35$/kg respectively. Table 3 shows the pollutant emissions that generate unit energy quantity including distribution networks, CCHP and GB, which contain fossil energy sources.

Table 3
Pollutant emissions of unit energy supply.

Equipment	CO_2 (kg/MWh)	SO_2 (kg/MWh)	NOx (kg/MWh)
DN	899.12	75.97	2.21
CCHP/E	972.41	8.98	2.62
CCHP/H	776.53	7.17	2.09
CCHP/C	310.62	2.87	0.84
GB	788.51	7.28	2.12

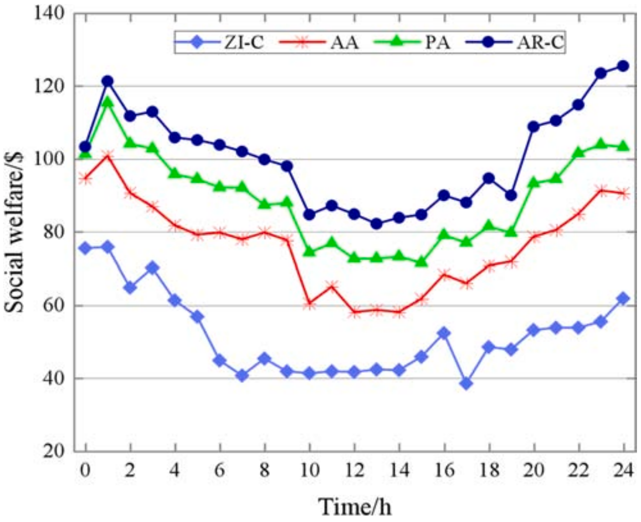


Fig. 7. Social welfare with different bidding strategies.

5.2.2. Economic comparison

Social welfare and allocation efficiency are used as evaluation indexes to analyze the effectiveness and economy of the four bidding strategies. Social welfare is the combination of all participants' economic benefit. It is an important performance indicator for the bidding strategy to appraise performance. Allocation efficiency is referred to as the difference between the social welfare of the bidding strategy and the optimal solution. In this case, the optimal solution is the total return of competitive equilibrium (*SWM*), and the transaction price of each transaction can be calculated according to Eq. (16).

The comparison of social welfare for bidding strategies in one day is shown in Fig. 7. It can be concluded that the social welfare of the three strategies with learning mechanism is significantly higher than the ZI-C strategy without learning mechanism. The result is that the learning mechanism can adjust the bidding strategy timely in the subsequent bidding price according to the previous market conditions, so as to obtain more transaction rates. The AA strategy forcibly divides the bidding attitude into three categories, and the adjustment means are too rigid. The PA strategy has a more flexible learning mechanism than the AA strategy so that the social welfare is higher. Because the AR-C strategy can not only analyze previous market information, but also adjust the reserve price appropriately according to the market information, it is superior to the PA strategy. At the same time, the dynamic compensation for fossil energy also reduces the price advantage of distribution networks. It can further improve overall social welfare through increasing the profitability of energy sellers within the system, particularly renewable energy such as WPP and PV. The simulation result

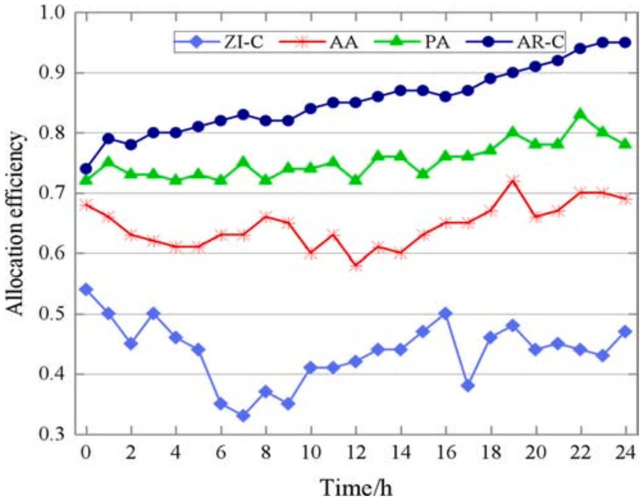


Fig. 8. Allocation efficiency with different bidding strategies.

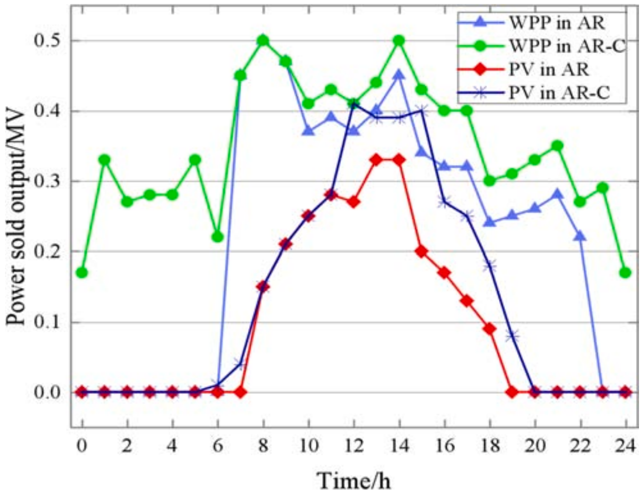


Fig. 9. Power sold output of WPP and PV with different bidding strategies.

based on one day demonstrates that the AR-C strategy has an obvious advantage in social welfare which is 93.7%, 31.3% and 12.9% higher than ZI-C strategy, AA strategy and PA strategy respectively.

The simulation results conclude that the average allocation efficiency of ZI-C, AA, PA and AR-C after 24 auctions are respectively 0.44, 0.67, 0.74 and 0.85. Fig. 8 shows that the trend of allocation efficiency is basically the same as the social welfare. Similarly, comparing with the other three strategies, the AR-C strategy is 94.7%, 31.7% and 12.9% higher than ZI-C strategy, AA strategy and PA strategy respectively in allocation efficiency. The absolute ideal allocation efficiency is equal to 1, which indicates that all buyers and sellers are bidding transactions conducted by linear programming in the double auction. In each auction, all participants clearly expect to achieve the highest return rather than meeting each other's needs. Therefore, this ideal bidding strategy in double auction does not exist in practice, but it can be used as a benchmark for economic comparison. The allocation efficiency of ZI-C strategy is the lowest and it is irregular fluctuation due to the lack of feedback to the market information. In the first few double auctions, the allocation efficiency of the other three strategies is slightly higher than the ZI-C strategy. The other three strategies have the slightly higher efficiency, and they are gradually increased due to the learning mechanism of market feedback. After the 20th transaction, the allocation efficiency of the AR-C strategy exceeded 0.9 that is gradually closer to the ideal situation.

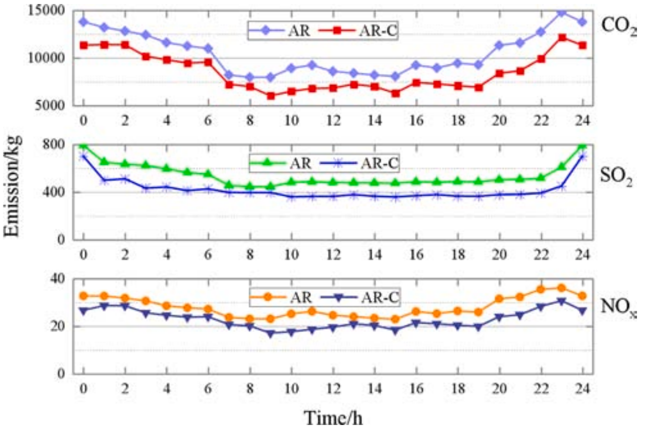


Fig. 10. Emissions of CO_2, SO_2 and NO_X with different bidding strategies.

5.2.3. *Environmental comparison*

The efficiency of renewable energy utilization can be improved by adding the dynamic compensation. The AR strategy without the compensation is simulated. We obtained renewable energy efficiency and pollutant emissions, and compared them with the AR-C strategy which add compensation based on the cost of polluting emissions from fossil fuels. Fig. 9 compares the power sold output of WPP and PV for one day in different strategies, and the electricity sales of WPP and PV in the AR-C strategy is more than the AR strategy 55.6% and 37.9% respectively. According to the simulation data, adding the dynamic bidding compensation increases the utilization rate of renewable energy by 50.2%.

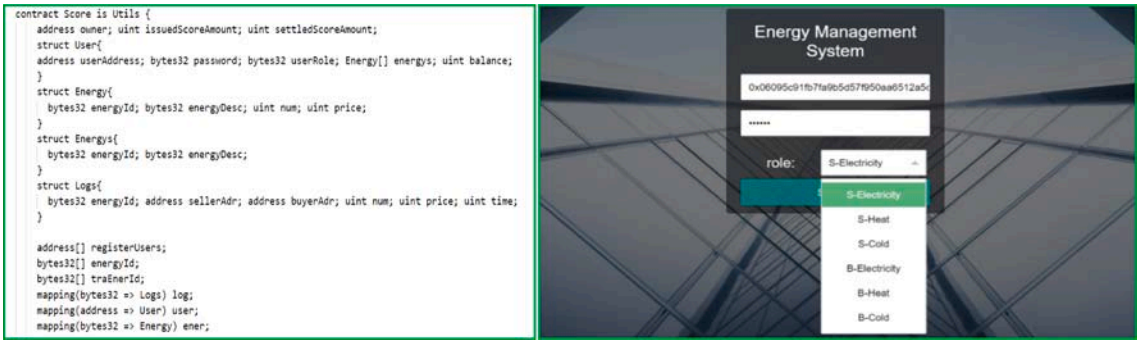
Fig. 10 shows the emissions of CO_2, SO_2 and NO_X in one day for the two strategies. Because the utilization efficiency of WPP and PV is improved by the dynamic bidding compensation, the energy supply - quantity of CCHP, GB and distribution networks will be reduced correspondingly. Therefore, the pollutant emissions from IES would be reduced. According to the simulation data, the emissions of CO_2, SO_2 and NO_X are reduced by 18.9%, 21.2% and 18.1% respectively due to the incentive of renewable energy supply in the AR-C strategy.

5.2.4. *Summary of different bidding strategies*

An experiment scenario conducted on Chinese typical grid-connected IES for 24 h is used to verify the effectiveness of the proposed methodology. The AR-C strategy has an obvious advantage in social welfare which is 93.7%, 31.3% and 12.9% higher than ZI-C strategy, AA strategy and PA strategy respectively. Meanwhile, compared with the other three strategies, the AR-C strategy is 94.7%, 31.7% and 12.9% higher than ZI-C strategy, AA strategy and PA strategy respectively in allocation efficiency.

It is worth noting that the experiment scenario and parameter settings are based on a typical IES of China. However, there is an international consensus that developing integrated energy systems and multi-energy markets can promote the use of renewable energy, expand profitability, and enhance environmental protection. Energy markets in developed regions such as the United States, Japan and Europe are also developing towards diversification of energy supply and distributed energy management. Therefore, the experimental background of this case is representative to some extent.

According to the simulation data, the dynamic compensation of the presented bidding strategy increases the utilization rate of renewable energy by 50.2%. The emissions of CO_2, SO_2 and NO_X are reduced by 18.9%, 21.2% and 18.1% respectively due to the incentive of renewable energy supply. Through these comparisons, it is clear that dynamic compensation methods can significantly improve the efficiency of renewable energy and play a positive role in reducing pollutant emissions.



(a)Procedure code of smart contracts

```
contract Score is Utils {
    address owner; uint issuedScoreAmount; uint settledScoreAmount;
    struct User{
    address userAddress; bytes32 password; bytes32 userRole; Energy[] energys; uint balance;
    }
    struct Energy{
      bytes32 energyId; bytes32 energyDesc; uint num; uint price;
    }
    struct Energys{
      bytes32 energyId; bytes32 energyDesc;
    }
    struct Logs{
      bytes32 energyId; address sellerAdr; address buyerAdr; uint num; uint price; uint time;
    }

    address[] registerUsers;
    bytes32[] energyId;
    bytes32[] traEnerId;
    mapping(bytes32 => Logs) log;
    mapping(address => User) user;
    mapping(bytes32 => Energy) ener;
```

(b) Operation in UI

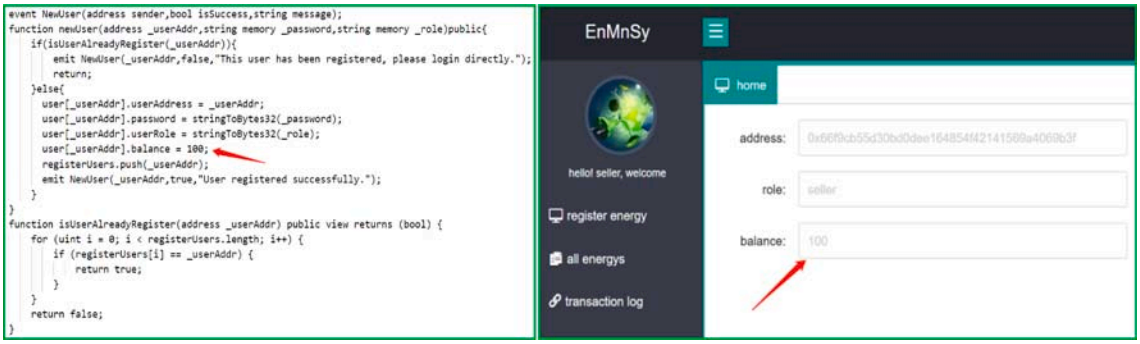
Energy Management System

0x06095c91fb7fa9b5d57f950aa6512a5c

******

role: S-Electricity

Fig. 11. New user creation and classification.



(a)Procedure code of smart contracts

```
event NewUser(address sender,bool isSuccess,string message);
function newUser(address _userAddr,string memory _password,string memory _role)public{
    if(isUserAlreadyRegister(_userAddr)){
        emit NewUser(_userAddr,false,"This user has been registered, please login directly.");
        return;
    }else{
      user[_userAddr].userAddress = _userAddr;
      user[_userAddr].password = stringToBytes32(_password);
      user[_userAddr].userRole = stringToBytes32(_role);
      user[_userAddr].balance = 100;
      registerUsers.push(_userAddr);
      emit NewUser(_userAddr,true,"User registered successfully.");
    }
}
function isUserAlreadyRegister(address _userAddr) public view returns (bool) {
    for (uint i = 0; i < registerUsers.length; i++) {
        if (registerUsers[i] == _userAddr) {
            return true;
        }
    }
    return false;
}
```

(b) Operation in UI

address: 0x66f9cb55d30bd0dee164854f42141569a4069b3f

role: seller

balance: 100

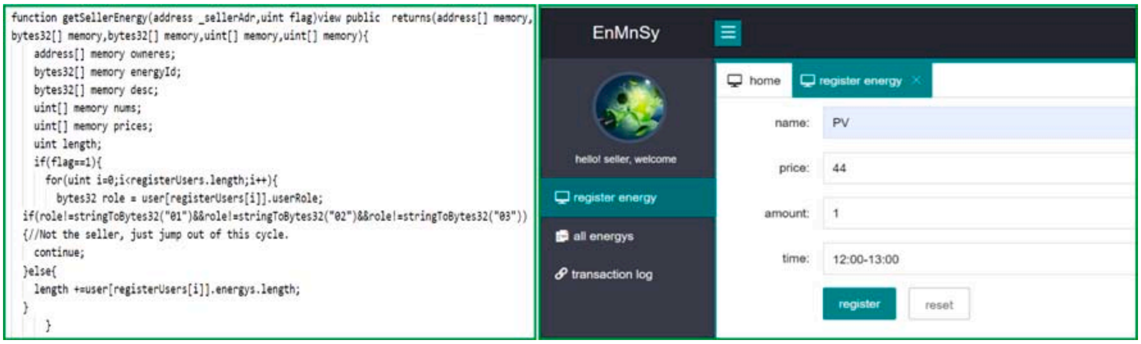
Fig. 12. Render the trading margin.

With the different energy supply equipment of fossil energy and the difference of environmental cost management cost in different regions, the dynamic bidding compensation *Dj* will be different. However, the efficiency of renewable energy equipment in the energy market will be partly motivated by flexible bidding compensation to reduce the impact of the energy system on the environment. At the same time, the operation or regulatory authorities of the energy system will receive increased revenue from the bidding compensation, which can be used for renewable energy subsidies, environmental governance and other aspects to promote the environmentally friendly of the region.

5.3. Blockchain implementation

The AR-C strategy is adjusted timely according to real-time market information, which has good economic and environmental performance. However, the transaction under traditional centralized control will increase the operating cost of the transaction center as the user grows. Centralized control is vulnerable to be attacked by external hackers, and the privacy of users and the security of transactions are not guaranteed. Therefore, we try to introduce the blockchain into our bidding strategy, making use of its decentralization, security and other advantages, to establish decentralized application (DApp) of blockchain can provide historical information and conduct real-time transactions.

We create a DApp named Energy Management System that can be used as the basic technical framework for multi-energy trading. This DApp is created with the Remix compiler based on the open source network of Ethereum. Energy Management System consists of two parts: the smart contract and the user interface (UI). The smart contract runs as code on the blockchain and is responsible for data interaction, and the UI is a front-end page implemented by HTML and JavaScript for users to operate on. Each buyer or seller can participate in the real-time energy management through simple operations on the UI and implement energy



(a)Procedure code of smart contracts

```
function getSellerEnergy(address _sellerAdr,uint flag)view public  returns(address[] memory,
bytes32[] memory,bytes32[] memory,uint[] memory,uint[] memory){
    address[] memory owneres;
    bytes32[] memory energyId;
    bytes32[] memory desc;
    uint[] memory nums;
    uint[] memory prices;
    uint length;
    if(flag==1){
      for(uint i=0;i<registerUsers.length;i++){
        bytes32 role = user[registerUsers[i]].userRole;
  if(role!=stringToBytes32("01")&&role!=stringToBytes32("02")&&role!=stringToBytes32("03"))
  {//Not the seller, just jump out of this cycle.
    continue;
  }else{
    length +=user[registerUsers[i]].energys.length;
  }
      }
```

(b) Operation in UI

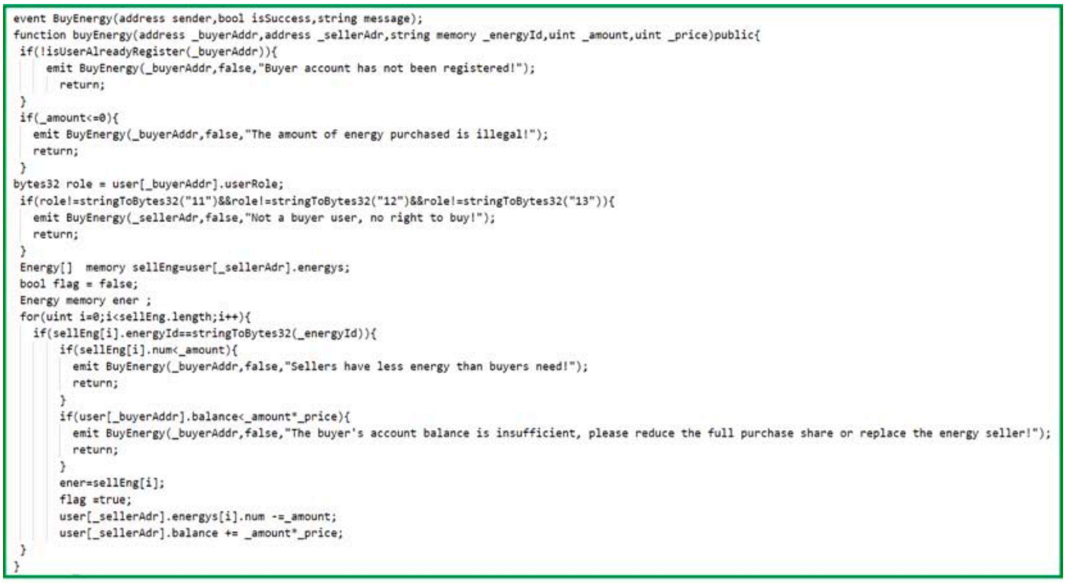
name: PV

price: 44

amount: 1

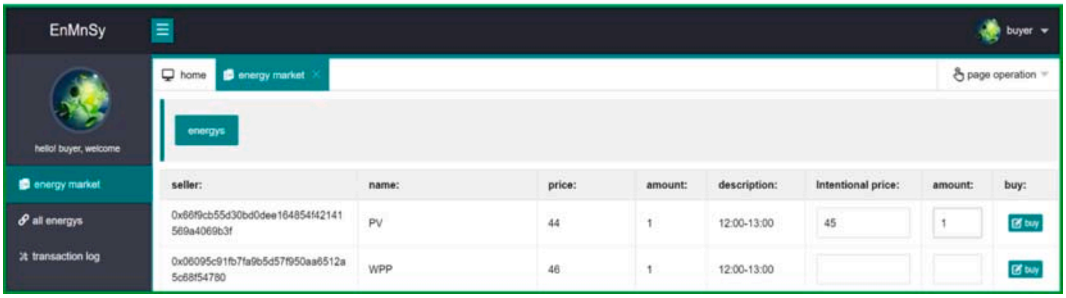
time: 12:00-13:00

Fig. 13. Energy sellers submit bidding information.



```
event BuyEnergy(address sender,bool isSuccess,string message);
function buyEnergy(address _buyerAddr,address _sellerAdr,string memory _energyId,uint _amount,uint _price)public{
 if(!isUserAlreadyRegister(_buyerAddr)){
     emit BuyEnergy(_buyerAddr,false,"Buyer account has not been registered!");
       return;
 }
 if(_amount<=0){
   emit BuyEnergy(_buyerAddr,false,"The amount of energy purchased is illegal!");
   return;
 }
bytes32 role = user[_buyerAddr].userRole;
 if(role!=stringToBytes32("11")&&role!=stringToBytes32("12")&&role!=stringToBytes32("13")){
   emit BuyEnergy(_sellerAdr,false,"Not a buyer user, no right to buy!");
   return;
 }
 Energy[]  memory sellEng=user[_sellerAdr].energys;
 bool flag = false;
 Energy memory ener ;
 for(uint i=0;i<sellEng.length;i++){
   if(sellEng[i].energyId==stringToBytes32(_energyId)){
       if(sellEng[i].num<_amount){
         emit BuyEnergy(_buyerAddr,false,"Sellers have less energy than buyers need!");
         return;
       }
       if(user[_buyerAddr].balance<_amount*_price){
         emit BuyEnergy(_buyerAddr,false,"The buyer's account balance is insufficient, please reduce the full purchase share or replace the energy seller!");
         return;
       }
       ener=sellEng[i];
       flag =true;
       user[_sellerAdr].energys[i].num -=_amount;
       user[_sellerAdr].balance += _amount*_price;
 }
}
```

(a) Procedure code of smart contracts



seller:	name:	price:	amount:	description:	Intentional price:	amount:	buy:
0x66f9cb55d30bd0dee164854f42141569a4069b3f	PV	44	1	12:00-13:00	45	1	buy
0x06095c91fb7fa9b5d57f950aa6512a5c68f54780	WPP	46	1	12:00-13:00			buy

(b) Operation in UI

Fig. 14. Enter into the energy trading contract.

agreements automatically in accordance with smart contracts.

The built DApp is deployed and run on the Ethereum virtual machine (EVM), an operating environment of blockchain network. We will discuss how to interact data by means of smart contracts and operate the system though UI in a step-by-step process as visualized in Figs. 11–15. All users can perform the following operations shown below based on the DApp.

(1) Account is created for a new user including energy attribute classification. Each new user gets a specific account through DApp which is the user's permanent identity. Fig. 11(a) is the key computer code for new users to join the system and energy attribute classification. Users register through the UI and can choose six identities for the transaction of electricity, heat and cold energy respectively seller of electricity, seller of heat, seller of cold, buyer of electricity, buyer of heat and buyer of cold as shown in Fig. 11(b).
(2) Users render the necessary trading margin to the platform. Margin is the working capital required to maintain the renewal of a transaction. It is specifically used for the settlement and performance guarantee of an energy order transaction. As the example shown in Fig. 12(a) and (b), each user must deposit a transaction currency of 100 in advance. It should be noted that the value of trading margin can be set flexibly according to the needs of the multi-energy market.
(3) Users can submit real-time bidding information to the blockchain network. In each double auction, users can submit real-time bidding information such as price, amount of energy and time to the DApp as shown in Fig. 13(a). Taking PV as an example, we submit the information to the system between 12:00 and 13:00, and can provide a unit electric power source with a bidding price of 44 as demonstrated in Fig. 13(b).
(4) Buyers and sellers could enter the energy trading contract. For example, PV and an electric buyer sign a smart contract at 45 per point. This will lead to a transaction of PV supplies electricity to this customer between 12:00 and 13:00. Fig. 14(a) and (b) illustrate the key procedure codes and user interface for energy smart contracts.
(5) After some transactions are completed, the trading data is open and transparent. The real-time data processor sends valuable information to each user in real time. As demonstrated in Fig. 15(a) and (b), an energy buyer or seller could extract and utilize all trading information completed.

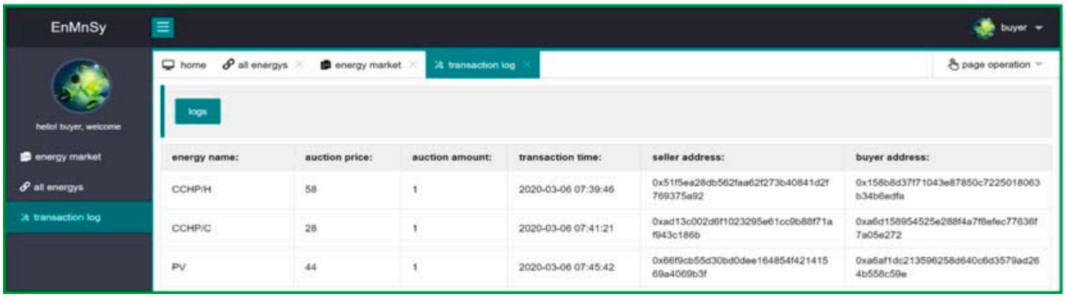
All the above energy trading processes can be completed automatically through the DApp almost without manual intervention, reducing the operating cost of the multi-energy system. More important, transaction data is sent in real time and stored in all energy nodes, so that each user can master the real-time information and enhance the bidding strategy.

The AR-C strategy proposed in this study is a typical real-time energy

```
  function getLogs(address _userAddr)view public returns(bool,string memory,bytes32[] memory,address[] memory,address[]
  memory,uint[] memory,uint[] memory,uint[] memory){
    uint length = traEnerId.length;
    bytes32[] memory enerIds=new bytes32[](length);
    address[] memory sellerAddr = new address[](length);
    address[] memory buyerAddr = new address[](length);
    uint[] memory nums = new uint[](length);
    uint[] memory prices = new uint[](length);
    uint[] memory times = new uint[](length);
    for(uint i=0;i<length;i++){
      enerIds[i]=log[traEnerId[i]].energyId;
      sellerAddr[i]=log[traEnerId[i]].sellerAdr;
      buyerAddr[i] = log[traEnerId[i]].buyerAdr;
      nums[i]=log[traEnerId[i]].num;
      prices[i]=log[traEnerId[i]].price;
      times[i]=log[traEnerId[i]].time;
    }
    return(true,"search successful!",enerIds,sellerAddr,buyerAddr,nums,prices,times);
  }

function getUserPara(address _userAddr)view public returns(bool,string memory,bytes32,uint){
  bytes32 role;
  uint balance;
  if (!isUserAlreadyRegister(_userAddr)) {
    return(false,"Account is not yet registered!",role,balance);
  }
  return(true,"Search successful",user[_userAddr].userRole,user[_userAddr].balance);
}
```

(a) Procedure code of smart contracts



energy name:	auction price:	auction amount:	transaction time:	seller address:	buyer address:
CCHP/H	58	1	2020-03-06 07:39:46	0x51f5ea28db562faa62f273b40841d2f769375a92	0x158b8d37f71043e87850c7225018063b34b6edfa
CCHP/C	28	1	2020-03-06 07:41:21	0xad13c002d6f1023295e61cc9b88f71af943c186b	0xa6d158954525e288f4a7f8efec77636f7a05e272
PV	44	1	2020-03-06 07:45:42	0x66f9cb55d30bd0dee164854f42141569a4069b3f	0xa6af1dc213596258d640c6d3579ad264b558c59e

(b) Operation in UI

Fig. 15. Extract the trading information.

management method. The decentralized network structure of blockchain technology will enhance the strong timeliness. In summary, the benefits of blockchain for participants involved in the multi-energy market include but are not limited to the following aspects: Firstly, the threshold for energy producers has been lowered by blockchain, prompting more energy sellers to join multi-energy market. These sellers adjusted their bidding strategies according to the updated real-time information on DApp to improve the transaction rate and sales revenue. Secondly, energy buyers can freely choose the mode of energy use according to real-time information on the blockchain network, and promote the reduction of energy consumption cost. Thirdly, the decentralized trust method of blockchain can eliminate the central institution or third-party intermediary, which helps the IES to save operating costs, avoid energy monopoly and reduce the risks of data security and privacy. Finally, the local multi-energy market is strengthened by the blockchain technology, which reduces the energy consumption of long-distance transportation. Meanwhile, the efficient utilization of distributed renewable energy reduces the impact of energy system on ecology and environment.

6. Conclusion

The study presents a bidding strategy to fill the gap between multi-energy market and blockchain technologies. To the best of our knowledge, this method is the first research specifically designed for real-time energy management and double auction mechanism in integrated energy system. The proposed method and its novelties can be summarized as following:

(1) This paper designs three interactive energy trading platforms for the multi-energy market, so that the multi-energy buyers and sellers can trade independently through the double auction mechanism. This energy management mode facilitates seamless access to a variety of energy supply and conversion devices, and promotes energy instantaneous balances and real-time prices update.
(2) The proposed bidding strategy has adaptive learning ability and adjusts the reserve price according to the real-time market information. Moreover, the bidding strategy has an innovative dynamic compensation which can reduce the price advantage of fossil energy and increase the local consumption of renewable energy. Dynamic compensation which is based on the characteristics of energy systems in different regions has strong flexibility and applicability.
(3) An experiment scenario conducted on a typical grid-connected integrated energy system for 24 h is used to verify the effectiveness of the proposed methodology. According to the simulation data, our bidding strategy has an obvious advantage in social welfare and allocation efficiency than existing bidding strategies. Moreover, the problem of environmental pollution can be solved to a certain extent through dynamic compensation.
(4) A decentralized application of blockchain is developed to ensure the seamless and effective performance of the presented bidding strategy, and it can realize real-time energy management and

transaction in practice. This work provides reference for comprehensive energy utilization and diversified energy market transactions.

(5) While the system is designed based on a multi-energy market, it is also suitable to be used in other energy system such as microgrids and virtual power plants. Therefore, the proposed trading model is expected to stimulate the energy market vitality and improve the energy efficiency worldwide.

In future work, we will adapt the bidding strategy to be combined with the multi-energy system containing some energy storage devices that could show its wider applicability. Moreover, we would put more effort into the research on the shortcomings of blockchain and try to solve the problems of low operating efficiency and high energy consumption on energy blockchain network. Overall, the method presented in our study can realize real-time energy management and further reduce the environmental pollution while ensuring the multi-energy market economy.

CRediT authorship contribution statement

Longze Wang: Conceptualization, Investigation, Methodology, Software, Writing - original draft, Writing - review & editing, Data curation, Project administration. **Jinxin Liu:** Supervision, Writing - original draft, Writing - review & editing, Formal analysis, Data curation, Investigation. **Rongfang Yuan:** Supervision, Writing - review & editing, Formal analysis, Investigation. **Jing Wu:** Supervision, Writing - review & editing, Formal analysis, Investigation. **Delong Zhang:** Investigation, Methodology, Conceptualization, Supervision. **Yan Zhang:** Funding acquisition, Project administration, Resources, Validation. **Meicheng Li:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing - review & editing.

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.

Acknowledgement

This work is supported partially by National Natural Science Foundation of China (Grant nos. 71974055). This work is supported partially by Natural Science Foundation of Beijing Municipality (L172036), National Natural Science Foundation of China (Grant nos. 51772096), Science and Technology Project of SGCC (SGJX0000KXJS1900321), Beijing Science and Technology Project (Z181100005118002), Joint Funds of the Equipment Pre-Research and Ministry of Education (6141A020225), Par-Eu Scholars Program, Science and Technology Beijing 100 Leading Talent Training Project, the Fundamental Research Funds for the Central Universities (2017ZZD02) and the NCEPU "Double First-Class" Program.

References

[1] Wang Y, Li J, Wang S, Yang J, Qi C, Guo H, et al. Operational optimization of wastewater reuse integrated energy system. Energy 2020;200:117309. https://doi.org/10.1016/j.energy.2020.117309.
[2] Andoni M, Robu V, Flynn D, Abram S, Geach D, Jenkins D, et al. Blockchain technology in the energy sector: a systematic review of challenges and opportunities. Renew Sustain Energy Rev 2019;100:143–74. https://doi.org/10.1016/j.rser.2018.10.014.
[3] Asl DK, Seifi AR, Rastegar M, Mohammadi M. Optimal energy flow in integrated energy distribution systems considering unbalanced operation of power distribution systems. Int J Electr Power Energy Syst 2020;121:106132. https://doi.org/10.1016/j.ijepes.2020.106132.
[4] Tang F, Dai H, Chen X, Zhao Y. Integrated energy technology and service trend in China: investigation and analysis on over 1800 development zones in different regions. In: 2018 IEEE 2nd International Electrical and Energy Conference (CIEEC), Beijing, China, 2018; pp. 428–433. https://doi.org/10.1109/CIEEC.2018.8745735.
[5] Ceseña E, Capuder T, Mancarella P. Flexible distributed multienergy generation system expansion planning under uncertainty. IEEE Trans Smart Grid 2015;7(1):348–57. https://doi.org/10.1109/TSG.2015.2411392.
[6] Peiyun L, Tao D, Zhixiang Z, Yongheng Y. Integrated demand response for a load serving entity in multi-energy market considering network constraints. Appl Energy 2019;250:512–29. https://doi.org/10.1016/j.apenergy.2019.05.003.
[7] Kaiping Q, Tao Y, Linni H, Bo Y, Xiaoshun Zh. Decentralized optimal multi-energy flow of large-scale integrated energy systems in a carbon trading market. Energy 2018;149:779–91. https://doi.org/10.1016/j.energy.2018.02.083.
[8] Zhang X, Zhu S, He J, Yang B, Guan X. Credit rating based real-time energy trading in microgrids. Appl Energy 2019;236:985–96. https://doi.org/10.1016/j.apenergy.2018.12.013.
[9] Misra S, Bera S, Ojha T, Mouftah HT, Anpalagan A. ENTRUST: Energy trading under uncertainty in smart grid systems. Comput Netw 2016;110:232–42. https://doi.org/10.1016/j.comnet.2016.09.021.
[10] Woo CK, Chen Y, Zarnikau J, Olson A, Moore J, Ho T. Carbon trading's impact on California's real-time electricity market prices. Energy. 2018;159:579–87. https://doi.org/10.1016/j.energy.2018.06.188.
[11] Meisel S, Merfeld T. Assessing the financial value of real-time energy trading services for privately owned non-commercial electric vehicles. Transp Res Part D: Transp Environ 2020;80:102229. https://doi.org/10.1016/j.trd.2020.102229.
[12] Pesaran HM, Nazari-Heris M, Mohammadi-Ivatloo B, Seyedi H. A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks. Energy 2020;209:118218. https://doi.org/10.1016/j.energy.2020.118218.
[13] Decerle J, Grunder O, El Hassani AH, Barakat O. A hybrid memetic-ant colony optimization algorithm for the home health care problem with time window, synchronization and working time balancing. Swarm Evol Comput 2019;46:171–83. https://doi.org/10.1016/j.swevo.2019.02.009.
[14] Edis Emrah B, Ilgin Mehmet Ali, Edis Rahime Sancar. Disassembly line balancing with sequencing decisions: a mixed integer linear programming model and extensions. J Cleaner Prod 2019;238:117826. https://doi.org/10.1016/j.jclepro.2019.117826.
[15] Wang Y, Ma Y, Song F, Ma Y, Qi C, Huang F, et al. Economic and efficient multi-objective operation optimization of integrated energy system considering electro-thermal demand response. Energy 2020;205:118022. https://doi.org/10.1016/j.energy.2020.118022.
[16] Noor S, Yang W, Guo M, van Dam KH, Wang X. Energy Demand Side Management within micro-grid networks enhanced by blockchain. Appl Energy 2018;228:1385–98. https://doi.org/10.1016/j.apenergy.2018.07.012.
[17] Bahrami S, Sheikhi A. From demand response in smart grid toward integrated demand response in smart energy hub. IEEE Trans Smart Grid 2015;7(2):650–8. https://doi.org/10.1109/TSG.2015.2464374.
[18] Wu Y, Ravey A, Chrenko D, Miraoui A. A real time energy management for EV charging station integrated with local generations and energy storage system. IEEE 2018. https://doi.org/10.1109/ITEC.2018.8450235.
[19] Abeni L, Faggioli D. Using Xen and KVM as real-time hypervisors. J Syst Archit 2020;106:101709. https://doi.org/10.1016/j.sysarc.2020.101709.
[20] Lebedev D, Rosin A, Kütt L. Simulation of real time electricity price based Energy Management System. In: IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, 2016; pp. 2106–10, https://doi.org/10.1109/IECON.2016.7793991.
[21] Xia S, Bu S, Wan C, Lu X, Chan KW, Zhou B. A fully distributed hierarchical control framework for coordinated operation of DERs in active distribution power networks. IEEE Trans Power Syst 2019;34(6):5184–97. https://doi.org/10.1109/TPWRS.2018.2870153.
[22] Haoran W, Sijie C, Jian P. Transaction of charging rights in charging stations of electric vehicles based on blockchain: mechanism, model and method. Proc Chinese Soc Electric Eng 2020;40(02):425–36. https://doi.org/10.13334/j.0258-8013.pcsee.182244.
[23] Zhang Z, Wang Z, Gan C, Zhang P. A double auction scheme of resource allocation with social ties and sentiment classification for Device-to-Device communications. Comput Netw 2019;155:62–71. https://doi.org/10.1016/j.comnet.2019.03.018.
[24] Liang L, Xueying W, Guangyu C. Model of the zi-c experiment for double auction system. In: 2011 International Conference on E-Business and E-Government (ICEE). IEEE, 2011;1–5. https://doi.org/10.1109/ICEBEG.2011.5881340.
[25] Shishido H, Zeng D Z, Yang X. The second-price bidding system under uncertainty. In: 2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat No 04CH37583) 2004; IEEE. https://doi.org/10.1109/ICSMC.2004.1398444.
[26] Wang J, Wang Q, Zhou N, Chi Y. A novel electricity transaction mode of microgrids based on blockchain and continuous double auction. Energies 2017;10(2):1971. https://doi.org/10.3390/en10121971.
[27] Song Y, Zafer M, Lee K-W, editors. Optimal bidding in spot instance market. In: 2012 Proceedings IEEE Infocom; 2012; IEEE. https://doi.org/10.1109/INFCOM.2012.6195567.
[28] Foti M, Vavalis M. Blockchain based uniform price double auctions for energy markets. Appl Energy 2019;254:113604. https://doi.org/10.1016/j.apenergy.2019.113604.
[29] Li D, Yang Q, Yu W, An D, Zhang Y, Zhao W. Towards differential privacy-based online double auction for smart grid. IEEE Trans Inf Forensics Secur 2019;15:971–86. https://doi.org/10.1109/TIFS.2019.2932911.

[30] Yu X, Li G, Cheng C, Sun Y, Chen R. Research and application of continuous bidirectional trading mechanism in Yunnan electricity market. Energies 2019;12(24):4663. https://doi.org/10.3390/en12244663.

[31] Lin J, Pipattanasomporn M, Rahman S. Comparative analysis of auction mechanisms and bidding strategies for P2P solar transactive energy markets. Appl Energy 2019;255:113687. https://doi.org/10.1016/j.apenergy.2019.113687.

[32] Zhao S, Wang B, Li Y, Li Y. Integrated energy transaction mechanisms based on blockchain technology. Energies 2018;11(9):2412. https://doi.org/10.3390/en11092412.

[33] Long C, Wu J, Zhou Y, Jenkins N. Peer-to-peer energy sharing through a two-stage aggregated battery control in a community Microgrid. Appl Energy 2018;226:261–76. https://doi.org/10.1016/j.apenergy.2018.05.097.

[34] Wang J, Zhong H, Ma Z, Xia Q, Kang C. Review and prospect of integrated demand response in the multi-energy system. Appl Energy 2017;202:772–82. https://doi.org/10.1016/j.apenergy.2017.05.150.

[35] Kumar NM. Blockchain: Enabling wide range of services in distributed energy system. Beni-Suef Univ. J. Basic Appl. Sci. 2018;7(4):701–4. https://doi.org/10.1016/j.bjbas.2018.08.003.

[36] Yu S, Yang S, Li Y, Geng J. Distributed energy transaction mechanism design based on smart contract. In: 2018 China International Conference on Electricity Distribution (CICED). IEEE, 2018; 2790–93. https://doi.org/10.1109/CICED.2018.8592130.

[37] Hou J, Wang C, Luo S. How to improve the competiveness of distributed energy resources in China with blockchain technology. Technol Forecast Soc Chang 2020;151:119744. https://doi.org/10.1016/j.techfore.2019.119744.

[38] Guan Z, Lu X, Wang N, Wu J, Du X, Guizani M. Towards secure and efficient energy trading in IIoT-enabled energy Internet: a blockchain approach. Future Gen Comput Syst 2020;110:686–95. https://doi.org/10.1016/j.future.2019.09.027.

[39] Lu X, Guan Z, Zhou X, Du X, Wu L, Guizani M. A secure and efficient renewable energy trading scheme based on blockchain in smart grid. In: IEEE 17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems. IEEE, 2019; 1839–44. https://doi.org/10.1109/HPCC/SmartCity/DSS.2019.00253.

[40] Ahl A, Yarime M, Tanaka K, Sagawa D. Review of blockchain-based distributed energy: implications for institutional development. Renew Sustain Energy Rev 2019;107:200–11. https://doi.org/10.1016/j.rser.2019.03.002.

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

[42] Sikorski JJ, Haughton J, Kraft M. Blockchain technology in the chemical industry: machine-to-machine electricity market. Appl Energy 2017;195:234–46. https://doi.org/10.1016/j.apenergy.2017.03.039.

[43] Khaqqi KN, Sikorski JJ, Hadinoto K, Kraft M. Incorporating seller/buyer reputation-based system in blockchain-enabled emission trading application. Appl Energy 2018;209:8–19. https://doi.org/10.1016/j.apenergy.2017.10.070.

[44] Li Y, Yang W, He P, Chen C, Wang X. Design and management of a distributed hybrid energy system through smart contract and blockchain. Appl Energy 2019;248:390–405. https://doi.org/10.1016/j.apenergy.2019.04.132.

[45] Wu X, Duan B, Yan Y, Zhong Y, editors. M2m blockchain: The case of demand side management of smart grid. 2017 IEEE 23rd International Conference on Parallel and Distributed Systems (ICPADS); 2017; IEEE. https://doi.org/10.1109/ICPADS.2017.00113.

[46] Wang Y, Wang Y, Huang Y, Yu H, Du R, Zhang F, et al. Optimal scheduling of the regional integrated energy system considering economy and environment. IEEE Trans Sustainable Energy 2019;10(4):1939–49. https://doi.org/10.1109/TSTE.2018.2876498.

[47] Cho H, Smith AD, Mago P. Combined cooling, heating and power: a review of performance improvement and optimization. Appl Energy 2014;136:168–85. https://doi.org/10.1016/j.apenergy.2014.08.107.

[48] Bhandari B, Lee KT, Lee CS, Song CK, Maskey RK, Ahn SH. A novel off-grid hybrid power system comprised of solar photovoltaic, wind, and hydro energy sources. Appl Energy 2014;133:236–42. https://doi.org/10.1016/j.apenergy.2014.07.033.

[49] Li J, Fang J, Zeng Q, Chen Z. Optimal operation of the integrated electrical and heating systems to accommodate the intermittent renewable sources. Appl Energy 2016:244–54. https://doi.org/10.1016/j.apenergy.2015.10.054.

[50] Faqiry MN, Das S. Double auction with hidden user information: application to energy transaction in microgrid. IEEE Trans Syst, Man, Cybernet: Syst 2019:2326–39. https://doi.org/10.1109/TSMC.2018.2800006.

[51] Wang N, Xu W, Shao W, Xu Z. A Q-cube framework of reinforcement learning algorithm for continuous double auction among microgrids. Energies 2019;12:2891. https://doi.org/10.3390/en12152891.

[52] Notheisen B, Cholewa JB, Shanmugam AP. Trading real-world assets on blockchain. Bus Inform Syst Eng 2017;59(6):425–40. https://doi.org/10.1007/s12599-017-0499-8.

[53] Zheng Z, Gui Y, Wu F, Chen G. STAR: strategy-proof double auctions for multi-cloud, multi-tenant bandwidth reservation. IEEE Trans Comput 2014;64(7):2071–83. https://doi.org/10.1109/TC.2014.2346204.

[54] Krovvidi SS. Competitive microgrid electricity market design. Virginia Tech; 2010.

[55] Xiaocui W. Research on Agent-based continuous double-way auction strategy. Harbin Eng Univ 2016.

[56] Hu A, Matthews SA, Zou L. Risk aversion and optimal reserve prices in first-and second-price auctions. J Econ Theory 2010;145(3):1188–202. https://doi.org/10.1016/j.jet.2010.02.006.

[57] Liu M, Wang C, Guo L, Zhao B, Zhang X, Liu Y. An optimal design method of multi-objective based island microgrid. Dianli Xitong Zidonghua (Automation of Electric Power Systems) 2012;36(17):34–9.

[58] Songli F, Qian A, Xing H. Risk analysis on dispatch of virtual power plant based on chance constrained programming. Proc CSEE 2015;35(16):4025–34.

[59] Ju L, Tan Z, Yuan J, Tan Q, Li H, Dong F. A bi-level stochastic scheduling optimization model for a virtual power plant connected to a wind–photovoltaic–energy storage system considering the uncertainty and demand response. Appl Energy 2016;171:184–99. https://doi.org/10.1016/j.apenergy.2016.03.020.

[60] Wenfei Y, Yiwei Z, Yongzhang H, Cong L. Regional integrated energy system operation optimization considering integrated demand side response. J North China Electric Power Univ (Nat Sci Edit) 2019;46(03):33–41.