Cloud-edge-based We-Market: Autonomous Bidding and Peer-to-peer Energy Sharing Among Prosumers

Fangyuan Si, *Member*, *IEEE*, Yinghua Han, Qinqin Xu, Jinkuan Wang, *Member*, *IEEE*, and Qiang Zhao

***Abstract*—With the extensive penetration of distributed renewable energy and self-interested prosumers, the emerging power market tends to enable user autonomy by bottom-up control and distributed coordination. This paper is devoted to solving the specific problems of distributed energy management and autonomous bidding and peer-to-peer (P2P) energy sharing among prosumers. A novel cloud-edge-based We-Market is presented, where the prosumers, as edge nodes with independent control, balance the electricity cost and thermal comfort by formulating a dynamic household energy management system (HEMS). Meanwhile, the autonomous bidding is initiated by prosumers via the modified Stone-Geary utility function. In the cloud center, a distributed convergence bidding (CB) algorithm based on consistency criterion is developed, which promotes faster and fairer bidding through the interactive iteration with the edge nodes. Besides, the proposed scheme is built on top of the commercial cloud platform with sufficiently secure and scalable computing capacity. Numerical results show the effectiveness and practicability of the proposed We-Market, which achieves 15% cost reduction with shorter running time. Comparative analysis indicates better scalability, which is more suitable for larger-scale We-Market implementation.**

***Index Terms*—We-Market, bidding, energy sharing, prosumer, peer-to-peer, cloud-edge.**

Nomenclature

A. Sets and Indices

$D_{N\times T}^{seller}$	Set of seller users
$D_{N\times T}^{buyer}$	Set of buyer users
i, j	Indices of prosumers
k	Index of iterations
l, w, pv	Indices of load, wind power, and photovoltaic (PV)
N	Total number of prosumers
t	Time slot
T	Total scheduling time

B. Parameters

α^i	Willingness to purchase/sell electricity
β^i	Penalty coefficient for energy imbalance
θ^k	Iterative parameters
ε	Iteration step
η^i	Battery leakage rate
τ^i	Factor of building thermal inertia
γ^i	Performance coefficient of air conditioner
a^i	Ambient temperature
$e^{i,l}$	Prediction error of loads
$e^{i,w}$	Prediction error of wind power
$e^{i,pv}$	Prediction error of PV power
K^i	Building insulation coefficient
$P^{i,l}$	Day-ahead prediction of loads
$P^{i,w}$	Day-ahead prediction of wind power
$P^{i,pv}$	Day-ahead prediction of PV power

C. Variables

λ^i	Generated dual variables of prosumer
ρ	Coefficient of quadratic penalty term
δu^{ij}	Power gaps between transaction parties
b^i	Quotations of prosumers
$b^{i,*}$	Optimal quotations of prosumers
u_1^i	Power discharged from battery for home usage
u_2^i	Unit power consumption of air conditioner ($u_2^i>0$ when air conditioner is in use, and $u_2^i<0$ otherwise)
u_3^i	Actual tradable electricity ($u_3^i>0$ indicates the purchased electricity from the main grid or other prosumers, and $u_3^i<0$ indicates the sold electricity)
$u^{i,trade}$	Actual trading electricity
$u^{i,trade,*}$	Optimal trading electricity

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x_1^i	Battery state of charge
x_2^i	Indoor temperature of prosumers
x_3^i	State of electricity balance

I. Introduction

RENEWABLE energy and smart grid technology are effective ways to deal with the energy trilemma [1]. With the extensive penetration of renewable energy generation and controllable loads into power systems, more and more traditional power users are gradually transformed into self-interested prosumers with autonomous capability, participating in the electricity market through renewable energy generation, e.g., small wind turbines and rooftop photovoltaic (PV) panels, coordination control of energy storage, and flexible load. The traditional centralized electricity market is further transformed to decentralized retail markets [2], [3]. In this context, a reasonable energy management strategy and a retail electricity market operation mode are of great significance to deeply tap user flexibility, improve energy efficiency, and ensure the interests of the prosumers.

To coordinate transactive prosumers in emerging electricity markets, many recent studies contribute to the peer-to-peer (P2P) models [4]. In general, the P2P models consist of energy management and bidding strategy. Taking into account some influence factors such as the uncertainty of renewable energy [5], supply and demand balance [6], and power flow security [7], the P2P energy management focuses on the optimal energy sharing among prosumers. In [8], a non-cooperative energy sharing game is presented for the selfish buildings, which further analyzes the relationship between generalized Nash equilibrium and energy sharing payments. In [9], a two-level energy sharing strategy is further introduced to find the optimal distributed energy sharing way. Furthermore, the P2P energy management can be extended to the optimal scheduling problem of transactive multi-energy systems to support multi-energy complementarity and integrated demand response [10], [11]. These efforts are devoted to optimizing energy management. However, it is difficult to capture conflicting interests and fairness of the trading without considering the autonomy of prosumers and diversified control objectives.

To balance the optimality of energy management and the fairness of the trading, the local energy market (LEM), as one possible implementation of a citizen energy community, comes into being to coordinate the increasing number of prosumers [12]. It ideally considers the prosumers' preferences, ensures trading fairness and efficient operation, reduces transmission costs, and enhances local communities by enabling prosumers to actively negotiate and trade residual energy [13]. To this end, the P2P-based bidding mechanism becomes an important part of energy sharing in the LEM, which can be roughly divided into three categories: auction-based bidding, game-based bidding, and convergence bidding (CB). For example, an iterative double auction mechanism is designed to maximize the social welfare in the P2P energy trading among electric vehicles [14]. In [15], a surrogate LEM prediction model is developed to learn prosumer bidding actions, which facilitates prosumers actively participating in the continuous double auction-based LEM. In [16], the continuous double auction problem moves towards a Pareto efficient allocation. However, it proves that the generation or load curtailment may occur under the auction-based bidding mechanism. The game-theoretic approach is used in [17] to capture the conflicting interests in the decision-making process of the LEM. In [18], a stochastic leader-follower game approach is presented considering the social attributes of prosumers, which provides a trade-off solution between dynamic prices and load distributions. To increase the prosumer participation, a motivation psychology framework and a game-theoretic P2P energy trading scheme are presented in [19]. Though the game-based bidding strategy shows its potential to attract prosumers to participate in the LEM, Nash equilibrium solutions may not always exist, especially for large-scale nonlinear P2P energy management and bidding problems in some real scenarios. To this end, a CB strategy is proposed in [20] to reduce the price gap between the day-ahead and the real-time LEM prices. In [21], a bi-level optimization CB strategy is formulated to maximize the profits from the point of view of the bidders. It also analyzes how such a strategy affects the price gap. Based on the previous studies, the common ground of the three methods [19]-[21] is based on a virtual center responsible for integrating participants. The most essential difference is whether the optimization and decision-making processes are separated, which is determined by different structures of the markets. For the auction-based methods in [14]-[16], the optimization and decision-making processes are separated, which are implemented by different subjects. Specifically, the optimization process is performed by a virtual center, and the specific model parameters of agents need to be known. The decision-making process is executed by agents according to the optimization results fed back by the virtual center. On the contrary, the optimization and decision-making processes can be integrated into agents and executed in parallel by the CB method. Here, the virtual center is mainly responsible for coordinating and matching participants and rarely participates in optimization and decision-making. In other words, the CB method uses the local solving and extensive communication abilities of prosumers to share the computation burden of the virtual center. Therefore, it is expected to give full play to the autonomy of prosumers and improve optimization efficiency.

From the perspectives of systemic energy management and bidding mechanism, the related research shows potential in solving the previous P2P trading problems. Although it is more popular and easier for the system operator to implement top-down control, such a framework may lead to the following problems: ① the access of large-scale self-interested prosumers leads to the increase of computation complexity of centralized optimizer, which is difficult to guarantee efficiency, real-time property, and scalability of the retail electricity market; ② the centralized optimizer has full control of the LEM, which makes it difficult to further stimulate prosumers' autonomy to participate in the market; ③ and privacy security is a concern. Once the centralized database storage is attacked, all information will be leaked. Motivated by the emerging edge empowerment techniques, the cloud-edge collaboration and its extended application have become alternative solutions [22], [23]. There have been some attempts in the electricity market. In [24], a cloud-edge collaborative decision-making approach is presented for demand response enabled fast frequency response service provision. Results show that the cloud-edge computing is a comprehensive approach to deploying new distributed energy market architectures. In [25], a two-stage community energy trading model under end-edge-cloud orchestration is proposed to solve the trading problems between the retailer and energy communities and increase the transaction efficiency. Therefore, the cloud-edge collaboration has the potential to improve the scalability of the LEM and the autonomy of users by transferring computing power and privacy information to edge nodes.

In terms of previous studies, the research gaps are mainly reflected in the following aspects. ① From the perspective of prosumers' interests, there is little research on the design of bottom-up market mechanism. ② For prosumers with computing power, their dynamic energy management and participation in market bidding are still lack of interaction. ③ For an LEM, the optimization and decision-making processes need to be further integrated into prosumers to improve optimization efficiency and avoid the failure of the whole market mechanism caused by the unavailability of edge nodes. Therefore, the distributed solution method for quickly coordinating large-scale prosumers to access the market needs to be redesigned. Accordingly, the key contributions of this paper to these problems can be summarized as follows.

1) A cloud-edge-based We-Market mechanism is designed to improve the fairness and efficiency of P2P trading. Compared with the traditional centralized optimization method of the LEM, it enables prosumers to carry out autonomous energy management and bidding by using the local solving abilities of edge nodes and their extensive information interaction in the cloud center.

2) A dynamic household energy management system (HEMS) model is developed to integrate dynamic energy management and autonomous bidding into prosumers. It fully considers the dynamic characteristics of energy management and the preference for participating in the market, and balances local electricity cost and thermal comfort in the process of participating in the We-Market.

3) A CB method is proposed based on the consistency criterion for the cloud-edge-based We-Market. The optimization and decision-making processes are integrated into prosumers so that the computing services are transferred from the center to the edge of the network for parallel computing. Therefore, it reduces the computation burden of the center and improves the optimization efficiency. It is also proven to have better scalability.

The remainder of this paper is organized as follows. Section II describes the basic need and formally defines the cloud-edge-based We-Market including the dynamic HEMS and quotation models of prosumers. Section III presents the P2P energy trading in the We-Market. Numerical experiments, as well as performance analysis and necessary discussion, are conducted in Section IV. Finally, Section V summarizes the main findings and future works.

II. Cloud-edge-based We-Market

Prosumers, as energy suppliers, consumers, and managers, may have great enthusiasm and initiative to participate in and benefit from energy trading. Since the traditional centralized optimization method of the LEM suffers from the problems of limited computing power, autonomy, and privacy security, it is bound to promote two aspects of reform: ① edge intelligence; and ② autonomous trading. At the same time, difficulties and challenges may arise: ① how to transfer the autonomous control to prosumers to meet the personalized needs of users participating in the market? ② how does the market coordinate large-scale self-interested prosumers to improve efficiency and scalability? Inspired by the bottom-up energy management structure [26] and the concept of We-Media on the Internet [27], [28], the novel concept of the We-Market is put forward for the first time. It is defined as a self-organizing LEM with the important characteristics of distributed, full-duplex, local intelligent control, P2P energy sharing, and autonomous bidding. The main players of the We-Market are a large number of prosumers with distributed generation, energy storage, and controllable loads. They have complete autonomy over local energy management by integrating optimization and decision-making [29]. Therefore, the citizen energy community can realize energy sharing and self-sufficiency in a bottom-up flat energy interaction way. Compared with the decentralized P2P models, the advantages of the cloud-edge-based We-Market are mainly reflected in the following two aspects.

1) The optimization program is executed in parallel among prosumers rather than overall coordination through the center, which can meet the autonomy needs of prosumers and reduce the computation burden of the center, so as to improve the market efficiency.

2) Dynamic energy management of prosumers is closely related to autonomous bidding behavior, which provides prosumers with a basis for the optimal coordination of local flexible resources and a fair guarantee for the participation in the market.

A. System Description

As illustrated in Fig. 1, the We-Market is a bottom-up control framework, which is based on cloud-edge collaboration and frequent interaction. The operation of the system includes the following links. Firstly, prosumers use local computing power to solve the dynamic HEMS models to coordinate the internal energy storage, controllable loads, and renewable energy outputs. At the same time, prosumers formulate the quotation strategies according to the local energy coordination results and the quotation models. Here, the solution program is executed in parallel by decentralized prosumers, and the tradable power and quotation information of each prosumer are output and uploaded to the cloud center. Then, according to the uploaded information, the cloud center uses the CB method to match the transaction parties and feeds back tradable power and quotation gaps to prosumers. Next, both transaction parties adjust energy management and quotation strategies and update the upload information. Finally, a win-win deal consensus is reached after several interactions and iterations among the cloud and prosumers. As a result, it has the potential to improve the autonomy of prosumers and market efficiency. Given these features, technical details of the dynamic HEMS, quotation models, and the CB algorithm are presented in the following sections.

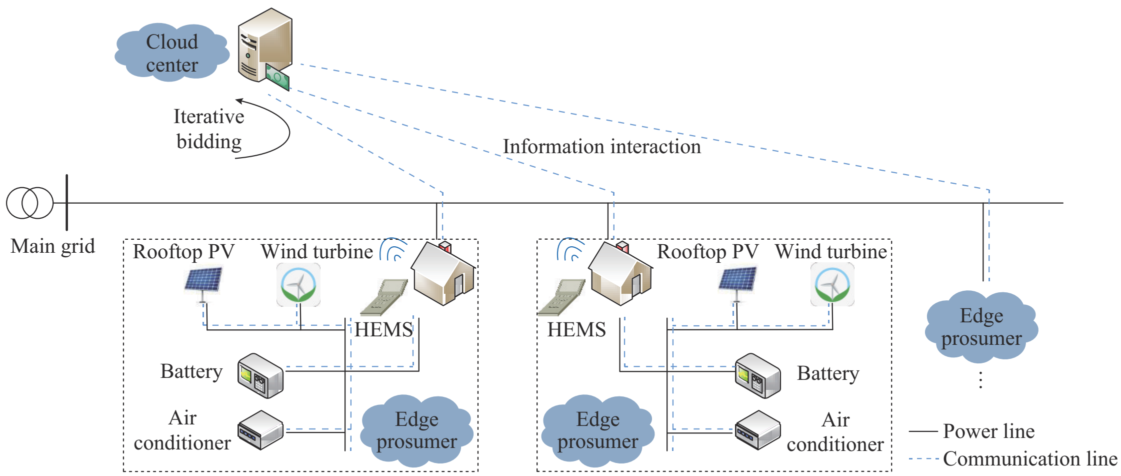

Fig. 1. Diagram of cloud-edge-based We-Market.

Particularly, [16] investigates the impact of the technical constraints of the low-voltage distribution network for P2P energy trading. It constructs and introduces power flow constraints into the optimization problem to ensure that the energy exchange of each node in the distribution network does not violate network constraints. However, since the proposed We-Market focuses on energy sharing within the local community (which can be regarded as a node in the distribution network), the power transmission distance is short and the power loss can be ignored, and thus the system modeling does not consider the power flow constraints. From a wide-area perspective, i.e., cross-community energy trading, a detailed distribution network power flow model needs to be introduced based on the We-Market to solve the problems of network congestion and voltage stability, such as the Distflow-based modeling method for distribution networks.

B. Dynamic HEMS Model

Consider a total of N prosumers that participate in the We-Market. According to Fig. 1, it is assumed that a household wind turbine and a rooftop PV are available as renewable energy generators for each prosumer $i \in \{1, 2, ..., N\}$. It should be noted that as distributed power sources, household wind turbines and rooftop PVs have become new and promising ways of comprehensive energy utilization with their small modular, decentralized, and efficient generation mode arranged near users [30], [31]. Besides, as an indoor thermostat, the air conditioner is a controllable load. The battery is connected to renewable energy generators and air conditioners to provide power reserves. Besides, some other uncontrollable and known appliances are considered as base loads, such as lighting and refrigerators. Theoretically, the base loads and the output power of the household wind turbine and rooftop PV are random and fluctuating. Therefore, they can be modeled as $P^{i,l}+e^{i,l}$, $P^{i,w}+e^{i,w}$, and $P^{i,pv}+e^{i,pv}$, respectively. Here, the prediction error e obeys the Gaussian distribution with zero mean and variance σ^2. As for the ambient temperature, it is assumed that the meteorological data are accurate and known.

Based on the dynamic state of charge (SOC) and building thermal models in [32], the whole HEMS can be formulated by introducing the differential equation of electricity balance [33] as:

$$\begin{bmatrix} \dot{x}_1^i \\ \dot{x}_2^i \\ \dot{x}_3^i \end{bmatrix} = \boldsymbol{A} \begin{bmatrix} x_1^i \\ x_2^i \\ x_3^i \end{bmatrix} + \boldsymbol{B} \begin{bmatrix} u_1^i \\ u_2^i \\ u_3^i \end{bmatrix} + \boldsymbol{C} \begin{bmatrix} P^{i,w}+e^{i,w} \\ P^{i,pv}+e^{i,pv} \\ P^{i,l}+e^{i,l} \end{bmatrix} + \boldsymbol{d} \tag{1}$$

where the outputs of the renewable generators, i.e., $P^{i,w}+e^{i,w}$ and $P^{i,pv}+e^{i,pv}$, act as the input power to the battery; and the third row describes the dynamics of the supply-demand balance. Therefore, the dynamic states are x_1^i, x_2^i, and x_3^i and the decision variables include u_1^i, u_2^i, and u_3^i.

Equations (2)-(5) provide the detailed parameter matrices and vectors in (1).

$$\boldsymbol{A} = \begin{bmatrix} 1-\eta^i & 0 & 0 \\ 0 & \tau^i - 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

$$\boldsymbol{B} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -\gamma^i (1-\tau^i) K^i & 0 \\ 1 & -1 & 1 \end{bmatrix} \tag{3}$$

$$\boldsymbol{C} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -1 \end{bmatrix} \tag{4}$$

$$\boldsymbol{d} = \begin{bmatrix} 0 & (1-\tau^i)a^i & 0 \end{bmatrix}^{\mathrm{T}} \tag{5}$$

where τ^i is dependent on the function of thermal conductivity and time constant; $-\gamma^i (1-\tau^i) K^i$ indicates the combined factor considering the building thermal inertia and the air conditioner performance [34], [35]; γ^i is used to adjust the indoor temperature comfortably; and K^i is used to represent the ratio between the total thermal output of the air conditioner and the consumed electricity.

The above HEMS model provides a basis for realizing multiple flexible resource decoupling, dynamic household energy management, and decision-making of tradable electricity. However, it is important that the energy trading in the We-Market should be rational according to the principle of maximizing the interests of the prosumers. Therefore, a fair quotation model is developed in the following sections.

C. Quotation Model

According to the above HEMS model, the trading price needs to be reasonably quantified during the transaction. Here, the classic Stone-Gear utility function in economics is introduced. It organically integrates three key elements in the transaction process, i. e., tradable quantity, preference, and utility [36]. Compared with linear/quadratic utility functions that are widely used in the power system area, the Stone-Gear utility function not only combines the energy management and quotation of prosumers but also quantifies their preferences to participate in the market, which presents a good practical application prospect. Its first-order derivative is clear though it is nonlinear. Relevant studies have proven the effectiveness of the Stone-Geary utility function in characterizing the trading willingness of users [14].

Here, suppose u_3^i and $u^{i,base}$ are the actual and basic tradable electricity, respectively. In the case of $u_3^i>0$, let the actual trading electricity $u^{i,trade}=u_3^i-u^{i,base}$. Then, the corresponding Stone-Geary utility function U for all prosumers can be formulated as:

$$U=\prod_{i=1}^{N}(u^{i,trade})^{\alpha^i} \tag{6}$$

By the monotonic transformation of (6), the same preference function can be obtained for any prosumer as:

$$U(u_3^i)=\alpha^i \ln u^{i,trade} \tag{7}$$

To avoid the case of $u_3^i=u^{i,base}$, (7) can be rewritten as:

$$U'(u_3^i)=\alpha^i \ln(u^{i,trade}+1) \tag{8}$$

To reduce the computation complexity, the nonlinear $U'(u_3^i)$ can be approximated by the first-order Taylor series as:

$$U'(u_3^i)=\alpha^i\sum_{n=0}^{\infty}\frac{(-1)^n}{n+1}(u^{i,trade})^{n+1}\approx \alpha^i u^{i,trade} \tag{9}$$

Besides, the state of electricity balance x_3^i is a critical condition for prosumers during their P2P trading in the We-Market. In other words, each prosumer should comprehensively consider the willingness to purchase/sell electricity and its residual power status. For each round of bidding, its quotation strategy is a weighted form as:

$$b^i=\alpha^i u^{i,trade}+\beta^i x_3^i \tag{10}$$

The quotation model for the case of $u_3^i<0$ is similar and can be obtained by changing the sign from positive to negative.

D. Trade-off Analysis

Each prosumer can formulate a dynamic optimization problem via the proposed HEMS and the quotation models to coordinate the operation of the renewable generator output, battery, and air conditioner, to balance the cost of power consumption and indoor temperature comfort. At any time t, the trade-off framework is to balance the controllable load $u_2^i(t)$ and the trading electricity $u^{i,trade}(t)$. Accordingly, the total utility for the prosumer can be modeled as a quadratic function as:

$$\begin{aligned} f^i(u_1^i(t),u_2^i(t),u_3^i(t))=\epsilon(P^{i,l}(t)+e^{i,l}(t)+u_2^i(t))-b^i(t)u^{i,trade}(t)+\\ \lambda(x_2^i(t)-x_d^i(t))^2 \end{aligned} \tag{11}$$

where at the right side, the first term denotes the cost of electricity consumption; the second term denotes the revenue from electricity sales for the case of $u_3^i>0$ (if $u_3^i<0$, it changes to the purchase cost); and the third term denotes the penalty of the deviation between the current temperature and the desired temperature $x_d^i(t)$. Given the current state follows the dynamic characteristics in (1) and the quotation strategy in (10), an equilibrium strategy concerning the cost of power consumption and indoor temperature comfort can be obtained using the dynamic programming [32]. Besides, it also provides the optimal trading electricity $u^{i,trade,*}(t)$ and the initial quotation $b^{i,*}(t)$ for each prosumer.

III. P2P Energy Trading in We-Market

Based on the proposed HEMS and quotation models, the whole system operation turns out to be a distributed optimization problem with frequent information interaction and P2P bidding. Since the computation complexity may increase exponentially or polynomially with the number of prosumers, the centralized optimization across all prosumers is not practical. To this end, the distributed CB algorithm is developed for the cloud-edge-based We-Market to support autonomous bidding and P2P energy sharing.

A. Distributed CB Algorithm

Algorithm 1 describes the control and update of the prosumers. It updates the status of prosumers by actively adjusting decision variables $u_3^{i,k}$ and quotation coefficients α_k^i and β_k^i according to the HEMS and quotation models, i.e., (1)-(11). Algorithm 2 provides the distributed CB algorithm for the cloud of the We-Market. It matches the transaction parties following the principle of minimum deviation, which guides the prosumers to actively adjust the states by updating the iterative parameters θ^k until the optimal trading electricity and price are consistent.

The overall bidding procedure for the cloud-edge-based We-Market and the distributed CB algorithm is shown in Fig. 2, and is performed through the following processes.

1) According to Algorithm 1, the local energy management problem is tackled via the dynamic HEMS and quotation models of each prosumer in parallel. And the trading electricity $u_k^{i,trade}(t)=u^{i,trade,*}(t)$ and the initial quotation $b_k^i(t)=b^{i,*}(t)$ are uploaded to the cloud center.

2) According to Algorithm 2, the cloud center matches the transaction parties and provides power and quotation gaps, i.e., Δu^{ij} and Δb^{ij} $(j\neq i)$, respectively, by minimizing deviations.

3) Next, both transaction parties use these gaps to update residual power status $u_{k+1}^{i,trade}(t)$ and quotation $b_{k+1}^i(t)$, and interact with the cloud center again until a deal consensus is reached.

Algorithm 1: control and update of prosumers

for $t=1{:}T$
  for $i=1{:}N$
    Solve HEMS model in (1)-(11) using dynamic programming
    Obtain $u^{i,trade,*}(t)$ and $b^{i,*}(t)$ of all prosumers
    while $u^{i,trade,*}(t)\neq 0$
      Upload $u^{i,trade,*}(t)$ and k to cloud center
      Download $\Delta u_k^{ij}(t)$ and θ^{k+1} from cloud center
      if $\Delta u_k^{ij}(t)\neq 0$
        Resolve HEMS model with $u_3^{i,k+1}=u_3^{i,k}-\theta^{k+1}$ for sellers and $u_3^{j,k+1}=u_3^{j,k}+\Delta u_k^{ij}(t)+\theta^{k+1}$ for buyers, and upload $u_{k+1}^{i,trade}(t)$ and $u_{k+1}^{j,trade}(t)$ to cloud center
      else
        Download $\Delta b_k^{ij}(t)$ from cloud center
        if $\Delta b_k^{ij}(t)\neq 0$
          Update the quotation coefficients with $\alpha_{k+1}^{i}=\alpha_k^i-\Delta b_k^{ij}(t)$, $\beta_{k+1}^{i}=\beta_k^i-\Delta b_k^{ij}(t)$, $\alpha_{k+1}^{j}=\alpha_k^j+\Delta b_k^{ij}(t)$, and $\beta_{k+1}^{j}=\beta_k^j+\Delta b_k^{ij}(t)$, resolve the HEMS, and upload b_{k+1}^{i} and b_{k+1}^{j} to cloud center
        else
          Output the optimal results of trading electricity $u_k^{i,trade,*}(t)$ and $u_k^{j,trade,*}(t)$, and the trading price $b_k^{i,*}(t)$ and $b_k^{j,*}(t)$
        end if
      end if
    end while
  end for
end for

Algorithm 2: distributed CB algorithm

Obtain $u^{i,trade,*}(t)$ and $b^{i,*}(t)$ from prosumers
if $u^{i,trade,*}(t)>0$
  Build seller set $D_{N\times T}^{seller}(i,t)=u^{i,trade,*}(t)$
else
  Build buyer set $D_{N\times T}^{buyer}(i,t)=u^{i,trade,*}(t)$
  for $t=1{:}T$
    for $i=1{:}N$
      while $u_k^{i,trade}(t)=u^{i,trade,*}(t)>0$
        Find $j=\arg\min\{|u_k^{i,trade}(t)+D_{N\times T}^{buyer}(:,t)|\}$
        if $\Delta u_k^{ij}(t)=u_k^{i,trade}(t)+u_k^{j,trade}(t)\neq 0$
          Download $\Delta u_k^{ij}(t)$ and $\theta^{k+1}=\theta^k+\varepsilon$ to prosumers for updates, in which $\theta^0=0$
        else if $\Delta u_k^{ij}(t)=0$ and $\Delta b_k^{ij}(t)=b_k^i(t)-b_k^j(t)\neq 0$
          Download $\Delta b_k^{ij}(t)$ to prosumers for updates
        end if
      until $\Delta u_k^{ij}(t)=0$ and $\Delta b_k^{ij}(t)=0$
      end while
      Record the optimal trading electricity $u_k^{i,trade,*}(t)=-u_k^{j,trade,*}(t)$ and the trading price $b_k^{i,*}(t)=b_k^{j,*}(t)$
    end for
  end for
end if

4) Finally, the prosumers determine whether another round of the We-Market is required based on the decision variables $u_3^{i,*}$ and $u_3^{j,*}$. If $u_3^{i,*}>0$ is not satisfied, output the trading results. Otherwise, another round of the We-Market needs to be organized to maximize the utilization of renewable energy and the benefits of prosumers.

Note that, the distributed CB algorithm matches the two sides of the transaction following the principle of minimizing the deviation. It is a kind of priority, which avoids the situation where a prosumer matches several prosumers at the same timeslot. Therefore, it also ensures the uniqueness and traceability of transactions. Besides, it can also be observed that the center of the distributed CB algorithm is mainly responsible for coordinating and matching participants, and computation tasks are transferred to prosumers for parallel execution, which meets the autonomy needs of prosumers and reduces the computation burden of the center, so as to improve the market efficiency.

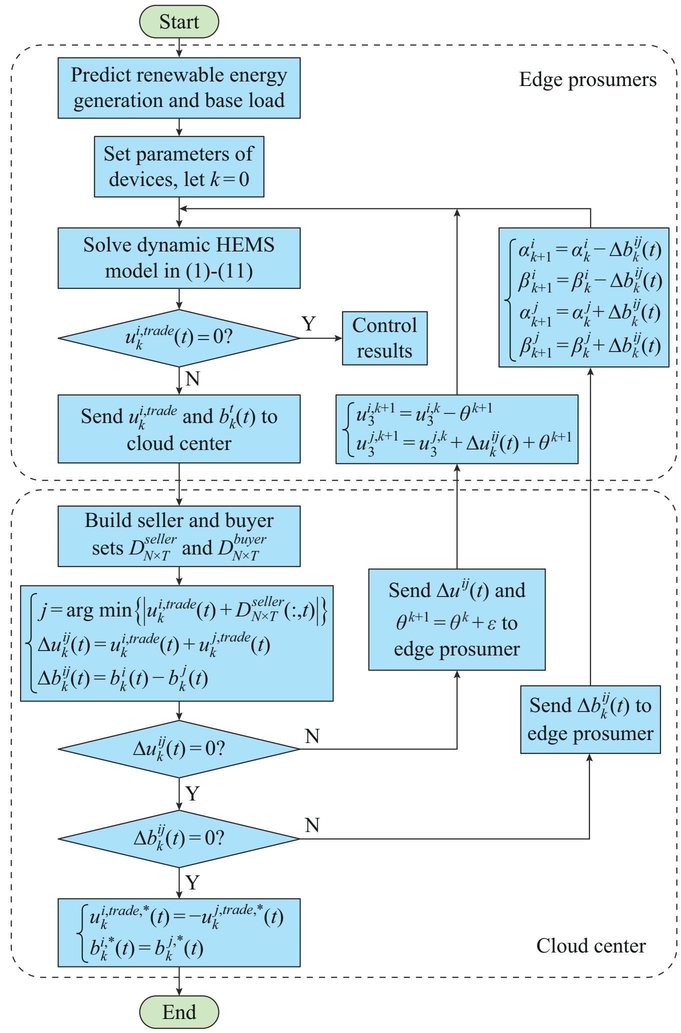

Fig. 2. Overall procedure for cloud-edge-based We-Market and distributed CB algorithm.

B. Convergence Analysis

According to (11) and the distributed CB algorithm, the local augmented Lagrangian function of the prosumer i can be formulated as:

$$\min_{u^{i,trade},u^{j,trade},\lambda^i} \mathcal{L}_{\mathrm{CB}}^i=f^i+\sum_j \lambda^i\,(u^{i,trade}+u^{j,trade})+\frac{\rho}{2}\left\|(u^{i,trade}+u^{j,trade})\right\|_2^2 \tag{12}$$

Given the prosumers are connected with the cloud in a period T, the convergence performance of the algorithm is closely related to the step size ε, and we have:

$$0<\varepsilon<1/\varpi \tag{13}$$

where $\varpi=\sup_{k\le 0}\max \pi_k^{ij}$, and π_k^{ij} is an element in a time-varying Laplace matrix $\boldsymbol{L}_k$, which can be expressed as:

$$\pi_k^{ij}=\begin{cases}\sum_j \lambda_k^i & i=j\\ -\lambda_k^i & i\neq j\end{cases} \tag{14}$$

For the sake of proof, define $\boldsymbol{H}_T^k = \sum_{t=k}^{t+T-1} \boldsymbol{h}_k$ as a positive definite invertible matrix, and let:

$$\boldsymbol{h}_k \le (2/\varpi)\boldsymbol{\Lambda}_\Gamma^{-1} = \boldsymbol{I}/\varpi \tag{15}$$

where $\boldsymbol{\Lambda}_\Gamma = \mathrm{diag}(\Gamma_1, \Gamma_2, ..., \Gamma_n)$ is a diagonal matrix composed of Lipschitz constants of the gradients [37]; and $\boldsymbol{I}$ is the unit matrix.

Lemma 1: λ_k^i is the generated dual variable of the prosumer i and the step size ε follows (13)-(15). Then, the augmented Lagrangian function $\mathcal{L}(\lambda_k^i)$ is decreasing periodically, i.e.,

$$\left\| \mathcal{L}(\lambda_{(k+1)T}^i) - \mathcal{L}(\lambda_{kT}^i) \right\| \le \varrho \left\| \boldsymbol{H}_{kT} \nabla \mathcal{L}(\lambda_{kT}^i) \right\|^2 \tag{16}$$

Proof: see Appendix A Section A.

On this basis, the convergence of the augmented Lagrangian function $\mathcal{L}(\lambda_k^i)$ is proven below.

Theorem 1: supposing $\mathcal{L}^*$ is the optimal solution, the augmented Lagrangian function is convergent, i.e., $\lim_{k \to \infty} \mathcal{L}(\lambda_k^i) = \mathcal{L}^*$.

Proof: see Appendix A Section B.

IV. Results and Discussions

A. System Parameters

The proposed cloud-edge-based We-Market and the distributed CB algorithm are applied to a feeder section consisting of 100 prosumers. Each prosumer is equipped with a rooftop PV, a small wind turbine, a battery, and an air conditioner, as illustrated in Fig. 1. The statistical box chart of the actual renewable energy generation, basic loads, and ambient temperature of all the prosumers on a typical day is provided in Fig. 3. Relevant data are taken from a power utility in Tongliao, Inner Mongolia, China. Figure 3(a) shows the statistics of the renewable energy generation of the prosumers. It can be observed that the outputs of the rooftop PV and wind turbines are intermittent and fluctuating. Figure 3(b) shows the statistics of the basic loads and ambient temperature of the prosumers. It can be observed that there are also strong uncertainties in basic loads and ambient temperature. In this case, the mismatch between supply and demand leads to the inevitable energy surplus or shortage of the prosumers.

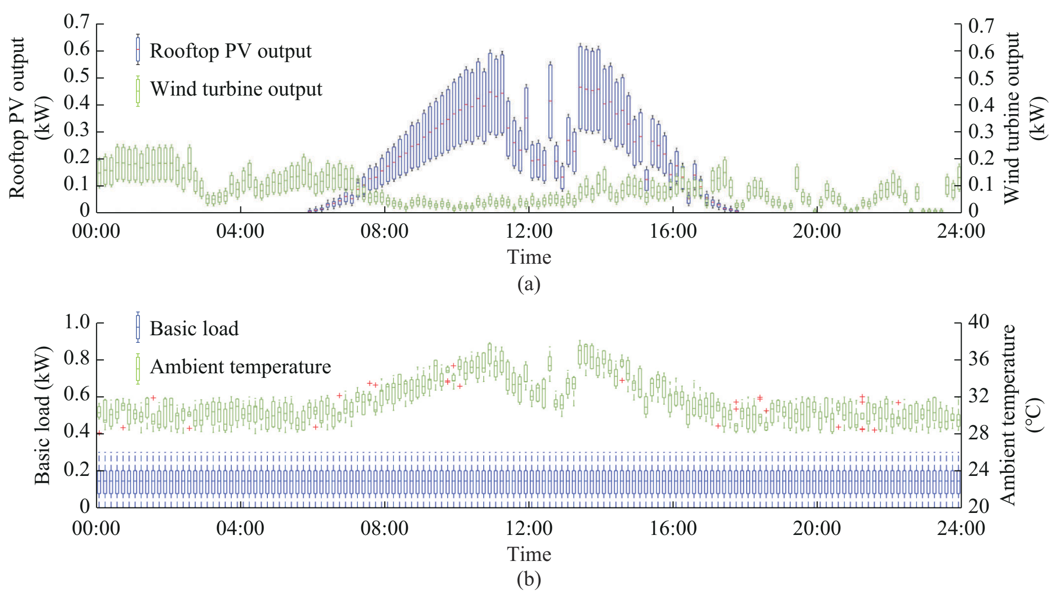

Fig. 3. Box chart of actual data on a typical day. (a) Renewable energy generation. (b) Basic loads and ambient temperature.

Besides, the trading period is from 00:00 to 24:00 and a 10-min time slot is set. Considering the diverse power consumption behaviors and thermal comfort requirements of prosumers, five kinds of setting temperatures are adopted, i.e., 18 °C, 20 °C, 22 °C, 24 °C, and 26 °C during the period. In particular, the capacity of the battery is 6 kWh for each prosumer, and the maximum discharging power per time slot t is 0.4 kW, i.e., $u_1^i \le 0.4$ kW. The usage of the air conditioner is a binary variable, so $u_2^i = 0$ kW or $u_2^i = 0.3$ kW per time slot t according to its conventional power consumption. Other related parameters of the HEMS are listed in Table I in detail. According to [18], surplus electricity can be sold to the main grid at a lower price, while insufficient electricity can also be purchased from the main grid. The prices are 0.35 CNY/kW and 1.0 CNY/kW for selling the surplus electricity and purchasing electricity, respectively.

TABLE I
Related Parameter of HEMS

Parameter	Value	Parameter	Value
η^i	10^{-3}	λ	1
τ^i	0.1	α_0^i	2.7
γ^i	0.9	β_0^i	10
K^i	3	ε	10^{-3}
ϵ	1		

The simulations are carried out on top of the commercial cloud platform using an optimization server with Docker Swarm as distributed HEMS and Amazon EC2 as the backend public cloud [38], which can provide sufficient secure and scalable computation capacity by deploying the above We-Market in the optimization server.

B. Results Analysis

This subsection aims at illustrating the effectiveness of the proposed cloud-edge-based We-Market and the distributed CB algorithm on a synthetic example. Figure 4 shows the P2P trading results using the proposed approach.

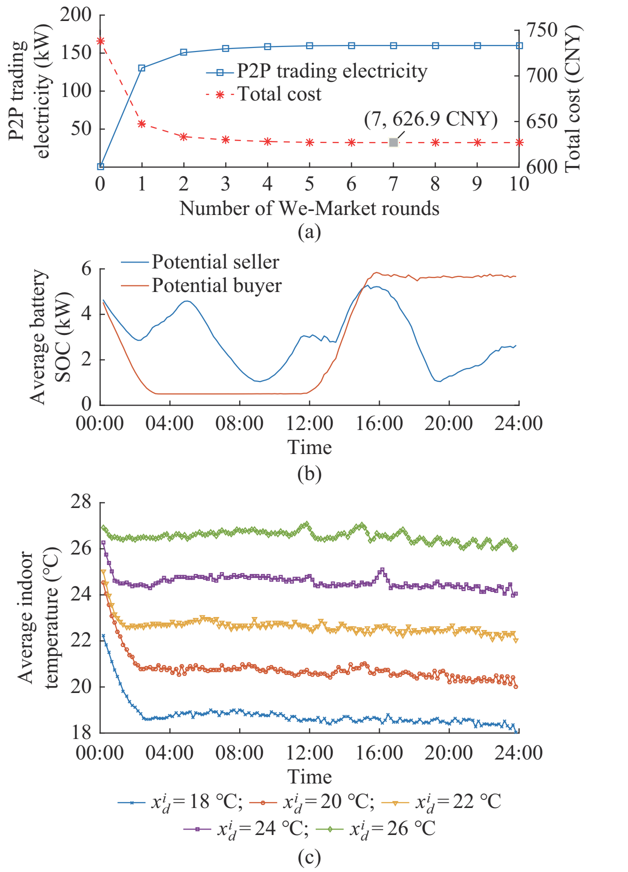

Fig. 4. P2P trading results. (a) P2P trading electricity and total cost of each We-Market round. (b) Average battery SOC after the 7th round of We-Market. (c) Average indoor temperature after the 7th round of We-Market.

In Fig. 4, a total of 159.99 kW of residual electricity has been successfully traded in P2P mode, which brings about 15% cost reduction compared with the situation without a P2P transaction (the starting point of the total cost curve), as shown in Fig. 4(a). Note that, since the proposed We-Market focuses on energy sharing within the local community, the power transmission distance is short and the power loss can be ignored, so the network usage costs are not included in financial accounting. Besides, without P2P transactions, prosumers have to trade with the main grid at selling and purchasing prices of 0.35 CNY/kW and 1.0 CNY/kW, respectively, which is a choice to the detriment of interests. In the We-Market, more reasonable transaction prices can be obtained because the prosumers would make a bidding strategy according to the modified Stone-Geary utility function. Just taking a transaction between two prosumers as an example, 0.23 kW power is traded with 0.58 CNY/kW between prosumer 20 and prosumer 64. For the buyer, it saves the cost by $0.23\times(1-0.58)=0.097$ CNY compared with purchasing electricity from the main grid; for the seller, it increases the revenue by $0.23\times(0.58-0.3)=0.064$ CNY compared with selling electricity to the main grid. As a result, more trading electricity will lead to more total cost reduction. It is also an incentive for more prosumers to participate in the We-Market. Figure 4(b) presents the optimal control of the battery storage, where about 50 batteries tend to be empty during 04:00-12:00. The most likely reason is that these prosumers are potential buyers due to insufficient renewable energy outputs and the high consumption of air conditioners. Figure 4(c) shows the average indoor temperature, where the indoor temperature fluctuates in a small range near the set temperature at most of the time. It indicates that the proposed approach simultaneously reduces the total cost and ensures the thermal comfort of end-users.

Based on the distributed CB algorithm and the HEMS of the prosumers, the complete cloud-edge-based We-Market procedure can be performed. As an example, the continuous P2P transaction process during 10:00-11:40 is presented to illustrate the convergence performance of the proposed approach, as shown in Fig. 5, where 20-8 means prosumer 20 is trading with prosumer 8 and others are the same.

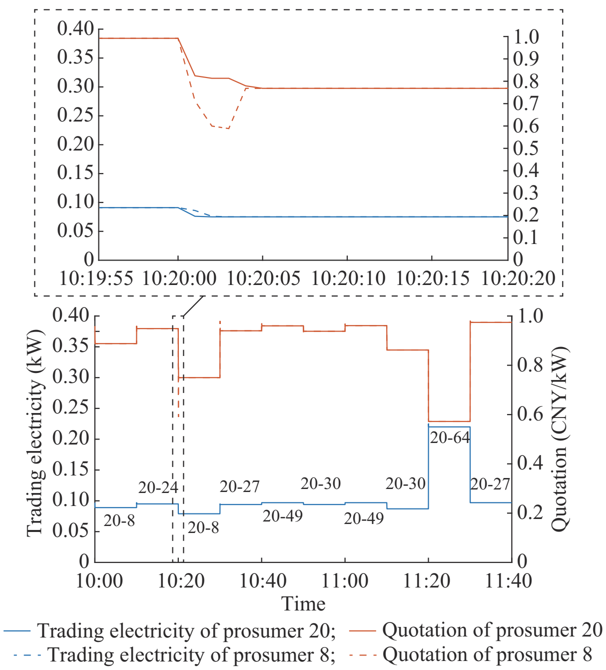

Fig. 5. P2P transaction process during 10:00-11:40.

Here, the scheme turns out to be multiple-stage edge-cloud-edge information exchanges and optimization processes with a 30 ms communication delay per interaction. After trading with prosumer 24, prosumer 20 performs HEMS again and uploads the surplus power of 0.08 kW and the initial quotation of 0.8 CNY/kW at 10:20:01. At the same time, it is matched with prosumer 8 (0.09 kW demand and 0.7 CNY/kW quotation) in the cloud center. Then, the two parties resolve the HEMS using the power gaps and upload the results to the cloud center, until the consistent trading electricity of 0.079 kW is reached at around 10:20:03. At this point, the quotations of the two parties are 0.79 CNY/kW and 0.59 CNY/kW, respectively. Next, the two parties re-bid in respective HEMS for minimizing the quotation gap. Eventually, a power transaction of 0.079 kW at 0.75 CNY/kW is a success at around 10:20:05. Besides, since the surplus power of each prosumer is not constant at different time slots, the matched transaction parties are changing. Despite this, reasonable transactions can still be completed in a short period, as shown in Fig. 5. Note that, the transaction prices are all within the range of [0.35, 1]CNY/kW so that the prosumers could make profits. In addition, the convergence rate is closely related to the speed of deviation reduction as well as the computation and communication complexities of the CB algorithm, so the algorithm is not fixed-time convergent.

C. Comparative Analysis

From the perspective of architecture, communication, basic theory, complexity, and cost reduction, a more detailed comparison of the cloud-edge-based We-Market and other similar schemes is listed in Table II.

TABLE II
COMPARISON TABLE FOR PROPOSED AND EXISTING SCHEMES

Scheme	Coordination structure	Communication extent	Information requirement	Theoretical basis	Computation complexity	Communication complexity	Cost reduction (%)
Proposed scheme	Distributed	Edge-cloud-edge	Local	CB algorithm	$O(k^{\max})$	$O(1)$	15
[5], [6], [9], [10]	Centralized	Centralized optimizer	Global	MIP	$O(N^2)$	$O(N\cdot\log(N))$	15
[14]-[16]	Decentralized	Neighboring agents	Local	Double auction	$O(N)$	$O(\log(N))$	15
[3], [11], [39]	Decentralized	Neighboring agents	Local	ADMM	$O(N)$	$O(\log(N))$	15
[17]-[19]	Decentralized	Leader-following agents	Local	Game theory	$O(N)$	$O(1)$	15
[40]	Distributed	Agents	Local	Consensus	$O(k^{\max})$	$O(1)$	15

The first four features describe the general attributes of the schemes and the last three features highlight the complexities and the cost reduction of the related algorithms. Note that, the distributed edge empowering and the edge-cloud-edge communication extent transfer the computation task to each prosumer, and the cloud is only responsible for the coordination and does not participate in decision-making. Since the proposed scheme allows local energy management in parallel, its computation complexity for a synchronization process is $O(k^{\max})$, where $k^{\max}$ is the maximum iteration of each prosumer. Note that, its value is closely related to the speed of deviation reduction as well as the computation and communication complexities of the CB algorithm, so the algorithm is not fixed-time convergent, and the average convergence time of each bidding is about 6 s. According to the CB algorithm, each prosumer only needs to interact with the cloud center with local information such as surplus power, quotations, and deviations, rather than all the information, so its communication complexity is $O(1)$. By comparison, the centralized schemes [5], [6], [9], [10] rely on mixed-integer programming (MIP) with the global information of the entire system. Therefore, the computation and communication complexities are $O(N^2)$ and $O(N\log(N))$, respectively. The middle two rows list the decentralized schemes based on the double auction [14]-[16] and the alternating direction method of multipliers (ADMM) methods [3], [11], [40], respectively. The local information here refers to all the information of the two agents participating in the P2P transaction. Consequently, the computation and communication complexities are $O(N)$ and $O(\log(N))$, respectively, which are influenced by the number of prosumers N. The difference is that the game theory based schemes [17]-[19] adopt leader-following communication extent, and the information interaction is only a deviation. However, it still needs decision-making on both sides of the leader and the followers. Therefore, its computation complexity is $O(N)$, but its communication complexity is lower than other decentralized schemes, which is $O(1)$. Although there are significant differences in architecture, communication, basic theory, and complexity among various schemes, the same operating cost reduction, i. e., 15%, is obtained because the objective functions of these models are to minimize the total cost of the system with the same constraints of the internal equipment operation of prosumers. In particular, since the computing power is transferred to prosumers or agents, the consensus-based scheme in [40] achieves the same performance as the proposed scheme. Nevertheless, the consensus-based scheme adopts the way of direct communication among agents, which may lead to the following problems: ① whether the communication parties can be trusted; and ② the malicious party can collect and infer the opponent's sensitive decision information for profit. Instead, the proposed edge-cloud-based We-Market takes advantage of a trusted cloud to coordinate multi-party information interaction, which is convenient for market supervision, so as to effectively deal with the above problems. As a result, the proposed distributed CB algorithm and the edge-cloud-based We-Market have obvious advantages over other centralized and decentralized schemes, thereby demonstrating the earlier theoretic analysis.

From the perspective of running time with various scales, Fig. 6 presents the performance comparison between the proposed scheme and the recent P2P ADMM approach in [39], which is taken as the reference scheme. It can be observed that the running time of both approaches is not exponentially increased with the increase in system size, i. e., the maximum number of trading prosumers. However, for larger-scale systems, the proposed scheme has shorter running time than the reference scheme. For example, for the larger systems with different maximum numbers (90 and 180) of trading prosumers, the running time of the reference scheme is 117.6 s and 1022.9 s, while that of the proposed scheme is 67.75 s and 431.38 s, respectively. The most likely reason is that the reference scheme needs a centralized optimizer for the ADMM algorithm, while the proposed scheme reduces the computation complexity by transferring the computation tasks to prosumers for parallel computing. Consequently, the proposed scheme is higher scalable due to the distributed edge-cloud-edge communication extent and the edge empowering manner.

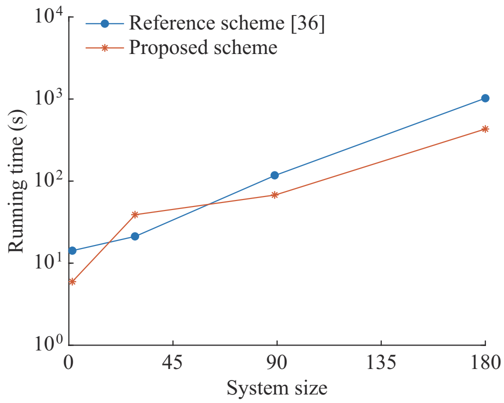

Fig. 6. Comparison of running time.

D. Discussions

In summary, aiming at the specific problems of autonomous bidding and P2P energy sharing, this paper proposes the cloud-edge-based We-Market architecture and model. Compared with the existing studies, its cloud services are available in the proximity of the prosumers, i.e., prosumers have more autonomy to participate in the We-Market. Furthermore, the conventional dense computation is performed in parallel, so that the proposed scheme is more efficient with less computation and communication complexities. Besides, the proposed CB algorithm is an iterative negotiation mechanism, which makes it easier to obtain a stable solution while ensuring trading fairness. Namely, it has faster convergence than other game-theoretic algorithms.

Note that the P2P trading result does not take into account the internal energy consumption for calculation and communication, which may influence the P2P energy sharing. In practical implementation, the energy consumption of the edge devices and the communication links is an issue that needs to be carefully handled for the cloud-edge collaboration schemes, due to the trade-off between ability and load. In general, centralized and decentralized approaches have the advantages of stronger computation capability at the central optimizer and less energy consumption on the edge devices and the communication links over the distributed approaches. Besides, the energy consumption is borne by the central optimizer in the centralized and decentralized approaches, but these loads will be borne by the end-users independently in the distributed approach, of which computation and communication resource allocation could become a critical issue. Besides, for the distribution networks, how to meet the operational constraints in P2P transactions such as power flow and voltage limitations should also be further discussed. However, it is out of the scope of the current research and will be addressed in future work.

V. Conclusion

The wide penetration of renewable energy and self-interested prosumers creates a strong demand for the bottom-up retail electricity market. This paper presents a novel concept and architecture of cloud-edge-based We-Market. For each prosumer, the proposed dynamic HEMS ensures the optimal trade-off between the electricity cost and thermal comfort. Based on the modified Stone-Geary utility function, a more reasonable bidding strategy is developed, so that the prosumers make profits. The results show that a total of 159.99 kW residual electricity has been successfully traded, which brings about 15% cost reduction under the proposed We-Market. Besides, the proposed CB algorithm shows well fairness and convergence performance through frequent interaction between the cloud and the prosumers. The comparative analysis indicates that the proposed cloud-edge-based We-Market scheme has lower complexity and better scalability compared with existing centralized and decentralized approaches. As a result, all these aspects demonstrate the effectiveness and practicability of the proposed approach in terms of computation efficiency and user utility.

Appendix A

A. Proof of Lemma 1

According to the norm properties, we have:

$$\sum_{t=k}^{k+T-1}\left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_k^i)\right\| \ge \left\| \sum_{t=k}^{k+T-1} \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_k^i)\right\| = \left\| \boldsymbol{H}_T^t \nabla\mathcal{L}(\lambda_k^i)\right\| \quad \text{(A1)}$$

Then, according to the triangle inequality, we have:

$$\left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_k^i)\right\| \le \left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_k^i) - \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_t^i)\right\| + \left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_t^i)\right\| \quad \text{(A2)}$$

Further using Lipschitz continuity of $\nabla\mathcal{L}$, we have:

$$\begin{aligned} &\left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_k^i) - \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_t^i)\right\| = \left\| \boldsymbol{H}^t (\nabla\mathcal{L}(\lambda_k^i) - \nabla\mathcal{L}(\lambda_t^i))\right\| \le \\ &\frac{2}{\varpi}\left\| \lambda_k^i - \lambda_t^i \right\| = \frac{2}{\varpi}\left\| \sum_{z=k}^{t-1} (\lambda_{z+1}^i - \lambda_z^i)\right\| \le \\ &\frac{2}{\varpi}\sum_{z=k}^{t-1}\left\| \lambda_{z+1}^i - \lambda_z^i \right\| = \frac{2}{\varpi}\sum_{z=k}^{t-1}\left\| \boldsymbol{H}^z \nabla\mathcal{L}(\lambda_z^i)\right\| \end{aligned} \quad \text{(A3)}$$

It is easy to obtain (A4) from the above derivation.

$$\begin{aligned} &\left\| \boldsymbol{H}_T^t \nabla\mathcal{L}(\lambda_k^i)\right\| \le \frac{2}{\varpi}\sum_{t=k}^{k+T-1}\sum_{z=k}^{t-1}\left\| \boldsymbol{H}^z \nabla\mathcal{L}(\lambda_z^i)\right\| + \\ &\sum_{t=k}^{k+T-1}\left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_t^i)\right\| \le \left[1 + \frac{2(T-2)}{\varpi}\right]\sum_{t=k}^{k+T-1}\left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_t^i)\right\| \end{aligned} \quad \text{(A4)}$$

Therefore, (A5) can be obtained from the norm properties, which follows the differentiability of the $\mathcal{L}(\lambda_k^i)$. Consequently, it completes the proof.

$$\begin{aligned} &\left\| \mathcal{L}(\lambda_{(k+1)T}) - \mathcal{L}(\lambda_{kT})\right\| \le \left\| \sum_{t=kT}^{(k+1)T-1} (\mathcal{L}(\lambda_{t+1}^i) - \mathcal{L}(\lambda_t^i))\right\| \le \\ &(\varpi - 1)\sum_{t=kT}^{(k+1)T-1}\left\| \boldsymbol{H}^t \nabla\mathcal{L}(\lambda_t^i)\right\|^2 \end{aligned} \quad \text{(A5)}$$

B. Proof of Theorem 1

According to Lemma 1, there exists a limit of the augmented Lagrange function, i.e., if $\left\| \lambda_k^i - \lambda^* \right\| \leq \zeta$, we have:

$$\left\| (\mathcal{L}(\lambda_{(k+1)T}^i) - \mathcal{L}^*) - (\mathcal{L}(\lambda_{kT}^i) - \mathcal{L}^*) \right\| = \left\| \mathcal{L}(\lambda_{(k+1)T}^i) - \mathcal{L}(\lambda_{kT}^i) \right\| \leq \varrho \left\| \mathcal{L}(\lambda_{kT}^i) - \mathcal{L}^* \right\|^2 \tag{A6}$$

where $\zeta > 0$ is any small positive number; and the coefficient $\varrho > 0$. Then, we can obtain:

$$\lim_{k\to\infty} \frac{\left\| (\mathcal{L}(\lambda_{(k+1)T}^i) - \mathcal{L}^*) - (\mathcal{L}(\lambda_{kT}^i) - \mathcal{L}^*) \right\|}{\left\| \mathcal{L}(\lambda_{kT}^i) - \mathcal{L}^* \right\|^2} = \varrho > 0 \tag{A7}$$

Accordingly, the augmented Lagrange function is square convergent, in which the second inequality in (A6) is mainly based on the following derivation:

$$\left\| \mathcal{L}(\lambda_{kT}^i) - \mathcal{L}^* \right\| \leq \left\| \nabla \mathcal{L}(\lambda_{kT}^i)^{\mathrm{T}} (\lambda_{kT}^i - \lambda^*) \right\| = \left\| \nabla \mathcal{L}(\lambda_{kT}^i)^{\mathrm{T}} (\boldsymbol{H}_T^{kT})^{\mathrm{T}} ((\boldsymbol{H}_T^{kT})^{\mathrm{T}})^{-1} (\lambda_{kT}^i - \lambda^*) \right\| \leq \left\| (\boldsymbol{H}_T^{kT})^{-1} \right\| \left\| \lambda_{kT}^i - \lambda^* \right\| \left\| \boldsymbol{H}_T^{kT} \nabla \mathcal{L}(\lambda_{kT}^i) \right\| \leq \frac{\zeta}{T} \left\| \boldsymbol{H}_T^{kT} \nabla \mathcal{L}(\lambda_{kT}^i) \right\| \tag{A8}$$

Given rank$(\boldsymbol{H}_T^k) = n-1$, $\left\| \boldsymbol{H}_T^k \right\| \leq 1/B$, and we have:

$$\left\| \boldsymbol{H}_T^{kT} \nabla \mathcal{L}(\lambda_{kT}^i) \right\|^2 \geq \frac{T^2 \left\| \mathcal{L}(\lambda_{kT}^i) - \mathcal{L}^* \right\|^2}{\zeta^2} \tag{A9}$$

After iteration and conversion, the periodic error of the augmented Lagrange function can be obtained as:

$$\left\| \mathcal{L}(\lambda_{kT}^i) - \mathcal{L}^* \right\| \leq \frac{\left\| \mathcal{L}(\lambda_0^i) - \mathcal{L}^* \right\|}{1 + \varrho k \left\| \mathcal{L}(\lambda_0^i) - \mathcal{L}^* \right\|} \tag{A10}$$

Therefore, $\lim_{k\to\infty} \left\| \mathcal{L}(\lambda_k^i) - \mathcal{L}^* \right\| = 0$, which completes the proof.

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