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A blockchain based peer-to-peer trading framework integrating energy and carbon markets

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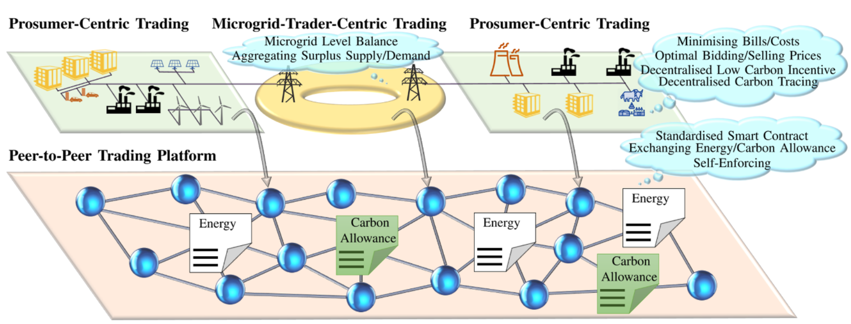
HIGHLIGHTS

- A trading framework is designed enabling the exchange of energy and carbon allowance.
- Smart contract is exploited to automate standardised auction procedure.
- The bidding/selling prices directly target on reshaping prosumption behaviours.
- Results prove that the proposed framework facilitates regional energy balance and carbon saving.

GRAPHICAL ABSTRACT



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ABSTRACT

Prosumers are active participants in future energy systems who produce and consume energy. However, the emerging role of prosumers brings challenges of tracing carbon emissions behaviours and formulating pricing scheme targeting on individual prosumption behaviours. This paper proposes a novel blockchain-based peer-to-peer trading framework to trade energy and carbon allowance. The bidding/selling prices of prosumers can directly incentivise the reshaping of prosumption behaviours to achieve regional energy balance and carbon emissions mitigation. A decentralised low carbon incentive mechanism is formulated targeting on specific prosumption behaviours. Case studies using the modified IEEE 37-bus test feeder show that the proposed trading framework can export 0.99 kWh of daily energy and save 1465.90 g daily carbon emissions, outperforming the existing centralised trading and aggregator-based trading.

1. Introduction

In energy sector, a majority of power demand is supplied by centralised fossil-fuelled generation including coal, gas, and oil [1]. Enormous carbon emissions are produced by the combustion of fossil fuels and energy loss of long-distance transmission, which leads to air pollution and irreversible effects of climate change [2]. To address this environmental issue, policy makers facilitate distributed renewable energy sources (DRESs) to be integrated into distribution systems [3]. Meanwhile, the carbon pricing scheme is formulated as a market-based climate policy to let carbon producers pay for allowance of carbon emissions [4]. The advances of smart grids enable increasing number of consumers to produce or store electricity at home through DRESs and batteries, leading to a new concept: prosumers. The term of prosumers was coined by Alvin Toffler in 1980 [5]. In the field of the DRESs, prosumers are residential, commercial, and industrial users, which actively produce surplus energy and feed into a distribution network

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after self-consumption; When prosumers demand cannot be met by self-generation, they consume energy from grids [6]. Although the emerging role of prosumers provides opportunities for local energy trading to achieve regional supply–demand balance of energy, there are several challenges. First, it is challenging to trace the carbon emissions caused by prosumption behaviours, in particular if distributed prosumers generate and consume energy simultaneously. Second, the centralised wholesale energy pricing is determined by the supply–demand balance between generators and retailers, and the centralised retail energy pricing, e.g. flat pricing, time-of-use pricing, and real-time pricing, is determined by the supply–demand balance between retailers and consumers [7]; The centralised carbon pricing is determined by the emissions trading scheme (ETS) [8]. These prices dynamically fluctuate with the supply–demand balance of overall markets and are uniform for all customers. Because these prices are independent of the exchange of energy or carbon allowance among individual prosumers, not every prosumer can be efficiently incentivised to reduce carbon emissions and participate in energy trading. Third, when prosumers proceed peer-to-peer trading, it is hard to ensure the settlement and delivery without a standardised negotiation and enforcing mechanism.

For the first challenge, tracing carbon emissions using power flow analysis is a solution. Researchers in [9] implemented the concept of carbon emissions flow (CEF) as a virtual network flow concurrent with power flow to trace carbon emissions caused by electricity generation, transmission, and consumption. The CEF approach was further investigated in [10] to formulate a mathematical model for calculating the CEF of each bus in power networks. Chen et al. [11] implemented the coupling of power flow and CEF into carbon intensity analysis of urban nexus. Nonetheless, when prosumers participate in the local energy trading, the prosumption behaviours include generation for self-consumption, consumption from self-generation, and generation (or consumption) for (or from) energy exchange with other prosumers. How to identify the CEF caused by these specific prosumption behaviours, and allocate responsibilities and credits for carbon reduction needs to be further investigated.

For the second challenge, designing a pricing incentive scheme targeting on individual prosumption behaviours is a complement approach for the centralised market pricing. Chiu et al. [12] proposed an energy pricing scheme to manage the energy imbalance caused by the integration of DRESs. The policy of feed-in tariff was implemented in energy markets to compensate renewable energy generators based on the generating costs of each source [13]. In the carbon markets, carbon price floor and ceiling were designed to complement the centralised price of the ETS by setting an additional price limits for the carbon emissions producers in certain regions [14]. For the case of the U.K. carbon market, because the carbon price of the E.U. ETS lay below the estimated carbon cost of the U.K. coal-fired generation, the carbon pricing scheme failed to incentivise the U.K. coal-to-gas transition before 2013 [8]. Afterwards, the U.K. formulated the carbon price support for its own carbon producers as an additional carbon price of the E.U. ETS [15]. The U.S. set a similar price floor and facilitated carbon auctions in 2009 [16]. By contrast, in New Zealand, a carbon price ceiling was enacted through fixed price option to prevent high carbon price and protect market competitiveness of generators [17]. Further research efforts have been dedicated to decentralising the pricing schemes in both energy and carbon markets. Ghosh et al. [18] proposed a platform to set the energy exchange prices for prosumers for the purpose of maximising the amount of energy exchange and reducing the consumption from conventional generation. Zhang et al. [19] developed a peer-to-peer system architecture based on game theory. A dynamic pricing for decentralised energy trading in microgrids is designed in [20]. Gkatzikis et al. [21] partitioned the power networks into several regions and introduced the role of aggregators as regional agents to formulate regional prices for their consumers. Li et al. [22] extended the function of aggregators to deliver the demand side management and DRESs for regional energy balance. Fan et al. [23] decentralised the carbon price by evaluating consumer's carbon emissions behaviours.

For the third challenge, blockchain technology (one of the distributed ledger technologies) [24] has the potential of establishing a decentralised trading platform with automated trading procedures and protected residential privacy. As one of the key blockchain technologies, smart contract enables executable programs to be performed in a manner of self-enforcing settlement and setting out negotiation [25]. The features of replicable, secure, and verifiable of smart contract [26] enable the trading, negotiation and agreement to become more trustworthy without the interference of centralised authority. In energy markets, the distribution of power losses to each transaction was investigated under the blockchain based microgrids [27]. Li et al. [28] applied smart contract into a distributed hybrid energy systems to facilitate energy exchange among end users. A combined analysis of optimal power flow and smart contract based energy trading was performed in [29], and the results demonstrated that the costs and peak energy imports were dramatically reduced. Kang et al. [30] proposed a localised peer-to-peer trading model for energy exchange among plug-in hybrid electric vehicles. Thomas et al. [31] applied the smart contract for controlling energy transfer process between separate distribution networks. In carbon markets, Khaqqi et al. [32] customised carbon allowance trading to industries using reputation based blockchain for encouraging low carbon behaviours. The application of blockchain in cap-and-trade scheme of carbon markets was investigated in [33].

Although extensive studies have been conducted to address those challenges, there are three major gaps as follows.

- The individual prosumers' carbon emissions caused by generation for self-consumption, consumption from self-generation, and generation (or consumption) for (or from) energy exchange with other prosumers cannot be traced using existing approaches and then incentivised properly. This is more challenging when prosumers trade energy or carbon allowance, because they need to know how much carbon allowance needs to be purchased as carbon cost.
- Existing pricing schemes are not prosumer-centric. A new peer-to-peer energy trading scheme needs to be designed, under which the bidding/selling prices of prosumers in energy and carbon markets are able to directly incentivise the reshaping of prosumption profiles to achieve carbon emissions reduction and regional energy balance.
- Separately designing energy or carbon markets is not efficient, because the purchasing of carbon allowance is a part of energy costs. A decentralised trading framework needs to be designed enabling prosumers to trade energy and carbon allowance together.

This paper proposes a novel peer-to-peer energy and carbon allowance joint trading framework to address these gaps. The primary differences between conventional centralised trading and our proposed blockchain based peer-to-peer trading are presented in Table 1. This paper offers following contributions.

- A carbon emissions tracing approach targeting on individual prosumers' behaviours is developed to ensure a fair allocation of low carbon incentives.

Table 1
Comparison between centralised trading and localised trading.

	Centralised trading	Peer-to-peer trading
Primary energy supplier	Large scale generators	Prosumers with DRESs
Pricing scheme	Centralised prices	Bidding/selling prices
Contract type	Idiosyncratic contract [34]	Standardised smart contract
Settlement enforcing [25]	Legal restraint	Self-enforcing
Trustee [25]	Third party	Smart meter & smart contract
Incentive supplier	Policy maker [16]	Consensus of network
Incentive update	Long-term policy [16]	Real-time update

- A new trading framework is designed enabling the exchange of energy and carbon allowance at both prosumer level and microgrid level, using a smart contract based trading platform. The proposed energy scheduling algorithms interact with the self-enforcing nature of smart contract to automate standardised auction procedure.
- Case studies show that the proposed trading framework achieves better energy balance and carbon-saving than those of centralised trading and aggregator-based trading.

The remaining parts of this paper are summarised as follows. Section 2 presents the proposed three-layer trading framework. Corresponding to each layer, the details of problem formulation and the smart contract based auction mechanism are described in Section 3. The results of case studies are presented in Section 4. Section 5 draws the conclusion and lists the future work.

2. Trading framework

This section describes the overall trading framework under which both energy and carbon allowance are exchanged within distribution networks. According to the commercial relations of market participants, i.e. prosumer and microgrid-trader (MT), as described in [19], the trading procedure is hierarchically categorised into three layers: prosumer-centric trading, MT-centric trading, and peer-to-peer trading platform. Fig. 1 shows the architecture and information flows of these three layers. The proposed framework is implemented in the day-ahead market to schedule energy prosumption and perform trading for the following day. The prosumers in the context of our research refer to a master of energy prosumption [5] which seeks for personal benefits, i.e. bill-saving or cost-saving, and environmental goal, i.e. carbon emissions reduction, by participating in both energy and carbon markets using their DRESs. Ethereum blockchain network [35] is used consisting of full nodes and light nodes. The market operator acts as full nodes to provide and manage the trading platform by offering computing power for block mining, storing all blocks, and earning rewards for mined blocks. Prosumers and MTs act as light nodes to store header chain and verify transactions. As the light nodes, prosumers and MTs do not need powerful computers. Hence, the trading process can be supported by smart meters or mobile phones. The specific design of each layer is described as follows and the problem formulation will be detailed in Section 3.

2.1. Prosumer-centric trading

The layer of prosumer-centric trading aims at using collected metering data to help individual prosumers make optimal decisions of reshaping prosumption profiles and bidding prices. The optimal decisions are yielded by solving optimisation problems with the objective of minimising electricity bills for buyers or maximising profits for sellers. The optimal decisions of reshaped prosumption are implemented by controllers, and the optimal decisions of bidding prices are sent to smart contract for auctions. Through evaluating the carbon emissions behaviours, blockchain automatically updates monetary incentives for individual prosumers. For regional energy balance and reducing transmission loss, prosumer-centric trading only applies for an ensemble of prosumers geographically in the same microgrid. The advantages of prosumer-centric trading are: (1) the reshaping of prosumption behaviours is directly incentivised by prosumers' bidding or selling prices, instead of central authority such as aggregator or energy retailer [22]; (2) the monetary incentive for carbon reduction is directly linked with individual prosumers considering their carbon emissions behaviours.

2.2. Microgrid-trader-centric trading

A group of physically connected prosumers is managed by a virtual entity, MT [19]. On the layer of MT-centric trading, MT aggregates the residual supply and demand of energy and carbon allowance for its ensemble of prosumers to trade with other MTs. The optimal decisions of bidding prices are also yielded by solving optimisation problems with the same objectives as those of prosumer-centric trading. The aim of MT-centric trading is to help an ensemble of prosumers in the same microgrid balance supply and demand by exchanging with other microgrids.

2.3. Peer-to-peer trading platform

The layer of peer-to-peer trading platform aims to provide a standardised negotiation and self-enforcing settlement for enabling buyers and sellers to proceed the trading of energy and carbon allowance. These functions are achieved by smart contract in the form of '*if an event happens, pay an amount of currency to the receiver on the self-enforcing basis*' [36]. In this paper, the event is the delivery of energy or carbon allowance which can be ensured by querying the smart meter.

The execution of smart contract includes initialisation, matching bids and offers, bidding, winner selection, and ownership exchange. The seller initialises the smart contract by specifying offer conditions. Buyers who meet the conditions will be optimally matched to deposit their bids on smart contract for auction. Until the auction ended, the buyer with the highest bid wins the auction. The rest of buyers can withdraw their deposits from smart contract. The smart contract directly queries the smart meter to ensure that agreed energy or carbon allowance is supplied by the seller at the agreed time, before

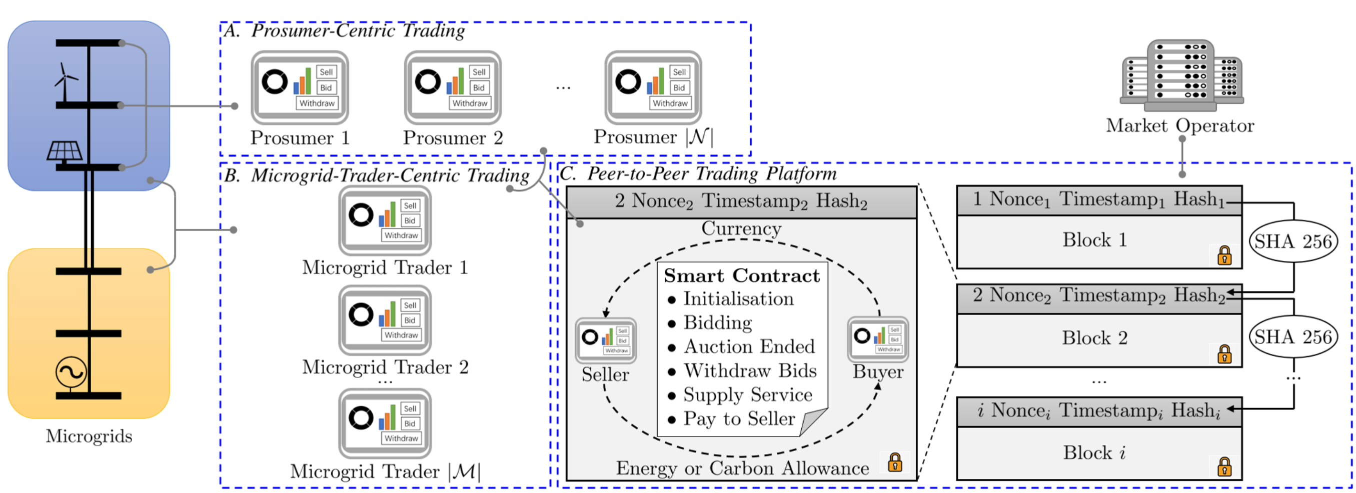

Fig. 1. Proposed framework of peer-to-peer energy trading. (*A*) Individual prosumers trade energy or carbon allowance on the layer of prosumer-centric trading. (*B*) The residual supply and demand for an ensemble of prosumers in the same microgrid are aggregated and traded by microgrid-traders on the layer of microgrid-trader-centric trading. (*C*) The trading of energy or carbon allowance is proceeded on the layer of peer-to-peer trading platform.

transferring the highest buyer's deposited bid to the seller.

All the transactions are stored, shared and audited by full nodes to validate authenticity and accuracy. The validated transactions are structured in publicly available blocks. The blocks are chronologically chained to each other through involving the hash of previous block into the current block, forming a blockchain. The validation is collectively achieved by all nodes through reaching a consensus of proof-of-work [37] which uses secure hash algorithm SHA-256 to protect all blocks. The inputs of SHA-256 are block number, nonce, timestamp, and hash output of previous block, and the output of SHA-256 is a fixed-length digest as a unique identity of block. This unique identity is guaranteed by specially mined nonce and collectively verification of all nodes, which means that if a malicious node changes one block, a different nonce will result in an unverified block, and if a malicious node changes all blocks, it will be extremely computationally difficult. Therefore, the chaining feature of blockchain and difficulty of solving a proof-of-work enable transactions to be traceable, verifiable and tempering resistance.

3. Problem formulation

This section describes the problem formulation of hierarchical 3-layer trading framework.

3.1. Decentralised low carbon incentive mechanism

In the conventional power systems, carbon emissions from large scale fossil-fuelled generators need to be traced [38]. According to the policy of carbon markets [39], these large scale fossil-fuelled generators report their annual fuel usage and electricity supply to evaluate the efficiency of electricity supply. With the information of the efficiency of electricity supply and carbon intensities of fuels [40], the carbon content of electricity supply can be traced [41]. By contrast, with the DRESs, prosumers play a role as both generators and consumers. New carbon tracing approaches should be designed to distinguish the following portions of carbon emissions: (1) carbon emissions caused by using prosumers' own generation for meeting their own demand; (2) carbon emissions caused by using prosumers' own generation for supplying other prosumers' demand; (3) carbon emissions caused by prosumers' demand being supplied by other prosumers' generation.

Building on existing work [10], we aim to investigate the CEF in a microgrid considering the bidirectional power flow caused by energy trading. The CEF represents a concurrent virtual network flow with power flow, which is ejected from outflowing buses, and delivered to inflowing buses. By abstracting network features, the carbon emissions caused by prosumers' behaviours at each bus can be evaluated.

A schematic illustration of how to trace the aforementioned three portions of carbon emissions is presented in Fig. 2. Let $\mathcal{I}$ denote the index set of energy sources and $\mathcal{K}$ denote the index set of loads of a prosumer. In Fig. 2 and (1), $r_{i,t}$ denotes the carbon emissions rate caused by power generation of source $i \in \mathcal{I}$ at scheduling time t, and $r_{k,t}$ denotes the carbon emissions rate caused by power consumption behaviour of load $k \in \mathcal{K}$ at scheduling time t, with unit of g/h. Prosumer A generates surplus energy after meeting its own demand, and supplies the surplus energy to prosumer B who is unable to generate enough energy to meet its own demand. The portion of carbon emissions caused by using prosumer A and prosumer B' s own generation for meeting their own demand can be quantified by $\sum_{k\in\mathcal{K}} r_{k,t}^{A}$ and $\sum_{k\in\mathcal{K}} r_{k,t}^{B}$, respectively. In addition, the portion of carbon emissions caused by using prosumers' own generation for supplying other prosumers' demand can be described as

$$r_{\text{net},t} = \sum_{i\in\mathcal{I}} r_{i,t} - \sum_{k\in\mathcal{K}} r_{k,t}, \tag{1}$$

where $r_{\text{net},t}$ denotes the amount of carbon emissions caused by using prosumers' own generation for supplying other prosumers' demand at scheduling time t. Hence, as shown in Fig. 2, the portion of carbon emissions caused by using prosumer A' s own generation for supplying prosumer B' s demand can be quantified by $r_{\text{net},t}^{A}$ which is the same amount for the portion of carbon emissions caused by prosumer B' s demand being supplied by prosumer A' s generation.

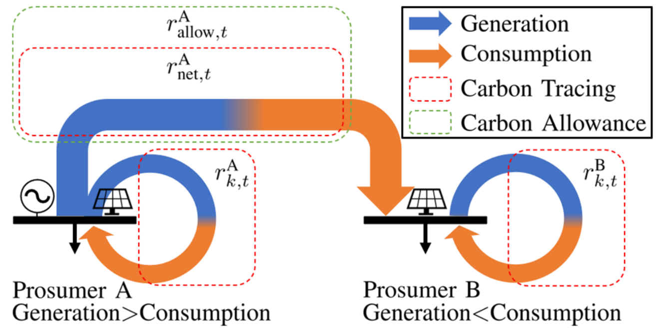

Fig. 2. Schematic illustration of carbon emissions tracing in a microgrid. Prosumer A supplies surplus energy to prosumer B. Prosumer A needs to have the carbon allowance ($r_{\text{allow},t}^{A}$) when supplying energy to prosumer B.

Once these amounts of carbon emissions are traced, the low carbon incentive can be formulated for individual prosumers in a form of monetary compensation. When a prosumer supplies energy to other prosumers, this prosumer needs to have the carbon allowance as a permission of pollutant emitting [39]. According to the research in [42], the initial carbon allowance is assigned by the blockchain system based on the carbon intensities of prosumer's generation sources and carbon reduction target of an ensemble of prosumers. In Fig. 2 and (2), $r_{\text{allow},t}$ denotes the carbon allowance of a prosumer at scheduling time t. If $r_{\text{net},t} > r_{\text{allow},t}$, a prosumer has to buy the carbon allowance from other prosumers; If $r_{\text{net},t} < r_{\text{allow},t}$, a prosumer can not only sell the extra carbon allowance to other prosumers, but also receive monetary compensation generated by the consensus of peer-to-peer trading networks. Additionally, to ensure the high-carbon prosumers to be primarily targeted, the monetary compensation at high-level of carbon emissions is higher than that at low-level of carbon emissions, which means that the marginal monetary compensation increases with the increase of $r_{\text{allow},t}$, i.e. $(\partial^2\gamma(r_{\text{allow},t}, r_{\text{net},t})/\partial r_{\text{allow},t}^2) > 0$, where $\gamma(\cdot)$ denotes the monetary compensation function of a prosumer with unit of £. Hence, the low carbon incentive can be given by [43]

$$\gamma(r_{\text{allow},t}, r_{\text{net},t}) = \begin{cases} \alpha\cdot\sqrt{(r_{\text{allow},t}\cdot\Delta t)^2 - (r_{\text{net},t}\cdot\Delta t)^2}, & r_{\text{allow},t} > r_{\text{net},t}, \\ 0, & r_{\text{allow},t} \leqslant r_{\text{net},t}, \end{cases} \tag{2}$$

where α denotes the monetary compensation rate with unit of £/g, and Δt denotes the scheduling interval.

3.2. Prosumer-centric algorithm

The prosumer-centric trading enables prosumers in the same microgrid to exchange energy or carbon allowance with neighbouring prosumers for the purpose of regional balance. When a prosumer is unable to generate enough energy to meet its own demand, this prosumer needs to buy energy from other prosumers as an energy buyer. The objective of a prosumer as an energy buyer is to minimise its bills by strategically deciding the bidding prices of energy and reshaping prosumption behaviours as

$$\min_{g_{i,t}, d_{k,t}, b_{\text{energy},t}} : \sum_{t\in\mathcal{T}_{\text{buyer}}} \left(\sum_{k\in\mathcal{K}} d_{k,t} - \sum_{i\in\mathcal{I}} g_{i,t} \right) \cdot \Delta t \cdot b_{\text{energy},t}, \tag{3}$$

s.t.:

$$\sum_{i\in\mathcal{I}} g_{i,t} < \sum_{k\in\mathcal{K}} d_{k,t}, \tag{4}$$

$$b_{\text{energy},t}^{\text{highest}} < b_{\text{energy},t}, \quad \sum_{t \in \mathcal{T}_{\text{buyer}}} \left(\sum_{k \in \mathcal{K}} d_{k,t} - \sum_{i \in \mathcal{I}} g_{i,t} \right) \cdot \Delta t \cdot b_{\text{energy},t} \leqslant \pi, \tag{5}$$

where $d_{k,t}$ denotes the power consumption of a prosumer's load $k \in \mathcal{K}$ at scheduling time t, $g_{i,t}$ denotes the power generation of a prosumer's own source $i \in \mathcal{I}$ at scheduling time t, $b_{\text{energy},t}$ denotes the bidding price of a prosumer at scheduling time t for buying energy, with unit of £/kWh, $\mathcal{T}_{\text{buyer}}$ denotes the index set of scheduling time for an energy buyer, π denotes the account balance of a buyer with unit of £, and $b_{\text{energy},t}^{\text{highest}}$ denotes the highest bidding price for the energy selling at scheduling time t over all energy buyers updated by the blockchain network. Let $\mathcal{B}_{\text{energy},t}$ denote the set of bidding prices submitted by all energy buyers for the offer of selling energy at scheduling time t. Hence, $b_{\text{energy},t}^{\text{highest}} = \max{:}\mathcal{B}_{\text{energy},t}$.

When a prosumer generates surplus energy after meeting its own demand, this prosumer can sell the surplus energy to other prosumers as an energy seller. Recall that in Section 3.1, when a prosumer sells energy to other prosumers, this prosumer needs to have the carbon allowance. When the assigned carbon allowance $r_{\text{allow},t}$ is given, if $r_{\text{net},t} > r_{\text{allow},t}$, a prosumer has to buy the carbon allowance as a part of generating cost; If $r_{\text{allow},t} > r_{\text{net},t}$, a prosumer can sell the extra carbon allowance and be compensated as a part of revenue. The trading of carbon allowance can be described as

$$c_{\text{carbon}}(r_{\text{net,t}}) = \begin{cases} (r_{\text{net,t}} - r_{\text{allow},t}) \cdot \Delta t \cdot b_{\text{carbon},t}^{\text{highest}} - \gamma(r_{\text{allow},t}, r_{\text{net},t}), & r_{\text{allow},t} > r_{\text{net},t}, \\ (r_{\text{net,t}} - r_{\text{allow},t}) \cdot \Delta t \cdot b_{\text{carbon},t}, & r_{\text{allow},t} < r_{\text{net},t}, \end{cases} \tag{6}$$

where $c_{\text{carbon}}(\cdot)$ denotes the carbon cost (or revenue) function of an energy seller with unit of £, $b_{\text{carbon},t}$ denotes the bidding price of a prosumer at scheduling time t for buying carbon allowance with unit of £/g, and $b_{\text{carbon},t}^{\text{highest}}$ denotes the highest bidding price for the carbon allowance selling at scheduling time t over all carbon allowance buyers updated by the blockchain network. Let $\mathcal{B}_{\text{carbon},t}$ denote the set of bidding prices submitted by all the carbon allowance buyers for the offer of selling carbon allowance at scheduling time t, $b_{\text{carbon},t}^{\text{highest}} = \max{:}\mathcal{B}_{\text{carbon},t}$. When $r_{\text{allow},t} > r_{\text{net},t}$, c_{carbon} is negative indicating the revenue of selling carbon allowance.

Apart from the carbon cost, other generating costs are evaluated by the levelised cost of electricity generation as [44]

$$c(g_{i,t}) = \sum_{i \in \mathcal{I}} g_{i,t} \cdot \Delta t \cdot \delta_i, \tag{7}$$

where δ_i denotes the cost coefficient of source i with unit of £/kWh.

The objective of a prosumer as an energy seller is to maximise its profits by strategically deciding the bidding price of carbon allowance and reshaping prosumption behaviours as

$$\max_{g_{i,t}, d_{k,t}, b_{\text{carbon},t}} : \sum_{t \in \mathcal{T}_{\text{seller}}} \left(\sum_{i \in \mathcal{I}} g_{i,t} - \sum_{k \in \mathcal{K}} d_{k,t} \right) \cdot \Delta t \cdot b_{\text{energy},t}^{\text{highest}} - \sum_{t \in \mathcal{T}_{\text{seller}}} [c_{\text{carbon}}(r_{\text{net,t}}) + c(g_{i,t})], \tag{8}$$

s.t.:

$$\sum_{k \in \mathcal{K}} d_{k,t} < \sum_{i \in \mathcal{I}} g_{i,t}, \tag{9}$$

$$b_{\text{carbon},t}^{\text{highest}} < b_{\text{carbon},t}, \quad \sum_{t \in \mathcal{T}_{\text{seller}}} c_{\text{carbon}}(r_{net,\text{t}}) \leqslant \pi, \tag{10}$$

where $\mathcal{T}_{\text{seller}}$ denotes the index set of scheduling time for an energy seller. The decision variable $b_{\text{carbon},t}$ and (10) only hold when a prosumer buys carbon allowance.

3.3. Microgrid-trader-centric algorithm

After the completion of the prosumer-centric trading, there might be residual supply or demand which cannot be met inside the microgrid due to the surplus or scarcity generation of all prosumers in the same microgrid. The MT-centric trading aims to help an ensemble of prosumers in the same microgrid aggregate the residual supply and demand. Through solving (3)–(5) or (8)–(10) in the prosumer-centric algorithm, the optimal power generation of source i and power consumption of load k for an individual prosumer at each scheduling time t are yielded, denoted as $g_{i,t}^*$ and $d_{k,t}^*$. Let $\mathcal{N}$ denote the index set of prosumers in the same microgrid. The total power generation and consumption of each prosumer can be described as (11) and (12), respectively.

$$g_{n,t} = \sum_{i \in \mathcal{I}} g_{i,t}^*, \tag{11}$$

$$d_{n,t} = \sum_{k \in \mathcal{K}} d_{k,t}^*, \tag{12}$$

where $g_{n,t}$ denotes the total power generation of prosumer $n \in \mathcal{N}$ at scheduling time t, and $d_{n,t}$ denotes the total power consumption of prosumer $n \in \mathcal{N}$ at scheduling time t.

When an ensemble of prosumers in the same microgrid is unable to meet their own demand, i.e. $\sum_{n \in \mathcal{N}} d_{n,t} > \sum_{n \in \mathcal{N}} g_{n,t}$, MT needs to help its prosumers buy energy from other microgrids or import from main grid. The objective of MT as an energy buyer is to minimise overall electricity bills for its prosumers by strategically deciding the optimal bidding price of energy as

$$min_{b_{\text{energy},t}}: \sum_{t \in \mathcal{T}_{\text{buyer}}} \sum_{n \in \mathcal{N}} (d_{n,t} - g_{n,t}) \cdot \Delta t \cdot b_{\text{energy},t}, \tag{13}$$

$$\text{s. t. :} b_{\text{energy},t}^{\text{highest}} < b_{\text{energy},t}, \quad \sum_{t \in \mathcal{T}_{\text{buyer}}} \sum_{n \in \mathcal{N}} (d_{n,t} - g_{n,t}) \cdot \Delta t \cdot b_{\text{energy},t} \leqslant \pi. \tag{14}$$

When an ensemble of prosumers in the same microgrid generates surplus energy after meeting their own demand, i.e. $\sum_{n \in \mathcal{N}} g_{n,t} > \sum_{n \in \mathcal{N}} d_{n,t}$, MT can help its prosumers sell energy to other microgrids. Meanwhile, MT can help its energy sellers trade residual carbon allowance with other microgrids. If the net carbon emissions of an ensemble of prosumers in the same microgrid exceed the carbon allowance of this microgrid, MT has to help its prosumers buy carbon allowance from other microgrids. If the net carbon emissions of an ensemble of prosumers in the same microgrid are less than the carbon allowance of this microgrid, MT can help its prosumers sell the extra carbon allowance and earn the monetary compensation for its prosumers. This relationship has similar format as (6). Hence, the objective of MT as an energy seller is to maximise the overall profits for its prosumers by strategically deciding optimal bidding price of carbon allowance as

$$\max_{b_{\text{carbon,t}}} : \sum_{t \in \mathcal{T}_{\text{seller}}} \sum_{n \in \mathcal{N}} [(g_{n,t} - d_{n,t}) \cdot \Delta t \cdot b_{\text{energy},t}^{\text{highest}} - c_{\text{carbon},n} - c_n], \tag{15}$$

$$\text{s. t. :} b_{\text{carbon},t}^{\text{highest}} < b_{\text{carbon},t}, \quad \sum_{t \in \mathcal{T}_{\text{seller}}} \sum_{n \in \mathcal{N}} c_{\text{carbon},n} \leqslant \pi, \tag{16}$$

where $c_{\text{carbon},n}$ denotes the carbon cost (or revenue) of prosumer n, and c_n denotes other costs of prosumer n.

3.4. Smart contract based auction mechanism

In the layer of peer-to-peer trading platform, the proposed smart contract based auction mechanism is applicable for both prosumers and MTs to trade either energy or carbon allowance, under the standardised negotiation and self-enforcing of smart contract. The auction consists of the following steps: initialisation, matching, bidding, withdrawal, and pay-to-seller. Each step is performed by a function of smart contract, denoted as $f_{\text{init}}(\cdot)$, $f_{\text{match}}(\cdot)$, $f_{\text{bid}}(\cdot)$, $f_{\text{withdraw}}(\cdot)$, and $f_{\text{pay}}(\cdot)$, respectively. Let $\mathcal{U}$ denote the index set of sellers, and $\mathcal{V}$ denote the index set of buyers. The trading algorithm, as shown in Algorithm 1, is written in the Solidity language and stored in the Ethereum blockchain. Detailed steps of executing the auction are described as:

Algorithm 1. Smart contract based auction procedure.

1: **function: initialisation** $f_{\text{init}}(\cdot)$
2: Input: id_u, ε, β, m, s_u, $b_{u,t}^{\min}$, $b_{u,t}^{\text{highest}}$, τ_u
3: Output: O_u
4: **function: matching** $f_{\text{match}}(\cdot)$
5: for $v \in \mathcal{V}$
6: find optimal offers combination $\mathcal{U}_v^*$ by (18) (19)
7: end for
8: **function: bidding** $f_{\text{bid}}(\cdot)$
9: Input: τ_{now}, b_v^*, m_v, π_v
10: require $\tau_{\text{now}} \leqslant \tau$, $m_v = m_u$, $b_{u,t}^{\min} \leqslant b_{u,t}^{\text{highest}} < b_v^* \cdot s_u \leqslant \pi_v$
11: submit bids and update the highest bidding price by (21)
12: end
13: Output: $b_{u,t}^{\text{highest}'}$
14: **function: withdrawal** $f_{\text{withdraw}}(\cdot)$
15: Input: τ_{now}, b_v^*, π_v
16: require $\tau_{\text{now}} > \tau$, $v \in \mathcal{V}$, $v \neq v^*$
17: unsuccessful buyers withdraw their bids by (23)
18: end
19: Output: π_v'
20: **function: pay-to-seller** $f_{\text{pay}}(\cdot)$
21: Input: τ_{now}, b_v^*, π_u
22: require$\tau_{\text{now}} > \tau$, $v = v^*$
23: pay the deposited highest bid to seller by (24)
24: end
25: Output: π_u'

Step 1: Each seller calls the initialisation function $f_{\text{init}}(\cdot)$ from smart contract to specify the seller address, trading type (energy or carbon allowance), seller type (prosumer or MT), microgrid number, selling amount, minimal accepted bidding price, the currently highest bid, and the time of auction ended (line 1–3 in Algorithm 1) as

$$O_u = f_{\text{init}}(\text{id}_u, \varepsilon, \beta, m_u, s_u, b_{u,t}^{\min}, b_{u,t}^{\text{highest}}, \tau_u), \tag{17}$$

where O_u denotes the offer initiated by seller $u \in \mathcal{U}$, id_u denotes the encrypted address of seller u, $\varepsilon \in \{0, 1\}$ denotes a binary value indicating if the trading type is energy or carbon allowance, $\beta \in \{0, 1\}$ denotes a binary value indicating if the seller type is prosumer or MT, m_u denotes the microgrid index of seller u which enables buyers to find sellers in the same microgrid, s_u denotes the amount of energy or carbon allowance to be supplied by seller u, $b_{u,t}^{\min}$ denotes the minimal accepted bidding price specified by seller u for the energy or carbon allowance to be provided at scheduling time t, $b_{u,t}^{\text{highest}}$ denotes the currently highest bidding price ($b_{u,t}^{\text{highest}} = b_{u,t}^{\min}$ at the initialisation) for the energy or carbon allowance to be provided by the seller u at scheduling time t, and τ_u denotes the time of auction ended specified by seller u. The blockchain stores and updates the offers of all the sellers.

Step 2: In the proposed auction mechanism, each buyer needs to bid with a higher price than the currently highest bid over all the buyers. Hence, the matching function $f_{\text{match}}(\cdot)$ aims to help buyers automatically match the optimal offers combination to submit their bids, according to the criteria of: (1) meeting the demand of energy or carbon allowance for buyer $v \in \mathcal{V}$, denoted as d_v; (2) the selected optimal offers have the minimal summation of the currently highest bidding prices, which allows buyers to bid with minimal bidding prices. This criteria can be described (line 4–7 in Algorithm 1) as

$$\mathcal{U}_v^* = \underset{u}{\text{argmin}}: \sum_{u \in \mathcal{U}} b_{u,t}^{\text{highest}} \cdot s_u, \tag{18}$$

$$\text{s. t.} \sum_{u \in \mathcal{U}} s_u \geqslant d_v, \tag{19}$$

where $\mathcal{U}_v^*$ denotes the set of optimal offers combination that can meet buyer v' s demand with minimal required bidding prices.

Step 3: The bidding function $f_{\text{bid}}(\cdot)$ enables buyers to submit their bids after checking the conditions that: (1) the auction is not ended, i.e. $\tau_{\text{now}} \leqslant \tau_u$, where τ_{now} is the current time; (2) the microgrid index of buyer v, denoted as m_v, matches m_u (3) buyer has enough balance to provide a higher bid than the currently highest bidding price as

$$b_{u,t}^{\text{highest}} \cdot s_u < b_v^* \cdot s_u \leqslant \pi_v, \tag{20}$$

where b_v^* denotes the optimal bidding price of buyer v yielded by solving the optimization in prosumer-centric algorithm or MT-centric algorithm, and π_v denotes the account balance of buyer v.

After a buyer successfully submits a bid, the highest bidding price of seller u' s offer is updated (line 8–13 in Algorithm 1) as

$$b_{u,t}^{\text{highest}'} = f_{\text{bid}}(\tau_{\text{now}}, b_v^*, m_v, \pi_v), \tag{21}$$

where $b_{u,t}^{\text{highest}'}$ denotes the updated currently highest bidding price for the energy or carbon allowance to be provided by the seller u at scheduling time t. Before the auction is ended, all the bids are frozen by the smart contract, which means that the buyers are unable to withdraw their bids back to their account.

Step 4: When the auction is ended, i.e. $\tau_{\text{now}} > \tau$, the buyer with the highest bidding price wins the auction as

$$v^* = \underset{v}{\text{argmax}}: \mathcal{B}_t, \tag{22}$$

where v^* denotes the buyer with the highest bidding price, and $\mathcal{B}_t$ denotes the set of bidding prices submitted by all buyers for the energy or carbon allowance provided at scheduling time t.

The rest of unsuccessful buyers $v \in \mathcal{V}$, $v \neq v^*$ withdraw their previously submitted bids by calling the withdraw function $f_{\text{withdraw}}(\cdot)$ (line 14–19 in Algorithm 1) as

$$\pi_v' = f_{\text{withdraw}}(\tau_{\text{now}}, b_v^*, \pi_v), \tag{23}$$

where $\pi_v' = \pi_v + b_v^* \cdot s_u$ denotes the updated account balance of buyer v after withdrawing the bid for seller u' s offer.

Step 5: Once the smart contract confirms that the energy or carbon allowance is delivered by querying the smart meter, the deposited final highest bid for offer u, denoted as $b_{u,t}^{\text{highest}*}$ is paid to the seller by the pay-to-seller function $f_{\text{pay}}(\cdot)$ (line 20–25 in Algorithm 1) as

$$\pi_u' = f_{\text{pay}}(\tau_{\text{now}}, b_{u,t}^{\text{highest}*}, \pi_u), \tag{24}$$

where $\pi_u' = \pi_u + b_{u,t}^{\text{highest}*} \cdot s_u$ denotes the updated account balance of seller u after receiving the payment.

4. Case studies

Case studies are performed using the modified IEEE 37-bus test feeder [45] as shown in Fig. 3. The network is partitioned into five interconnected microgrids with arbitrarily assigned diesel generators and DRESs including solar, wind, and bioenergy. The coefficients of costs and carbon intensities are shown in Supplementary Materials S1. The loads data of residential demand is collected by using EFERGY monitor hub (See Supplementary Materials S2). The solar generation data is obtained from the U.K. rooftop solar generation of endpoint consumers [46], and the generation of diesel, wind, and biomass are scaled down by 2.5×10^7 times from the U.K. power systems [47] (See Supplementary Materials S3). The scheduling interval is set as 0.5 h, according to the U.K. energy market settlement period [7]. The data of centralised prices of energy and carbon allowance is obtained from the U.K. energy retail market [48] and the U.K. carbon market [15] (the E.U. ETS plus the U.K. carbon price support), respectively. These centralised prices are set as the minimal accepted bidding price of each seller, such that during the auction process, the buyers can provide higher prices than the centralised prices through solving their own objective functions to decide optimal bidding prices. As studied in [18], this design encourages more prosumers to sell their surplus energy or carbon allowance and reduces the import from central markets. The smart contract is written in the Solidity 0.6.0 and executed on the Ethereum virtual machine. The prosumer-

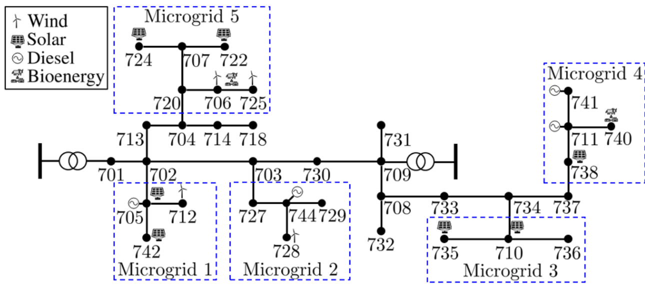

Fig. 3. Modified IEEE 37-bus test feeder. The network is partitioned into 5 microgrids. Each bus represents a prosumer. The DRESs are arbitrarily assigned to each microgrid by connecting to prosumers' nodes.

centric and MT-centric algorithms are developed by using MATLAB and solved by optimisation toolbox.

4.1. Benchmark

To illustrate the efficiency of the proposed trading framework, the following trading schemes are used as benchmarks.

4.1.1. Centralised trading

The trading of energy or carbon allowance is only performed on the centralised markets. The prices of energy [47] and carbon allowance [15] in central markets are applied in the centralised trading.

4.1.2. Aggregator-based trading

As the trading framework in [22], the reshaping of prosumption behaviours is managed by relatively decentralised agents, i.e. aggregators, with the same objectives of minimising bills for buyers or maximising profits for sellers. Aggregators then pay prosumers the monetary compensation for the reshaping. The trading of energy or carbon allowance is only performed by aggregators.

4.2. Balance of energy and carbon allowance

Fig. 4 shows the total power balance of the modified IEEE 37-bus test feeder. The positive net power means the total generation is greater than the total demand. The negative net power means the total generation is less than the total demand, and the distribution network has to import energy from the main grid. Through the proposed peer-to-peer trading framework, the summation of daily net energy is 0.99 kWh, which indicates a better energy balance, compared to -4.50 kWh in the aggregator-based trading and -46.44 kWh in the centralised trading.

Fig. 5 shows the surplus carbon allowance of the overall distribution network. The positive surplus carbon allowance means the total carbon emissions produced by the distribution network are less than the total carbon allowance, whereas the negative surplus carbon allowance means the total carbon emissions produced by distribution network exceed the total carbon allowance. The proposed peer-to-peer trading framework can

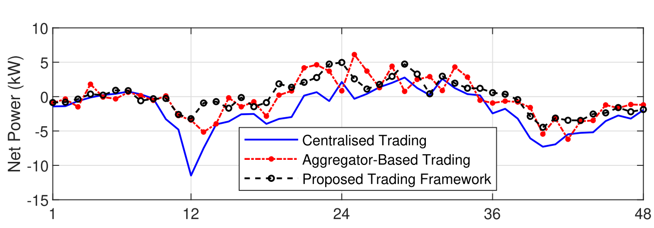

Fig. 4. Total Power balance of the modified IEEE 37-bus test feeder. The positive value of y-axis means the total generation is greater than the total demand. The negative value of y-axis means the total generation is less than the total demand.

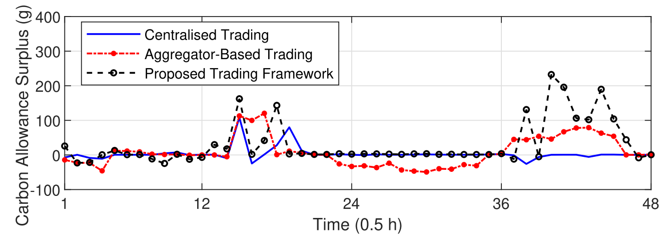

Fig. 5. Surplus carbon allowance of the modified IEEE 37-bus test feeder. The positive value of y-axis means the total carbon emissions are less than the total carbon allowance. The negative value of y-axis means the total carbon emissions exceed the total carbon allowance.

save total daily carbon emissions from carbon allowance by 1465.90 g with baseload of 235.51 kW, approximately 6 times higher than the aggregator-based trading (385.91 g) and 9 times higher than the centralised trading (168.65 g). It is particularly for the period from the thirty-sixth scheduling time to the forty-eighth scheduling time, during which more carbon emissions are saved. Although the aggregator-based trading also achieves the carbon saving during this period, it results in that the carbon emissions exceed the carbon allowance during the period from the twenty-second scheduling time to the thirty-fifth scheduling time.

4.3. Interface between scheduling and smart contract

The optimal energy scheduling and bidding prices for each of the individual prosumers obtained by prosumer-centric algorithm are shown in Fig. 6, relative to the case with no scheduling, i.e. original prosumption. For the microgrid at scheduling intervals during which all prosumers of this microgrid cannot generate surplus energy to trade, there is no energy seller and bidding price. By comparing the scheduled prosumption and original prosumption, it can be observed that during the peak demand periods for a majority of prosumers (from the twelfth scheduling time to the thirty-sixth scheduling time), the generation is scheduled to increase whereas the consumption is shifted to the off-peak demand periods (rest scheduling time). When the prosumers experience high power consumption and low power generation, by appropriately scheduling, the bidding prices stabilise at around 10 pence/kWh without dramatic increase. The slight fluctuation of bidding prices dynamically reflect the actual supply–demand balance of power.

The interface between scheduling decisions and smart contract is shown in Fig. 7. Through solving prosumer-centric algorithm, the optimal bidding prices of prosumers as buyers (indicated by the colourbar) are automatically sent to smart contract for auction. The highest bidding prices (indicated by the red line) would be accepted by sellers. For the microgrid at scheduling intervals during which all prosumers of this microgrid cannot generate surplus energy to trade, there is no auction proceeded (indicated by the scheduling intervals without the red line). It can be seen from Fig. 7 that the auctions are proceeded over all the scheduling intervals of day at microgrid 4, whereas the auctions are only proceeded at a few scheduling intervals at microgrid 2. This is because the capacity of distributed generation at microgrid 2 cannot meet the demand. The MT 2 has to help its prosumers buy the energy from other MTs. Additionally, through the proposed peer-to-peer trading framework, the selling prices are stabilised between 6 pence/kWh and 10 pence/kWh over all the scheduling intervals, which is different from the aggregator-based trading [22] with dramatic peak prices and off-peak prices. The auction prices decided by individual prosumers can accurately target on the actual supply–demand relationship of prosumers.

4.4. Smart contract execution

The proposed auction mechanism is performed in the form of smart contract on the Ethereum blockchain. Fig. 8 shows an example of procedure for executing the auctions of energy and carbon allowance

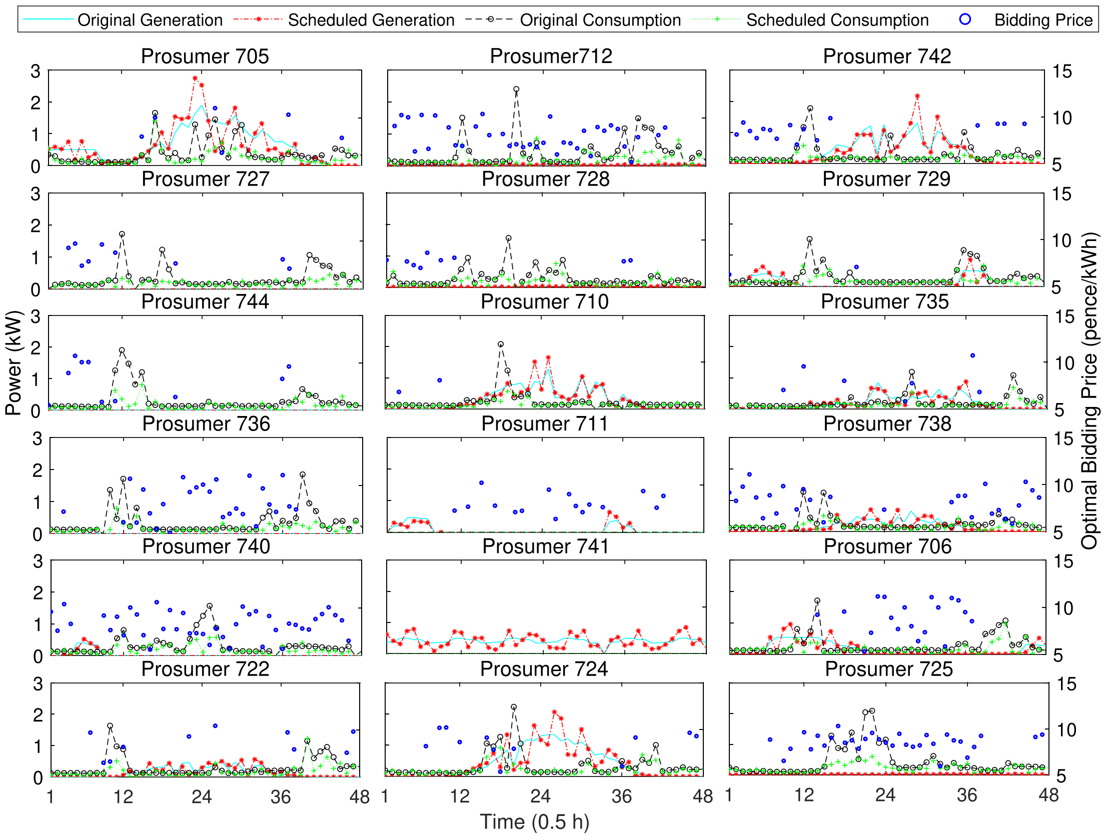

Fig. 6. Optimal energy scheduling and bidding prices obtained by prosumer-centric algorithm (relative to the case with no scheduling). The left *y* axes indicate the power of individual prosumers, and the right *y* axes indicate the optimal bidding prices. The *x* axes indicate the scheduling time of day.

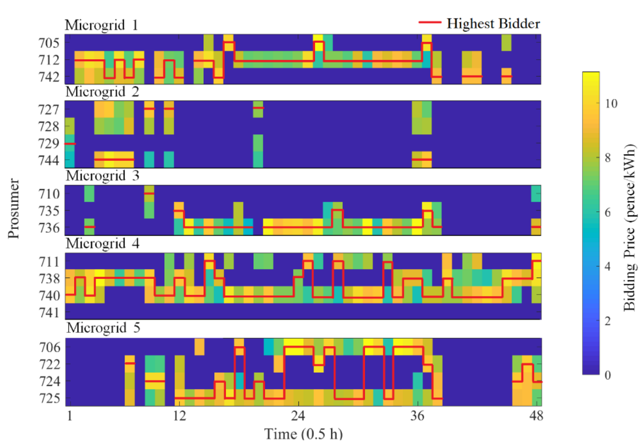

Fig. 7. Optimal bidding prices of energy buyers as an input of smart contract. The *y*-axis indicates the bus number of prosumers, assigned to corresponding microgrids. The *x*-axis indicates the scheduling time of day. The colourbar indicates the optimal bidding prices from each prosumer for a given 0.5 h scheduling interval. The red line indicates the highest bidding prices accepted by energy sellers. The scheduling interval without the red line means there is no surplus energy on the microgrid to trade.

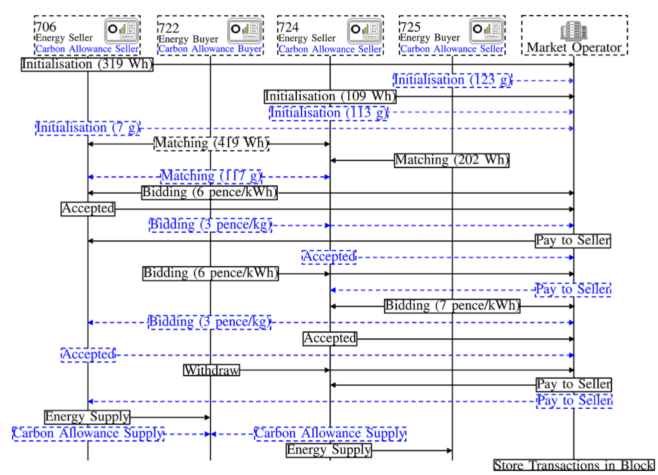

Fig. 8. Execution of smart contract based auction on the peer-to-peer trading platform. The black line is the execution of the energy trading, and the dashed blue line is the execution of the carbon allowance trading.

on the microgrid 5. Prosumers at bus 706 and bus 724 are energy sellers to supply 319 Wh and 109 Wh energy, respectively. Prosumers at bus 706, bus 724, and bus 725 are carbon allowance sellers to supply 7 g, 113 g, and 123 g carbon allowance, respectively. The sellers call the initialisation function from the full node to specify offer conditions. Prosumers at bus 722 and bus 725 are energy buyers with the demand of 419 Wh and 202 Wh, respectively. Prosumers at bus 722 is carbon allowance buyer with the demand of 117 g. The bids and offers are matched by the proposed matching criteria. For the auction of carbon allowance, there is a single buyer with multiple sellers. To meet the 117 g demand of carbon allowance, prosumer at bus 722 has the options of (1) buying 123 g allowance from prosumer at bus 725 with 4 pence/kg of bidding price; (2) buying 113 g from prosumer at bus 724 with 3 pence/kg of bidding price and buying another 7 g from prosumer at bus 706 with 3 pence/kg of bidding price. According to the matching criteria, the second option would be selected.

For the auction of energy, there are multiple buyers with multiple sellers. For the offer of selling 109 Wh energy by prosumer at bus 724, prosumers at bus 725 and bus 722 attempt to bid as buyers. The prosumer at bus 725 wins this auction with the 7 pence/kWh of the highest bidding price. The unsuccessful buyer at bus 722 then calls the withdrawal function from the full node to withdraw its bid. Once confirming the energy or carbon allowance is supplied, the smart contract pays to the sellers with the highest bids. The residual 123 g of carbon allowance and 93 Wh energy demand from prosumer at bus 725 and 100 Wh energy demand from prosumer at bus 722 are aggregated by MT 5 to trade with other MTs.

5. Conclusion

To achieve the regional energy balance and reduction of carbon emissions on distribution networks, a peer-to-peer trading framework is proposed to exchange energy and carbon allowance. The trading is proceeded under the standardised and self-enforcing smart contract. The optimal bidding/selling prices of prosumers and energy reshaping decisions are yielded by the proposed prosumer-centric and microgrid-trader-centric algorithms. The designed decentralised low carbon incentive mechanism provides macro policy makers with a potential policy design for carbon mitigation in energy sector, which allows the monetary incentive of carbon reduction to be accurately allocated according to the real-time prosumption behaviours in specific location and time period. Simulation results show that the proposed peer-to-peer trading framework is capable of exporting 0.99 kWh of daily energy to the main grid and save 1465.90 g of daily carbon emissions from carbon allowance, outperforming the aggregator-based trading and the centralised trading. The proposed trading framework and demonstrated benefits can encourage more passive consumers to invest in the DRESs and participate in the local energy exchange.

The idiosyncratic prosumption patterns of individual prosumers are worth for further investigation. For instance, if a prosumer has high price elasticities of generation and buying carbon allowance, whereas low price elasticities of consumption during the peak demand period, this prosumer is inherently willing to increase generation irrespective of generating costs and carbon price. However, this prosumer is reluctant to curtail or shift consumption. Considering these features into the scheduling to decide the prosumption behaviours and bidding/selling prices can be taken as a future work.

CRediT authorship contribution statement

Weiqi Hua: Conceptualization, Methodology, Software, Investigation, Formal analysis, Data curation, Writing - original draft, Visualization. **Jing Jiang:** Validation, Resources, Data curation, Writing - review & editing, Visualization, Supervision, Project administration. **Hongjian Sun:** Conceptualization, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Jianzhong Wu:** Validation, Resources, Writing - review & editing, Visualization, Supervision.

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.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.apenergy.2020.115539.

References

[1] Shindell D, Smith CJ. Climate and air-quality benefits of a realistic phase-out of fossil fuels. Nature 2019;573(7774):408–11.
[2] Zeyringer M, Price J, Fais B, Li P-H, Sharp E. Designing low-carbon power systems for Great Britain in 2050 that are robust to the spatiotemporal and inter-annual variability of weather. Nat Energy 2018;3(5):395.
[3] Surana K, Jordaan SM. The climate mitigation opportunity behind global power transmission and distribution. Nat Clim Change 2019;9(9):660–5.
[4] Klenert D, Mattauch L, Combet E, Edenhofer O, Hepburn C, Rafaty R, et al. Making carbon pricing work for citizens. Nat Clim Change 2018;8(8):669–77.
[5] Toffler A. The third wave: The classic study of tomorrow, New York: Bantam; 1984.
[6] Parag Y, Sovacool BK. Electricity market design for the prosumer era. Nat Energy 2016;1:16032.
[7] Wright AC. Reform of power system governance in the context of system change. IET Smart Grid 2018;1(1):19–23.
[8] Hirst D. Carbon price floor (CPF) and the price support mechanism, Tech. rep., House of Commons Library; 2018.
[9] Li B, Song Y, Hu Z. Carbon flow tracing method for assessment of demand side carbon emissions obligation. IEEE Trans Sust Energy 2013;4(4):1100–7.
[10] Kang C, Zhou T, Chen Q, Wang J, Sun Y, Xia Q, et al. Carbon emission flow from generation to demand: a network-based model. IEEE Trans Smart Grid 2017;6(5):2386–94.
[11] Chen S, Chen B. Coupling of carbon and energy flows in cities: a meta-analysis and nexus modelling. Appl Energy 2017;194:774–83.
[12] Chiu W, Sun H, Poor HV. Energy imbalance management using a robust pricing scheme. IEEE Trans Smart Grid 2013;4(2):896–904.
[13] Couture T, Gagnon Y. An analysis of feed-in tariff remuneration models: Implications for renewable energy investment. Energy Policy 2010;38(2):955–65.
[14] Brauneis A, Mestel R, Palan S. Inducing low-carbon investment in the electric power industry through a price floor for emissions trading. Energy Policy 2013;53:190–204.
[15] Smith T. Carbon price floor: reform and other technical amendments, Tech. rep., HM Revenue and Customer; 2014.
[16] Newbery D, Reiner D, Ritz R. When is a carbon price floor desirable?; 2018.
[17] Jiang N, Sharp B, Sheng M. New Zealand's emissions trading scheme. New Zeal Econ Pap 2009;43(1):69–79.
[18] Ghosh A, Aggarwal V, Wan H. Exchange of renewable energy among prosumers using blockchain with dynamic pricing. CoRR abs/1804.08184. arXiv:1804.08184.
[19] Zhang C, Wu J, Zhou Y, Cheng M, Long C. Peer-to-peer energy trading in a microgrid. Appl Energy 2018;220:1–12.
[20] Liu Y, Zuo K, Liu XA, Liu J, Kennedy JM. Dynamic pricing for decentralized energy trading in micro-grids. Appl Energy 2018;228:689–99.
[21] Gkatzikis L, Koutsopoulos I, Salonidis T. The role of aggregators in smart grid demand response markets. IEEE J Sel Area Comm 2013;31(7):1247–57.
[22] Li D, Chiu W-Y, Sun H, Poor HV. Multiobjective optimization for demand side management program in smart grid. IEEE Trans Ind Inform 2017;14(4):1482–90.
[23] Fan J, Li J, Wu Y, Wang S, Zhao D. The effects of allowance price on energy demand under a personal carbon trading scheme. Appl Energy 2016;170:242–9.
[24] Mengelkamp E, Notheisen B, Beer C, Dauer D, Weinhardt C. A blockchain-based smart grid: towards sustainable local energy markets. Comput Sci Res Dev 2018;33(1–2):207–14.
[25] Buterin V, et al. A next-generation smart contract and decentralized application platform. White Pap 2014; 3: 37.
[26] Chapron G. The environment needs cryptogovernance. Nature 2017;545:403–5.
[27] Di Silvestre ML, Gallo P, Ippolito MG, Sanseverino ER, Zizzo G. A technical approach to the energy blockchain in microgrids. IEEE Trans Ind Informat 2018;14(11):4792–803.
[28] 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.
[29] van Leeuwen G, AlSkaif T, Gibescu M, van Sark W. An integrated blockchain-based energy management platform with bilateral trading for microgrid communities. Appl Energy 2020;263:114613.
[30] Kang J, Yu R, Huang X, Maharjan S, Zhang Y, Hossain E. Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains. IEEE Trans Ind Inform 2017;13(6):3154–64.
[31] Thomas L, Zhou Y, Long C, Wu J, Jenkins N. A general form of smart contract for decentralized energy systems management. Nat Energy 2019; 4. doi:10.1038/s41560-018-0317-7.
[32] 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.
[33] Alkawasmi E, Arnautovic E, Svetinovic D. Bitcoin-based decentralized carbon emissions trading infrastructure model. Syst Eng 2015;18(2):115–30.
[34] Electricity ten year statement, Tech. rep., National Grid (Nov. 2018).
[35] Wood G. Ethereum: A secure decentralised generalised transaction ledger. Ethereum Project Yellow Pap 2014;151:1–32.
[36] Christidis K, Devetsikiotis M. Blockchains and smart contracts for the internet of things. IEEE Access 2016;4:2292–303.
[37] Gilbert H, Handschuh H. Security analysis of sha-256 and sisters. In: Selected areas in cryptography, International Workshop, Sac, Ottawa, Canada, August, Revised Papers; 2003.
[38] Price J, Zeyringer M, Konadu D, Sobral Mourao Z, Moore A, Sharp E. Low carbon electricity systems for Great Britain in 2050: an energy-land-water perspective. Appl Energy 2018;228:928–41.
[39] Digest of UK energy statistics (DUKES), Tech. rep., Department for Business, Energy, and Industrial Strategy; 2020.
[40] Government emission conversion factors for greenhouse gas company reporting, Tech. rep., Department for Business, Energy and Industrial Strategy; 2020.
[41] Hawkes AD. Estimating marginal CO_2 emissions rates for national electricity systems. Energy Policy 2010;38(10):5977–87.
[42] Zhang N, Hu Z, Dai D, Dang S, Yao M, Zhou Y. Unit commitment model in smart

grid environment considering carbon emissions trading. IEEE Trans Smart Grid 2016;7(1):420–7.
[43] Hua W, Li D, Sun H, Matthews P. Stackelberg game-theoretic model for low carbon energy market scheduling. IET Smart Grid 2020;3:31–41. 10.
[44] Department for Business, Energy & Industrial Strategy, BEIS electricity generation cost report, Energy gener. cost projections. https://www.gov.uk/government/publications/beis-electricity-generation-costs-2020.
[45] Wang H, Huang T, Liao X, Abu-Rub H, Chen G. Reinforcement learning in energy trading game among smart microgrids. IEEE Trans Ind Electron 2016;63(8):5109–19.
[46] Wilcox M. Validation of photovoltaic connection assessment tool, Tech. rep., UK Power Networks (Operations) Limited; 2015.
[47] National Statistics, https://www.gov.uk/government/statistics; 2020.
[48] https://www.energybrokers.co.uk; 2020.