Enabling Localized Peer-to-Peer Electricity Trading Among Plug-in Hybrid Electric Vehicles Using Consortium Blockchains

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***Abstract*—We propose a localized peer-to-peer (P2P) electricity trading model for locally buying and selling electricity among plug-in hybrid electric vehicles (PHEVs) in smart grids. Unlike traditional schemes, which transport electricity over long distances and through complex electricity transportation meshes, our proposed model achieves demand response by providing incentives to discharging PHEVs to balance local electricity demand out of their own self-interests. However, since transaction security and privacy protection issues present serious challenges, we explore a promising consortium blockchain technology to improve transaction security without reliance on a trusted third party. A localized P2P Electricity Trading system with COnsortium blockchaiN (PETCON) method is proposed to illustrate detailed operations of localized P2P electricity trading. Moreover, the electricity pricing and the amount of traded electricity among PHEVs are solved by an iterative double auction mechanism to maximize social welfare in this electricity trading. Security analysis shows that our proposed PETCON improves transaction security and privacy protection. Numerical results based on a real map of Texas indicate that the double auction mechanism can achieve social welfare maximization while protecting privacy of the PHEVs.**

***Index Terms*—Consortium blockchain, decentralized energy trading, double auction, plug-in hybrid electric vehicle (PHEVs), security and privacy.**

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I. Introduction

With rapid development of energy harvesting and information communication technologies, more and more distributed renewable energy sources are integrated into smart grids [1]. On one hand, nodes in smart grids can harvest energy from different renewable energy sources to promote greener smart grids [2]. On the other hand, smart girds utilize sensors with energy harvesting ability to form wireless sensor networks for long-term monitoring and remote control [3], [4]. In smart grids, plug-in hybrid electric vehicles (PHEVs) play key roles in distributed renewable energy transportation and management. PHEVs can not only charge electricity from home grid with renewable energy sources [5], but can also get electricity from other PHEVs to shift peak load through vehicle-to-vehicle trading [6].

In social hotspots, e.g., parking lots or charging stations, PHEVs with bidirectional chargers can trade electricity in a localized peer-to-peer (P2P) manner (e.g., vehicle-to-vehicle) [6]. In a conventional power grid, the generated electricity is transported through a complex energy transportation mesh resulting in high losses in the T&D network and correspondingly low efficiency [5], [7]. Unlike so, PHEVs with surplus energy can discharge energy to satisfy electricity demand of local charging PHEVs, thus balancing electricity supply and demand locally in hotspots [6].

However, PHEVs with surplus electricity may be not willing to participate as energy suppliers in a localized P2P electricity trading market due to their concerns either over the lifetime of the battery or about privacy [5]. In this case, electricity supply and demand are unbalanced among PHEVs. Moreover, traditional centralized electricity trading relying on a trusted third party suffers from problems such as single point of failure and privacy leakage [8]. Therefore, it is necessary to encourage more PHEVs to perform discharging by designing proper incentives. In addition, it is important to design a secure decentralized electricity trading system such that the privacy of the PHEVs can be preserved during the trade [8].

Recently, a promising blockchain technology with advantages of decentralization, security, and trust has been introduced for electricity trading. The blockchain is a P2P distributed ledger technology, which enables electricity trading to be executed in decentralized, transparent, and secure market environments. A digital currency named "NRGcoin" based on blockchain protocols was presented for renewable energy trading in smart grids [9]. A demonstration platform for renewable energy exchange using NRGcoin was proposed in [10]. N. Z. Aitzhan *et al.* in [8] utilized a general blockchain with multisignature to address transaction security problems in decentralized smart grids. However, the existing methods do not work well in localized P2P electricity trading among PHEVs because of the disadvantage of high cost associated with establishing a blockchain in energy-limited PHEVs.

Motivated by these developments, in this paper, we exploit the consortium blockchain technology to develop a secure localized P2P electricity trading system. The consortium blockchain is a specific blockchain with multiple authorized nodes to establish the distributed shared ledger with moderate cost. Here, the authorized nodes are local aggregators (LAGs). A consortium blockchain is established on LAGs to publicly audit and share transaction records without relying on a trusted third party. Energy transaction records among PHEVs are uploaded to the LAGs after encryption. The LAGs run an algorithm to audit the transactions and record them into the shared ledger. This ledger is publicly accessed by PHEVs and LAGs connected to the consortium blockchain. Moreover, since electricity pricing along with the amount of traded electricity among PHEVs need to be optimized, an iterative double auction mechanism is presented to maximize social welfare in the system.

The contributions of this paper are summarized as follows.

1) Unlike existing blockchain-based energy trading system, we establish a consortium blockchain based on LAGs to audit and verify transaction records among PHEVs.
2) We design a localized P2P Electricity Trading system with COnsortium blockchaiN (PETCON) to achieve trustful and secure electricity trading.
3) To optimize electricity pricing and the amount of traded electricity among PHEVs in PETCON, an iterative double auction mechanism is proposed to maximize social welfare while protecting privacy of PHEVs.

The rest of this paper is organized as follows. We introduce core system components of PETCON in Section II. Detailed operations of PETCON are illustrated in Section III. The problem definition and the solution for localized P2P electricity trading are proposed in Section IV and Section V, respectively. Security analysis and numerical results are shown in Section VI before the paper is concluded in Section VII.

II. Core System Components for Localized Peer-to-Peer Electricity Trading

A. Entities for PETCON

The model for localized P2P electricity trading among PHEVs includes the following entities as shown in Fig. 1.

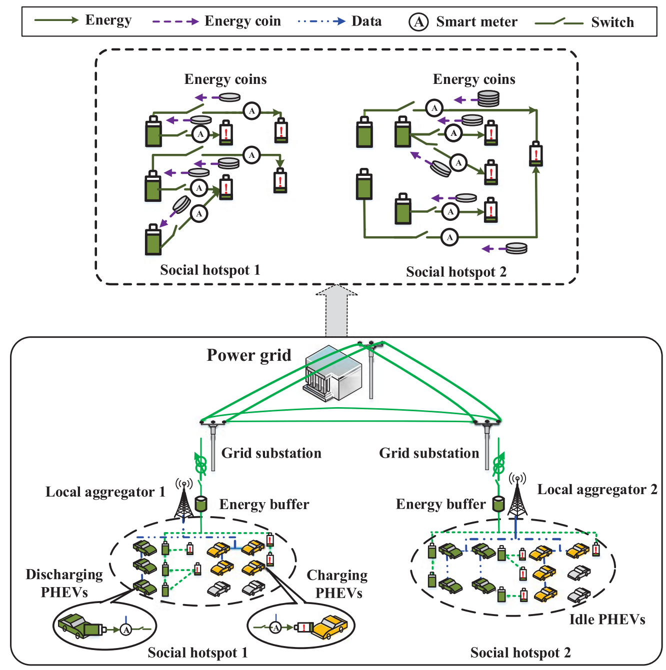

Fig. 1. Localized P2P electricity trading among PHEVs.

1) *PHEVs*: The PHEVs play different roles in localized P2P electricity trading at hotspots: charging PHEVs, discharging PHEVs, and idle PHEVs. Each PHEV chooses its own role according to current energy state and driving plan.

2) *LAGs*: LAGs work as energy brokers to provide access points of electricity and wireless communication services for PHEVs [11]. Each charging PHEV sends a request about electricity demand to the nearest LAG. The energy broker does a statistics of local electricity demand and announces this demand to local PHEVs. PHEVs with surplus electricity submit selling prices to the broker. The energy broker acts as an auctioneer to carry out an iterative double auction among PHEVs, and matches electricity trading pairs of PHEVs. (Details on this auction will be given in Sections IV and V.)

3) *Smart meters*: Each charging pole with a built-in smart meter calculates and records the amount of traded electricity in real time. The charging PHEVs pay to the discharging PHEVs according to the records in the smart meters.

B. Consortium Blockchain for PETCON

Blockchain is an emerging P2P technology for distributed computing and decentralized data sharing among network nodes. There is an important transaction audit stage, named consensus process, before transaction records form a blockchain. This stage is executed by all nodes in a traditional blockchain with high cost. In this paper, we use a consortium blockchain that is a special blockchain to perform consensus process by pre-selected LAGs. These authorized LAGs have right to control the consensus process and write the consortium blockchain with transactional data during localized P2P electricity trading. The consortium blockchain consists of three main components.

1) Transactions: Electricity trading information and digital asset records are stored in a consortium blockchain. The trading information includes PHEVs' pseudonyms used for privacy protection, data type, metadata tags for raw transactional data, complete index history of metadata, an encrypted linked to transaction records, and a timestamp of transaction generation. The information is encrypted and signed with digital signatures to guarantee authenticity and accuracy. Here, we will present a new digital cryptocurrency, named energy coin, as the digital asset to trade electricity.

2) Blocks About Transactional Data: All raw data of electricity transaction is stored, shared, and audited among authorized LAGs. Due to limitation of computation and storage, PHEVs store an index of metadata indicated a location of the metadata for decreasing system cost. The LAGs collect and manage their own local transaction records. These transaction records are encrypted and structured into blocks after being audited by all the authorized LAGs (i.e., the consensus process). Each block contains a cryptographic hash to the prior block in the consortium blockchain for traceability and verification. The blocks are added in a linear chronological order in the consortium blockchain. After the transaction records have been added to the consortium blockchain, the data becomes publicly accessible to PHEVs and LAGs in smart grids.

3) Proof-of-Work:

a) Proof-of-work for LAGs about data audit: Similar to Bitcoin, before a new data being inserted into immutable data storage, a consensus process carried by authorized LAGs should be reached by a mechanism named proof-of-work. The proof-of-work for LAGs about data audit is similar to traditional proof-of-work in Bitcoin, which generates a unique hash value with a certain difficulty for each block in the blockchain. The hash value is used to link a new block to the prior block. Each authorized LAG in the consortium blockchain competes to create a block by finding a valid proof-of-work. The fastest LAG is rewarded by a certain amount of energy coins. The LAG audits the transaction records and structures them into a new block for verification by other LAGs during consensus process.

b) Proof-of-work for PHEVs about energy contributions: The discharging PHEV with the most contribution on electricity supply in every LAG is also rewarded by energy coins, which is an incentive to encourage them to discharge electricity. The total amount of discharged energy is measured and recorded by smart meters, which is the specific proof-of-work for PHEVs about energy contributions.

III. Localized Peer-to-Peer electricity Trading System With Consortium Blockchain

A. An Overview of PETCON

As shown in Fig. 2, there are three entities in an LAG, i.e., a transaction server, an account pool, and a memory pool. The transaction server collects energy request from charging PHEVs and matches electricity trading pairs of PHEVs. The transaction server also controls switches of charging poles to finish localized P2P energy transportation. Each PHEV has an energy coin account that stores all transaction records, and a corresponding wallet to manage energy coins in the account. Here, we use random pseudonyms as public keys of PHEV's wallet named wallet addresses to replace the true address of the wallet for privacy protection. The mapping relationships about wallet addresses and the corresponding energy coin account are stored in the account pools.

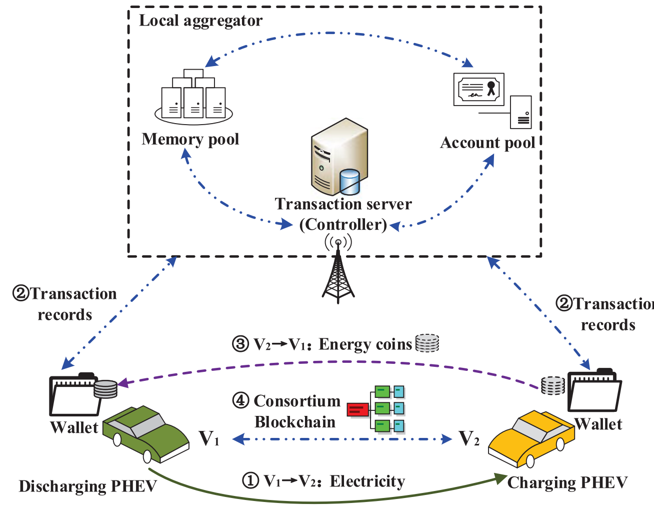

Fig. 2. Localized P2P electricity trading using energy coins.

During a localized P2P electricity trading, PHEVs first choose their own roles according to electricity demand and energy states. Charging PHEVs request energy from local discharging PHEVs. LAGs work as energy brokers for PHEVs to execute energy bidding and transaction through an iterative double auction mechanism. After that, the charging PHEVs pay to the discharging PHEVs using energy coins. With the help of proof-of-work for LAGs about data audit, transaction-related data in every LAG is audited and verified through a consensus process among authorized LAGs.

B. Operation Details of PETCON

1) System Initialization and Key Generation: In PETCON, we utilize elliptic curve digital signature algorithm and asymmetric cryptography for system initialization [8]. Each PHEV becomes a legitimate entity after registration on a trusted authority, such as a government department. A PHEV V_i with true identity ID_i joins the system and gets its public/privacy key and certificate (denoted as PK_i, SK_i, and $Cert_i$, respectively). $Cert_i$ can be used to uniquely identify the PHEV through binding registration information of the PHEV (e.g., license plate number). V_i requests a set of ν wallet addresses $\{WID_{i,k}\}_{k=1}^{\nu}$ from the authority. The authority generates a mapping list $\{PK_i, SK_i, Cert_i, \{WID_{i,k}\}_{k=1}^{\nu}\}$. When V_i executes system initialization, V_i uploads wallet addresses being used to the account pool of its nearest LAG. V_i checks the integrity of its wallet, and downloads the last data about its wallet through a memory pool. The memory pool stores all transaction records in the consortium blockchain.

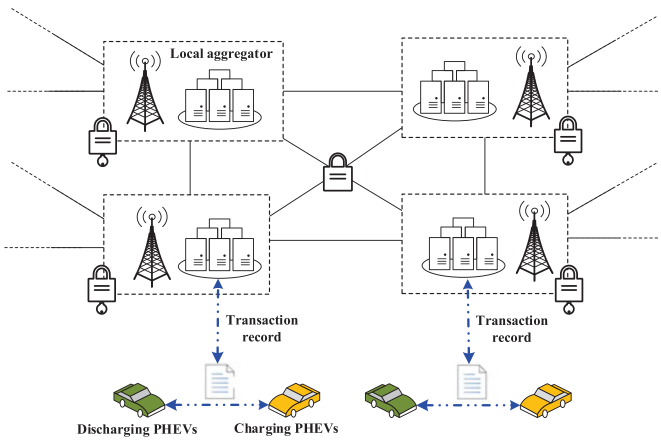

Fig. 3. Structure of our proposed consortium blockchain.

2) Choosing Different Roles in Electricity Trading: During electricity trading, PHEVs are divided into two groups (i.e., charging PHEVs and discharging PHEVs) according to their current energy states and future driving plans. PHEVs with surplus electricity may become discharging PHEVs to meet local electricity demands of charging PHEVs.

3) Selling and Buying Energy: Charging PHEVs send electricity requests including the amount of electricity and expected serving time to the transaction server of an LAG. The transaction server works as a controller to count the total electricity demands and broadcasts this demand to local discharging PHEVs. The discharging PHEVs determine their selling electricity and give responses back to the controller. The controller matches the electricity supply and demand among PHEVs. Here, we use a double auction mechanism to execute energy bidding, negotiation, and transactions among PHEVs. More details on the double auction mechanism will be given in Sections IV and V.

4) Paying and Earning Energy Coins: After electricity trading, a charging PHEV pays for the energy transaction through a wallet address of a discharging PHEV, as shown in Fig. 2. The charging PHEV transfers energy coins from its wallet to the given wallet address. The discharging PHEVs obtain the last blockchain from the memory pool of LAGs to verify the payment. The charging PHEVs generate transaction records, and the discharging PHEVs verify and digitally sign the transaction records and thus upload them to LAGs for audit. To balance electricity demand and supply, by providing incentives, we stimulate discharging PHEVs to meet local demand. During a certain period, the discharging PHEV with the most contribution on electricity supply in every LAG is rewarded by energy coins according to the proof-of-work for PHEVs about energy contributions.

5) Building Blocks and Finding Proof-of-Work: LAGs collect all local transaction records in a certain period, and then encrypt and digitally sign these records to guarantee authenticity and accuracy. The transaction records are structured into blocks, as shown in Fig. 3. Each block contains a cryptographic hash to the prior block in the consortium blockchain. Similar to Bitcoin, the LAGs try to find their own valid proof-of-work (i.e., a hash value which meets a certain difficulty). An LAG calculates the hash value of its block based on a random nonce value x and the previous block hash value, timestamp, transactions' merkle root and so on (denoted as p_data) [12]. Namely, $Hash(x + p\_data) < Difficulty$. Here, $Difficulty$ is a number controlled by system to adjust the speed of finding out a specific x.

6) Carrying Out Consensus Process: The fastest LAG with a valid proof-of-work (i.e., x) becomes a leader of the current consensus process. The leader broadcasts block data, timestamp, and its proof-of-work to other authorized LAGs for verification and audit. These LAGs audit the block data and broadcast their audit results with their signatures to each other for mutual supervision and verification. After receiving the audit results, each LAG compares its result with others and sends a reply back to the leader. This reply includes the LAG's audit result, comparison result, signatures, and records of received audit results. The leader does statistics of received replies from LAGs. If all the LAGs agree on the block data, the leader will send records including current audited block data and a corresponding signature to all authorized LAGs for storage. After that, this block is stored in the consortium blockchain in a chronological order, and the leader is awarded by energy coins. Once the authorized LAGs formation is complete and remains almost constant, the total time needed for reaching consensus of one new block is about 1 minute regardless of the network size [13]. If some LAGs don't agree on the block data, the leader will analyze the audit results, and send the block data to these LAGs once again for audit if necessary. Moreover, according to audit results and corresponding signatures, compromised LAGs will be found out and held accountable.

IV. Problem Definition for Electricity Trading

In this section, we present the problem definition about electricity pricing and the amount of traded electricity among PHEVs to maximize overall social welfare (i.e., the sum of nonlinear utilities of PHEVs). In each hotspot region, an LAG can communication with any local PHEVs to establish a real-time electricity trading market. LAGs facilitate electricity trading between any charging PHEV and any discharging PHEV in the network [14]. A local aggregator LAG_n acting as an energy broker manages local PHEVs to execute electricity trading operations. A set of LAGs (denoted as ι) is indexed by n, where $n \in \iota \triangleq \{1, 2 \ldots n\}$. Let us denote a set of charging PHEVs in LAG_n as $\upsilon \triangleq (CV_i^n | i \in \mathbb{C}, n \in \iota), \mathbb{C} = \{0, 1, 2, \ldots, I\}$. The discharging PHEVs in LAG_n are denoted as $\psi \triangleq (DV_j^n | j \in \mathbb{Z}, n \in \iota), \mathbb{Z} = \{0, 1, 2, \ldots, J\}$. $c_i^{n,\min}$ and $c_i^{n,\max}$ are the minimum and maximum of electricity demand for $CV_i^n \in \mathbb{R}$ in LAG_n, respectively. LAG_n must provide $c_i^{n,\min}$ energy to CV_i^n for normal driving.

Here, c_{ij}^n is the electricity demand of CV_i^n for discharging PHEV DV_j^n in LAG_n. The electricity demand vector of CV_i^n is

$\mathrm{C}_{\mathbf{i}}^{\mathbf{n}} \triangleq \{c_{ij}^n | j \in \mathbb{Z}\}$. In LAG_n, the total electricity demand of all charging PHEVs is $\mathbf{C}^{\mathbf{n}} \triangleq \{\mathbf{C}_{\mathbf{i}}^{\mathbf{n}} | i \in \mathbb{C}\}$. We define the energy state of CV_i^n before charging as STO_i^n. EV_i^{cap} is the battery capacity of CV_i^n. The satisfaction function of CV_i^n is

$$U_i(\mathbf{C}_{\mathbf{i}}^{\mathbf{n}}) = w_i \ln \left(\eta \sum_{j=1}^{J} c_{\mathrm{ij}}^n - c_i^{n,\min} + 1 \right) \tag{1}$$

where η is average charging efficiency from discharging PHEVs to CV_i^n. $w_i = \frac{\tau}{STO_i^n}$ is the charging willingness of CV_i^n, and τ is a constant.

For the discharging PHEVs, d_{ji}^n is the amount of electricity supply from discharging PHEV DV_j^n to CV_i^n in LAG_n. The electricity supply vector of DV_j^n is $\mathbf{D}_{\mathbf{j}}^{\mathbf{n}} \triangleq \{d_{ji}^n | i \in \mathbb{R}\}$. In LAG_n, the total electricity supply of all discharging PHEVs is $\mathbf{D}^{\mathbf{n}} \triangleq \{\mathbf{D}_{\mathbf{j}}^{\mathbf{n}} | j \in \mathbb{Z}\}$. The maximum of electricity supply for a discharging PHEV in LAG_n is $\mathrm{D}_j^{n,\max}$. In LAG_n, the cost function of DV_j^n is

$$L_j(\mathbf{D}_{\mathbf{j}}^{\mathbf{n}}) = l_1 \sum_{i=1}^{I} (d_{\mathrm{ji}}^n)^2 + l_2 \sum_{i=1}^{I} d_{\mathrm{ji}}^n \tag{2}$$

where l_1 and l_2 are cost factors. Here, $l_1 > 0$.

Since the local charging PHEVs want to maximize their utilities while the local discharging PHEVs try to minimize their cost, LAG_n working as the energy broker not only tries to meet the demand of charging PHEVs, but also maximize electricity allocation efficiency. From a social perspective, the localized P2P electricity trading should maximize social welfare and achieve effective market equilibrium [15]. The energy broker addresses the social welfare maximization problem (denoted as SW) to allocate energy between discharging PHEVs and charging PHEVs. Here, the objective function of social welfare problem is expressed as follows:

$$SW : \max_{\mathbf{C}^{\mathbf{n}}, \mathbf{D}^{\mathbf{n}}} \sum_{i=1}^{I} U_i(\mathbf{C}_{\mathbf{i}}^{\mathbf{n}}) - \sum_{j=1}^{J} L_j(\mathbf{D}_{\mathbf{j}}^{\mathbf{n}}). \tag{3}$$

$$\text{Subject to: } c_i^{n,\min} \leq \eta \sum_{j=1}^{J} c_{\mathrm{ij}}^n \leq c_i^{n,\max}, \forall i \in \mathbb{C},$$

$$\sum_{i=1}^{I} d_{\mathrm{ji}}^n \leq \mathrm{D}_j^{n,\max}, \forall j \in \mathbb{Z},$$

$$\rho d_{\mathrm{ji}}^n = c_{\mathrm{ij}}^n, \forall i \in \mathbb{C}, \forall j \in \mathbb{Z},$$

$$c_{\mathrm{ij}}^n \geq 0, \forall i \in \mathbb{C}, \forall j \in \mathbb{Z}. \tag{4}$$

Here, ρ is average electricity transmission efficiency of the local electricity trading. The objective function in (3) is strictly concave with compact and convex constraints, so there exists a unique optimal solution using Karush–Kuhn–Tucker (KKT) conditions [16]. We carry out relaxation of constraints yielding the following Lagrangian L_1:

$$\begin{aligned} L_1(\mathbf{C}^{\mathbf{n}}, \mathbf{D}^{\mathbf{n}}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}) &= \sum_{i=1}^{I} U_i(\mathbf{C}_{\mathbf{i}}^{\mathbf{n}}) - \sum_{j=1}^{J} L_j(\mathbf{D}_{\mathbf{j}}^{\mathbf{n}}) \\ &+ \sum_{i=1}^{I} \alpha_i \left(c_i^{n,\min} - \eta \sum_{j=1}^{J} c_{\mathrm{ij}}^n \right) + \sum_{i=1}^{I} \beta_i \left(\eta \sum_{j=1}^{J} c_{\mathrm{ij}}^n - c_{i,n}^{\max} \right) \\ &+ \sum_{j=1}^{J} \gamma_j \left(\sum_{i=1}^{I} d_{\mathrm{ji}}^n - D_{j,n}^{\max} \right) + \sum_{j=1}^{J} \sum_{i=1}^{I} \lambda_{\mathrm{ij}} (\rho d_{\mathrm{ji}}^n - c_{\mathrm{ij}}^n) \\ &- \sum_{j=1}^{J} \sum_{i=1}^{I} \mu_{\mathrm{ij}} c_{\mathrm{ij}}^n. \end{aligned} \tag{5}$$

Here, α_i, β_i, γ_i, λ_{ij}, and μ_{ij} are Lagrange multipliers for the constraints in (4). The corresponding sets are $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, $\boldsymbol{\lambda}$, and $\boldsymbol{\mu}$. From the stationary conditions, the optimal solution of SW meets following conditions:

$$\begin{aligned} \nabla_{c_{\mathrm{ij}}^n} L_1(\mathbf{C}^{\mathbf{n}}, \mathbf{D}^{\mathbf{n}}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}) &= \frac{\eta w_i}{\eta \sum_{j=1}^{J} c_{\mathrm{ij}}^n - c_i^{n,\min} + 1} \\ &- \eta \alpha_i + \eta \beta_i - \lambda_{\mathrm{ij}} - \mu_{\mathrm{ij}} = 0, \end{aligned} \tag{6}$$

$$\begin{aligned} \nabla_{d_{\mathrm{ji}}^n} L_1(\mathbf{C}^{\mathbf{n}}, \mathbf{D}^{\mathbf{n}}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}) &= -2 l_1 d_{\mathrm{ji}}^n - l_2 + \gamma_j \\ &+ \lambda_{\mathrm{ij}} \rho = 0. \end{aligned} \tag{7}$$

For the social welfare maximization problem, it is necessary for the energy broker to obtain true and complete information of all PHEVs' utility and cost functions, and thus to solve the problem using (6) and (7). The complete information of PHEVs includes current energy state, battery capacity and so on, which is private information for PHEVs. However, the PHEVs may not be willing to provide the above private information to the energy broker. To address the issue, the energy broker needs to design a mechanism to extract hidden information from the PHEVs. As each PHEV tries to maximize its own utility, the PHEVs are price taking entities that make the electricity trading market competitive. A double auction is efficient to elicit the hidden information in a real and competitive electricity trading market with enough PHEVs, which is individually rational and weakly budget balanced [17]. The individually rational and weakly budget balanced characteristics of double auction mean that the PHEVs bid truthfully according to privacy information and the energy broker would not lose money to conduct the auction, respectively.

V. Iterative Double Auction Mechanism

In this section, an iterative double auction mechanism is proposed to elicit hidden information about PHEVs to energy brokers in order to maximize social welfare. In a hotspot, an energy broker acts as an auctioneer to perform an iterative double auction according to buying prices from charging PHEVs and selling prices from the discharging ones. In this way, the auctioneer determines the final trading prices and the amount of traded electricity, which is useful to avoid directly revealing private information of PHEVs during electricity trading. More specifically, each charging PHEV CV_i submits a bid price $b_{\mathrm{ij}} \geq 0$ for each discharging PHEV DV_j to the auctioneer. And each discharging PHEV DV_j also submits a bid price $s_{\mathrm{ji}} \geq 0$ for each charging PHEV CV_i to the auctioneer. After receiving these bid prices, the auctioneer solves an optimal energy allocation problem based on the bids from PHEVs, and thus allocates electricity for every PHEV to achieve effective market equilibrium [17].

A. Entities in the Double Auction Mechanism

1) Charging PHEVs: The bid price vector of CV_i for buying energy in LAG_n is $\mathbf{B_i^n} \triangleq \{b_{\mathrm{ij}}^n | j \in \mathbb{Z}\}$. All bid prices of charging PHEVs in LAG_n are denoted as $\mathbf{B^n} \triangleq \{\mathbf{B_i^n} | i \in \mathbb{C}\}$. CV_i needs to solve the following optimal electricity buying problem $(EB, buyer)$ to determine its optimal bid price:

$$EB : \max_{\mathbf{B_i^n}} [U_i(\mathbf{C_i^n}) - pay_i(\mathbf{B_i^n})] \tag{8}$$

where $pay_i(\mathbf{B_i^n})$ is the payment function of CV_i given by the auctioneer.

2) Discharging PHEVs: The bid price vector of DV_j for selling electricity in LAG_n is denoted as $\mathbf{S_j^n} \triangleq \{s_{\mathrm{ji}}^n | i \in \mathbb{C}\}$. The bid price matrix of selling electricity is $\mathbf{S^n} \triangleq \{\mathbf{S_j^n} | j \in \mathbb{Z}\}$. DV_j solves an optimal electricity selling problem $(ES, seller)$ to determine its optimal bid price as follows:

$$ES : \max_{\mathbf{S_j^n}} [Rew_j(\mathbf{S_j^n}) - L_j(\mathbf{D_j^n})] \tag{9}$$

where $Rew_j(\mathbf{S_j^n})$ is a reward function of DV_j given by the auctioneer.

3) Auctioneer: The bid price matrices from charging and discharging PHEVs are submitted to the auctioneer for performing an iterative double auction mechanism with multiple iterations. The buyers and sellers respectively solve their own optimal electricity buying and selling problems at each iteration to update bid price vectors according to the auctioneer's newly allocated demand and supply, respectively. The auctioneer solves the following optimal allocation problem A to calculate the amount of traded electricity [18]:

$$A : \max_{\mathbf{C^n}, \mathbf{D^n}} \sum_{i=1}^{I} \sum_{j=1}^{J} [b_{\mathrm{ij}}^n \ln c_{\mathrm{ij}}^n - s_{\mathrm{ji}}^n d_{\mathrm{ji}}^n] \tag{10}$$

subject to the same constraints in (4). From (10), if the bid prices of charging and discharging PHEVs are given, the auctioneer can solve *Problem* A. Note that both *Problems* A and SW have the same constraints. *Problem* A is also strictly concave, which ensures that there exists a unique optimal solution for A. For (10), we carry out constraint relaxation through Lagrangian L_2. To ensure that the optimal solution of *Problem* A also solves *Problem* SW, it is necessary that all KKT conditions along with the stationary conditions are matched for both *Problem* A and *Problem* SW. Therefore, L_2 and L_1 have the same Lagrange multipliers. Applying the stationary conditions yield

$$\nabla_{c_{\mathrm{ij}}^n} L_2(\mathbf{C^n}, \mathbf{D^n}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \frac{b_{\mathrm{ij}}^n}{c_{\mathrm{ij}}^n} - \eta\alpha_i + \eta\beta_i - \lambda_{\mathrm{ij}} - \mu_{\mathrm{ij}} = 0, \tag{11}$$

$$\nabla_{d_{\mathrm{ji}}^n} L_2(\mathbf{C^n}, \mathbf{D^n}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}) = -s_{\mathrm{ji}}^n + \gamma_j + \lambda_{\mathrm{ij}}\rho = 0. \tag{12}$$

As the KKT conditions are the same, clearly, from (6), (7), (11), and (12), it is known that

$$b_{\mathrm{ij}}^n = \frac{\eta\tau c_{\mathrm{ij}}^n}{\left(\eta \sum_{j=1}^{J} c_{\mathrm{ij}}^n - c_i^{n,\min} + 1\right) STO_i^n}, \tag{13}$$

$$s_{\mathrm{ji}}^n = 2l_1 d_{\mathrm{ji}}^n + l_2. \tag{14}$$

Note that, if the bid prices of charging and discharging PHEVs, respectively, satisfy (13) and (14), both the optimal solution of *Problem* A and *Problem* SW are the same.

B. Pricing Rules

The payment function of CV_i and the reward function of DV_j are, respectively, expressed as

$$pay_i(\mathbf{B_i^n}) = \sum_{j}^{J} b_{\mathrm{ij}}^n, \tag{15}$$

$$Rew_j(\mathbf{S_j^n}) = \sum_{i}^{I} \frac{(s_{\mathrm{ji}}^n)^2}{4l_1} + r_j^{\min}. \tag{16}$$

For stimulation, $r_j^{\min}$ is a minimum reward for a discharging PHEV owing to the participation in local electricity trading.

Theorem 1: The pricing rules based on (15) and (16) make the optimal buying price and optimal selling price satisfy (13) and (14), respectively.

Proof: For CV_i, the optimal buying price satisfies the following condition from (8)

$$\frac{\partial U_i(\mathbf{C_i^n})}{\partial b_{\mathrm{ij}}^n} - \frac{\partial pay_i(\mathbf{B_i^n})}{\partial b_{\mathrm{ij}}^n} = 0. \tag{17}$$

According to (15), we obtain, $\frac{\partial U_i(\mathbf{C_i^n})}{\partial b_{\mathrm{ij}}^n} = \frac{\partial U_i(\mathbf{C_i^n})}{\partial c_{\mathrm{ij}}^n} \frac{\partial c_{\mathrm{ij}}^n}{\partial b_{\mathrm{ij}}^n} = \frac{\partial pay_i(\mathbf{B_i^n})}{\partial b_{\mathrm{ij}}^n} = 1$. Hence,

$$b_{\mathrm{ij}}^n = \frac{\partial U_i(\mathbf{C_i^n})}{\partial c_{\mathrm{ij}}^n} c_{\mathrm{ij}}^n = \frac{\eta\tau c_{\mathrm{ij}}^n}{(\eta \sum_{j=1}^{J} c_{\mathrm{ij}}^n - c_i^{n,\min} + 1) STO_i^n}. \tag{18}$$

Here, (18) and (13) are the same.

For DV_j, the optimal buying price satisfies the following condition from (9)

$$\frac{\partial Rew_j(\mathbf{S_j^n})}{\partial s_{\mathrm{ji}}^n} - \frac{\partial L_j(\mathbf{D_j^n})}{\partial s_{\mathrm{ji}}^n} = 0. \tag{19}$$

According to (16), we obtain, $\frac{\partial L_j(\mathbf{D}_\mathbf{j}^\mathbf{n})}{\partial s_{\mathrm{ji}}^n} = \frac{\partial L_j(\mathbf{D}_\mathbf{j}^\mathbf{n})}{\partial d_{\mathrm{ji}}^n}\frac{\partial d_{\mathrm{ji}}^n}{\partial s_{\mathrm{ij}}^n} = \frac{\partial Rew_j(\mathbf{S}_\mathbf{j}^\mathbf{n})}{\partial s_{\mathrm{ji}}^n} = \frac{s_{\mathrm{ji}}^n}{2l_1}$. Thus, we have

$$\frac{\partial d_{\mathrm{ji}}^n}{\partial s_{\mathrm{ij}}^n} = \frac{s_{\mathrm{ji}}^n}{2l_1(2l_1 d_{\mathrm{ji}}^n + l_2)}. \tag{20}$$

Based on (20), we consider that there exist linear correlations between s_{ji}^n and d_{ji}^n. We can easily obtain that

$$s_{\mathrm{ji}}^n = 2l_1 d_{\mathrm{ji}}^n + l_2. \tag{21}$$

Equations (21) and (14) are also the same. It is known that the pricing rules based on (15) and (16) can make optimal prices satisfy (13) and (14), respectively.

Algorithm 1: Iterative Double Auction Algorithm.

// $RDB = \left|b_{\mathrm{ij}}^{n^{(t)}} - b_{\mathrm{ij}}^{n^{(t-1)}}\right| / b_{\mathrm{ij}}^{n^{(t)}}$,
$RDS = \left|s_{\mathrm{ji}}^{n^{(t)}} - s_{\mathrm{ji}}^{n^{(t-1)}}\right| / s_{\mathrm{ji}}^{n^{(t)}}$.

Input: $\varepsilon, \eta, \tau, STO^n$;
Initialization: $\mathbf{B}^{\mathbf{n}^{(0)}}, \mathbf{S}^{\mathbf{n}^{(0)}}, t \leftarrow 0, flag \leftarrow 1$, $trigger \leftarrow 0$;
while $flag$ and $\sim trigger$ **do**
  if Participating PHEVs of current localized P2P electricity trading change **then**
    $trigger \leftarrow 1$, and the auctioneer terminates the procedure and prepares to restart Algorithm 1.
  else
    Based on $\mathbf{B}^{\mathbf{n}(t)}$ and $\mathbf{S}^{\mathbf{n}(t)}$, the auctioneer solves *Problem* A to get $\mathbf{C}^{\mathbf{n}^{(t)}}$ and $\mathbf{D}^{\mathbf{n}^{(t)}}$, and then broadcasts the optimized results to charging PHEVs and discharging PHEVs, respectively.
    Based on $\mathbf{C}^{\mathbf{n}^{(t)}}$ and $\mathbf{D}^{\mathbf{n}^{(t)}}$, charging PHEVs compute their optimal bid prices $\mathbf{B}^{\mathbf{n}^{(t+1)}}$ through solving *Problem* EB, and submit them to the auctioneer;
    Based on $\mathbf{C}^{\mathbf{n}^{(t)}}$ and $\mathbf{D}^{\mathbf{n}^{(t)}}$, discharging PHEVs compute their optimal bid prices $\mathbf{S}^{\mathbf{n}^{(t+1)}}$ through solving *Problem* ES, and also submit them to the auctioneer;
    $t \leftarrow t + 1$;
    if $RDB < \varepsilon$ and $RDS < \varepsilon$, **then**
      $flag \leftarrow 0, t \leftarrow t - 1$.
    end if
  end if
end while
Output: $\mathbf{C}^{\mathbf{n}(t)}, \mathbf{D}^{\mathbf{n}(t)}, \mathbf{B}^{\mathbf{n}(t+1)}, \mathbf{S}^{\mathbf{n}(t+1)}$

C. Algorithm Implementation

According to the proposed mechanism, the charging PHEVs and the discharging PHEVs submit initial bid price vectors (i.e., $\mathbf{B}^\mathbf{n}$ and $\mathbf{S}^\mathbf{n}$) based on their preferences to the auctioneer in the first iteration. Through these initial bid prices, the auctioneer solves *Problem* A to allocate the electricity demand and supply based on their individual bids. The auctioneer broadcasts a new allocation solution to the charging and discharging PHEVs. Then these PHEVs solve their own *Problem* ES and *Problem* EB in order to obtain optimal bid prices for the next iteration. The auctioneer checks a termination condition of Algorithm 1 based on newly submitted bid prices from the PHEVs. Here, the termination condition is that whether the newest bid prices satisfy the convergence criteria (i.e., $RDB < \varepsilon$ and $RDS < \varepsilon$) or not. If not, the entities in this algorithm repeatedly execute the above steps. *Problems* EB, ES, and A can be solved through multiple iterations. Here, ε determines the execution time of Algorithm 1 and accuracy of final results. When ε becomes smaller, the final results will get closer to the optimal values but increase time and iterations of the algorithm. Selection of the value of ε is a tradeoff between time and accuracy of the algorithm.

In addition, auctioneers monitor localized P2P electricity trading in real time. When some unexpected events happen, e.g., abrupt disconnection of scheduled PHEVs, a trigger will be activated. Then the auctioneers may restart Algorithm 1 and reinitialize parameters on demand. A new electricity trading procedure is executed in time. Besides, similar to that in [6], we consider that few PHEVs suddenly leave from scheduled trades in parking lots during a specified scheduling time period. The abruptly disconnected PHEVs will be held accountable and will be made pay for a penalty of disconnection. This algorithm is performed with acceptable overheads in practice with low frequency of restart. More details on the iterative double auction are given in Algorithm 1.

According to (18) and (21), it is known that each PHEV will bid truthfully and maximize their own utilities through solving *Problems* EB and ES. Each PHEV's utility is nonnegative. Our proposed auction is weakly budget balanced because the auctioneer does not suffer any loss while conducting the iterative double auction. Therefore, our proposed auction is truthful, individually rational, weakly budget balanced. This auction can achieve an optimal energy allocation solution with optimal social welfare in the energy market, where the auctioneer does not have complete information about PHEVs' utility and cost functions for privacy protection [14], [17].

VI. Security Analysis and Numerical Results

A. Security Analysis

PETCON has defense ability against many traditional security attacks through standard cryptographic primitives including asymmetric and symmetric key-based encryption. Meanwhile, the adversary cannot simulate an entity or forge messages of an entity due to its attached digital signatures in the messages.

PETCON can also satisfy the following blockchain-related security requirements:

1) *Without reliance on the only trusted third party*: PHEVs trade electricity in a P2P manner without a third party to make system robust and scalable.
2) *Privacy protection*: Due to the iterative double auction mechanism, PHEVs only submit bid prices to the auctioneer without private information during trading. All energy coin accounts of PHEVs are pseudonymous by

Fig. 4. Distribution of parking lots in the real map of Texas.

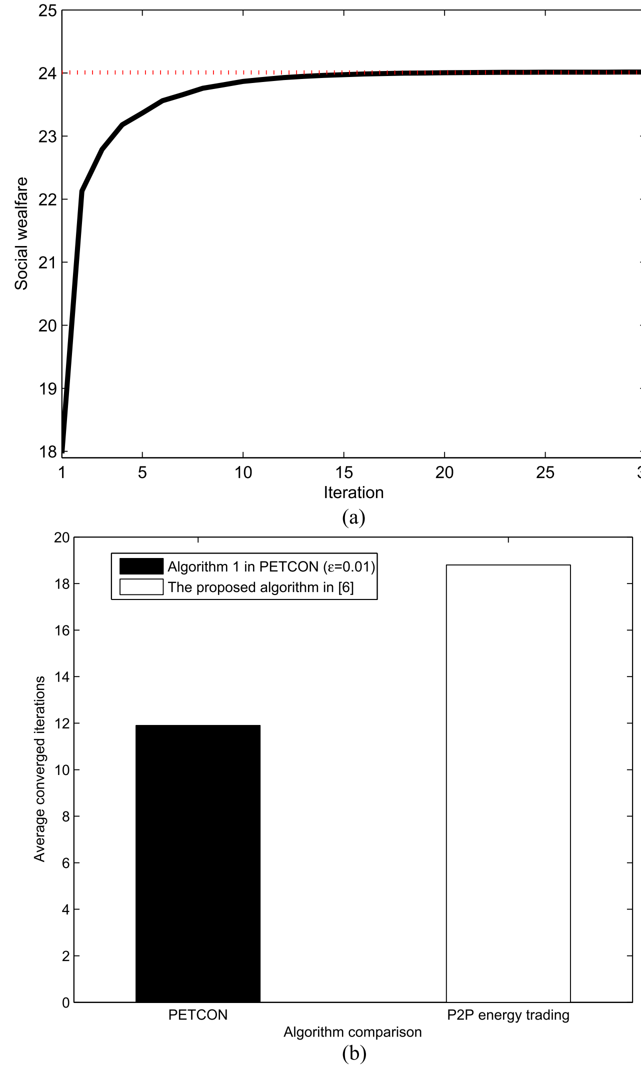

Fig. 5. (a) Evolution of social welfare with PETCON, (b) comparison between algorithms in terms of iterations.

multiple wallet addresses, it is useful to protect identity privacy and account security.

3) *Wallet security*: Without corresponding keys and certificates, no adversary can open a PHEV's wallet and steal energy coins from the wallet.
4) *Transaction authentication*: With the help of proof-of-work, all transaction data is publicly audited and authenticated by authorized LAGs. It is impossible to compromise all entities in our system due to overwhelming cost.
5) *Data unforgeability*: The decentralized nature of consortium blockchain combined with digitally signed transactions ensure that an adversary cannot pose as the user or corrupt the network, as that would imply the adversary forged a digital signature, or gained control over the majority of system resources.
6) *No double-spending*: Energy coin relies on digital signatures to prove ownership and a public history of transactions to prevent double-spending.

B. Numerical Results

We evaluate the performance of the proposed iterative double auction mechanism based on a real dataset [19] in a real urban area of Texas [20]. The latitude of observed area is from 30.256 to 30.276, and the longitude is from -97.76 to -97.725. The observed area is approximately 2.22×3.88 km^2 including 58 parking lots (see Fig. 4). We formulate electricity consumption behavior of PHEV as recorded in [19] and real data analysis in [6]. Therefore, we set the battery capacity of the PHEVs to 24 KWh. The minimum and maximum of electricity demand for charging PHEVs are $[5, 10]$ KWh and $[12, 18]$ KWh, respectively. The maximum of electricity supply for discharging PHEVs is $[10, 20]$ KWh. The cost factors of cost function, i.e., l_1 and l_2 in (2), are set to 0.01 and 0.015, respectively. The average charging efficiency η is 0.8 and the average electricity transmission efficiency ρ is 0.9. The minimum reward for a discharging PHEV $r_j^{\min}$ randomly ranges from 1 to 2 dollars. The convergence threshold ε is 0.001. We take a parking lot with 35 charging PHEVs and 45 discharging in LAG_1 as an example.

Fig. 5(a) shows the convergence evolution of social welfare achieved by our Algorithm 1. Note that the social welfare rapidly converges close to the optimal one (i.e., the dotted line) after 12 iterations. Fig. 5(b) shows iteration convergence comparison between Algorithm 1 used for PETCON and the P2P energy trading algorithm in [6]. After 1000 experiments of electricity trading with different energy demands from PHEVs, the average converged iterations of Algorithm 1 is 11.9, which is 36.7% less than that in [6]. From the figures, it is clear that our proposed Algorithm 1 is faster than the algorithm in [6].

Fig. 6 shows performance comparison between our PETCON and a hybrid energy trading model in [7]. In the hybrid energy trading model, energy buyers can not only trade electricity with local energy seller but also with the smart grid. Unlike so, we focus on localized P2P electricity trading between charging PHEVs (i.e., energy buyers) and discharging PHEVs (i.e., energy sellers) with 90% electricity transmission efficiency [21]. While there exist high energy transmission losses between the smart grid and energy buyers and sellers resulting in low

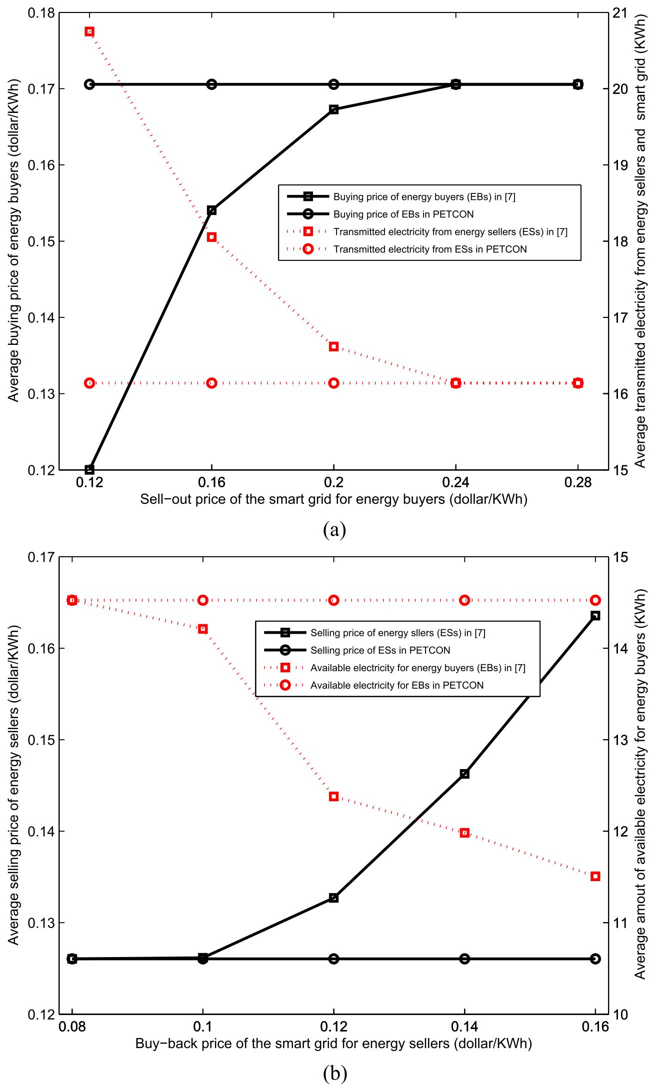

Fig. 6. (a) Average buying price and transmitted electricity, (b) average selling price and available electricity.

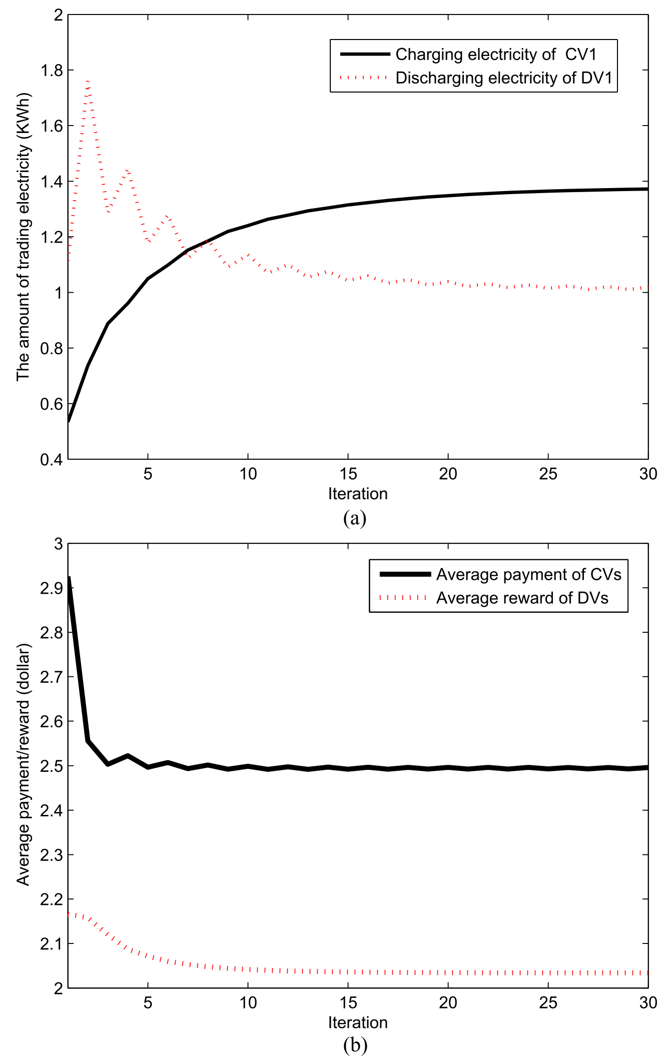

Fig. 7. Evolution of (a) amount of trading electricity and (b) average payment and average reward of PHEVs.

transmission efficiency (only 70%) [21]. Fig. 6(a) shows that when the sell-out price of the smart grid for energy buyers is smaller than that of local discharging PHEVs, the energy buyers obtain more benefits in [7] because of lower average buying price. However, because of high transmission losses, the average amount of transmitted electricity from both energy sellers and the smart gird is higher than that of PETCON. If the sell-out price of the smart grid is too high, the energy buyers will buy electricity from local energy sellers instead of the smart grid in [7], then obtain the same benefits as our PETCON. Similar results can be found in Fig. 6(b). Although the average selling price of energy sellers increases with the increasing buy-back price given by the smart grids in [7], the average available electricity for energy buyers is decreasing because of higher energy losses during electricity transmission. Therefore, compared with the trading model in [7], our PETCON has less energy loss and higher electricity utilization efficiency from the system's perspective.

Fig. 7(a) shows the convergence evolution of charged electricity and discharged electricity among PHEVs. Here, we randomly choose a charging PHEV (CV_1) and a discharging PHEV (DV_1) to observe their convergence evolution. The amount of CV_1's charged electricity from all the discharging PHEV converges when the number of iterations is 25, while DV_1 also finally converges after 30 iterations. Fig. 7(b) shows the convergence evolution of average payment for 35 charging PHEVs and average reward of 45 discharging PHEVs. The average payment of charging PHEVs for discharging PHEVs finally converges to 2.50 dollars. And the average reward of discharging PHEVs converges to 2.04 dollars after a few iterations. The difference between payment of charging PHEVs and reward of discharging PHEVs is the benefit of the auctioneer.

VII. Conclusion

We have proposed a localized P2P electricity trading model for PHEVs in smart grids. A consortium blockchain has been exploited to design a localized P2P electricity trading system, where charging and discharging PHEVs can trade electricity without reliance on a trusted third party. In this model, an iterative double auction mechanism for charging and discharging PHEVs is presented to maximize social welfare. The LAGs work as auctioneers to carry out the double auction among PHEVs according to their bid prices, which does not require private information about PHEVs. Security analysis shows that our proposed method can improve transaction security and privacy protection. Numerical results based on a real map indicate that the iterative double auction mechanism maximizes the social welfare.

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