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A Bayesian Game based Vehicle-to-Vehicle Electricity Trading Scheme for Blockchain-enabled Internet of Vehicles

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***Abstract*—With ever increasing people's awareness of low carbon and environmental protection, electric vehicles are gradually gaining wide popularity. However, the driving endurance of the electric vehicle is the biggest shortage that hinders the fully acceptance of this new vehicle technology. To deal with this shortage, this paper proposed a vehicle-to-vehicle (V2V) electricity trading scheme based on Bayesian game pricing in blockchain-enabled Internet of vehicles (BIoV). Specifically, the Bayesian game is adopted for pricing in the distributed BIoV with incomplete information sharing. The optimal pricing under the linear strategic equilibrium has been obtained which maximizes the utilities of both sides of electricity transaction. The transaction volume is determined from the formulated convex problem that maximizes the social welfare. Then, the pricing game is implemented by the dedicated smart contract. Blockchain guarantees its trustworthiness, security, and reliability. Finally, the experimental results show that referring to the benchmark of static game with complete information, the proposed Bayesian game with incomplete information can achieve approximate satisfaction of users. The degree of approximation can reach to 98% when the pricing ranges of buyers and sellers are close. Moreover, the proposed scheme has great advantages over the static game with complete information in terms of communication overhead and timeliness in the decentralized IoVs.**

***Key words*—Blockchain, Internet of vehicles, vehicle-to-vehicle, electricity trading, Bayesian game**

I. INTRODUCTION

The emergence of electric vehicles in the new energy market has great potential to ease the fossil fuel crisis and reduce toxic gas emissions, which has attracted worldwide attention. Electric vehicles have many advantages such as energy saving, emission reduction and environmental protection. However, the comprehensive development of electric vehicles still faces many challenges and bottlenecks. On the one hand, the driving endurance of electric vehicles is not strong enough to meet vehicle users' expectation, which brings certain inconvenience to long-distance travel. On the other hand, with the popularization of electric vehicles, the peak-valley gap of power grid load may become more obvious. In recent years, vehicle-to-vehicle (V2V) electricity trading as a new and flexible charging mode has been proposed and widely studied. Based on the self-advantages of electric vehicles, it is expected to enhance the cooperation between the vehicles to prolong the driving endurance and also effectively avoid the power grid overload problem.

There are many entities involved in the Internet of vehicles (IoV), and the transactions are scattered distributed. Therefore, it is a challenging problem to ensure the information security of users. The emergence of new technologies such as the Internet of things, artificial intelligence and blockchain have made great impact on the related fields of information technology [1]. In particular, blockchain is a decentralized transaction and data management technology which gained popularity since 2008 when S. Nakamoto posted the white paper - a blockchain application of a digital currency [2]. Blockchain technology makes use of the existing achievements of modern cryptography, including hash, digital signature, Merkle tree data structure, etc. The advantages of cryptography provide privacy protection and security protection for blockchain system. Besides, the consensus protocol is used to enable all nodes in the whole system to exchange data freely and safely in the untrusted environment. Further, the smart contract uses programmable algorithm to replace the traditional arbitration and contract execution. Smart contract is executed autonomously when the conditions programed in its source code are met. Within the blockchain environment, the smart contract can be executed in a trustworthy, transparent, and reliable way.

In this paper, a V2V electricity trading scheme in blockchain-enabled Internet of vehicles (BIoV) is proposed. Blockchain technology helps to guarantee the trustworthiness, security, and reliability of electricity transactions. Firstly, with blockchain, the public/private key pair and digital signature are adopted to solve the concern of the security of vehicle users. Secondly, the pricing mechanism is written into the smart contract for electricity transaction, which not only reduces the dependence on the middleman to the greatest extent, but also realizes the fairness of the transaction. Finally, all transactions can be permanently and accurately recorded on the blockchain ledger, which enables the traceability of transactions.

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The contributions of this paper are summarized as follows:

1) A V2V electricity trading scheme based on blockchain is proposed. All transactions can be recorded permanently and accurately on the blockchain ledger, which provides a secure trading platform for electric vehicle users. Simultaneously, smart contracts act as pricing agencies. When the transaction occurs, the trading mechanism designed in the smart contract is executed.
2) It is not trivial to acquire the full information in the decentralized IoV network timely, due to that communication and computation load grow exponentially with network size. The Bayesian game is adopted for pricing in the distributed BIoV with incomplete information sharing. The optimal pricing under the linear strategic equilibrium has been obtained which maximizes the utilities of both sides of electricity transaction, which stimulates the electric vehicle users to participate in the electricity trading. The transaction volume is determined from the formulated convex problem that maximizes the social welfare.
3) Finally, the electricity transaction between vehicle users based on blockchain is simulated, and the electricity trading mechanism of V2V is analyzed from different perspectives. Referring to the electricity trading based on the static game with complete information, when the electricity value range of buyers and sellers is close, the user satisfaction with incomplete information is close to 98% approximately. Furthermore, compared with a single fixed price, the pricing mechanism based on linear strategy proposed by this paper can make vehicle users get more benefits.

The remainder of this paper is organized as follows. Sec. II introduces the related work. The blockchain-based system model will be described in detail in Sec. III. Sec. IV presents and introduces V2V energy trading scheme in detail. Sec. V verifies the validity and feasibility of the proposed trading scheme through simulation experiment. Finally, Sec. VI concludes this paper.

II. Related Work

Internet of Things (IoT) is characterized by heterogeneous technologies, which concur to the provisioning of innovative services in various application domains [10]. With the development of new technologies, vehicles will no longer be isolated units, but become active network nodes [11]. Specially, the new era of IoT is driving the evolution of vehicular networks into IoV. With the rapid development of computation and communication technologies, IoV has possessed huge research value and attracted a large number of researchers. Kaiwartya *et al.* in [12] presented a comprehensive framework of IoV with emphasis on layered architecture, protocol stack, network model, challenges, and future aspects. Yang *et al.* in [13] proposed an abstract network model of the IoV, and presented different applications based on certain currently existing technologies. Zhang *et al.* in [14] proposed some measures to further promote the development of IoV. Singh *et al.* in [15] recommended a evaluation of lately proposed IoV architectures and deliberate their salient features. Ahmed *et al.* in [16] proposed a novel trust framework that studies all aspects of the trust in connected vehicle (CV) to CV communications. However, with the expansion of the vehicular network, the security of electricity trading is also a challenging issue.

In recent years, the emergence of blockchain technology has become a unique, most disruptive, and trending technology. Simultaneously, a lot of applications based on blockchain technology have emerged. Tanwar *et al.* in [17] presented detailed information on blockchian technology (BT) and machine learning (MT), along with their usages in smart applications and proposed an ML-BT based architecture. Bhattacharya *et al.* in [18] proposed a framework called as Blockchain-Based Deep Learning as-a-Service (BinDaaS), which integrates blockchain and deep-learning techniques for sharing the electronic health records among multiple healthcare users and operates. Mistry *et al.* in [19] presented an in-depth survey of state-of-the-art proposals having 5G-enabled IoT as a backbone for blockchain-based industrial automation for the applications such as Smart city, Smart Home, Healthcare 4.0, Smart Agriculture, Autonomous vehicles and Supply chain management.

The blockchain widely known as one of the disruptive technologies has emerged in recent years, has the potential to revolutionize intelligent transport system. Yuan *et al.* in [20] conducted a preliminary study of blockchain-based intelligent transportation systems. It is the first attempt in the literature to design the model and research framework, and discuss the potential applications of blockchain technology in transportation research. Lun *et al.* in [21] proposed an effective announcement network called CreditCoin, a novel privacy-preserving incentive announcement network based on blockchain via an efficient anonymous vehicular announcement aggregation protocol. Jiang *et al.* in [22] investigated how the blockchain technology could be extended to the application of vehicular network. Liu *et al.* in [23] proposed a novel deep reinforcement learning (DRL) based performance optimization framework for blockchain-enabled IoV. Chen *et al.* in [24] proposed a consortium blockchain-based data trading framework to provide a secure and truthful way for data trading in IoV. Li *et al.* in [25] exploited the consortium blockchain technology to propose a secure energy trading system named energy blockchain. Wang *et al.* in [26] introduced a novel permissioned energy blockchain system to implement secure energy delivery services for electric vehicles. Kang *et al.* in [27] proposed an enhanced DPoS consensus scheme with two-stage security solution. Aitzhan *et al.* in [28] implemented a proof-of-concept for decentralized energy trading system using blockchain technology. Huang *et al.* in [29] proposed a decentralized security model based on lightning network and smart contract.

To accommodate a large number of electric vehicles on the grid, it is necessary to coordinate their charging. Alvaro *et al.* in [30] presented a peer-to-peer (P2P) energy trading system between electric vehicles, which can be used to reduce the impact of peak power consumption on the power grid. Lin *et al.* in [31] created a mixed-integer linear programming model

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TABLE I: Comparison of the existing papers

Category	**Approach**	**Performance**		
		Security	Determinacy	Lowcost
· Centralized network with complete information	· Four-stage Stackelberg game to model the interactions among EVs, microgrids and the main grid [3].	✓	✗	✗
	· An energy scheduling algorithm to obtain the optimal allocation scheme to maximize the benefits to consumers [4].	✗	✓	✗
· Centralized network with incomplete information	· A comprehensive analysis of energy management strategies evolution toward blended mode and optimal control [5].	✗	✓	✗
· Decentralized network with complete information	· A fully distributed convex optimization solution for the plug-in electric vehicles cooperative charging [6].	✓	✗	✓
	· A distributed approach based on the progressive second price auction mechanism to coordinate the charging needs of electric vehicles [7].	✗	✓	✓
	· An Iceberg order execution algorithm based on blockchain to obtain an improved energy vehicle charging and discharging schedule [8].	✓	✗	✓
· Decentralized network with incomplete information	· An iterative double auction mechanism to maximize social welfare of the trading scheme [9].	✓	✓	✗
	· A Bayesian game based V2V electricity trading scheme for blockchain enabled Internet of vehicles in this paper.	✓	✓	✓

for a single user to reduce energy waste. Tedeschi *et al.* in [32] envisaged the possibility to implement bartering functionalities through blockchain and smart contracts. A contract needs to be signed between the two platforms, which will be sent as a multi-signature transaction and stored in the blockchain. In our V2V electricity trading scheme, smart contracts act as pricing agencies. When the transaction occurs, the trading mechanism designed in the smart contract is executed. Zou *et al.* in [7] adopted a distributed approach to coordinate the charging requirements of electric vehicles and ensure the compatibility of incentives. Chao *et al.* in [8] proposed an adaptive blockchain-based electric vehicle participation scheme. The objectives are to minimize the power fluctuation level in the grid network and overall charging cost for energy vehicle users. Kang *et al.* in [9] proposed a local P2P electricity trading model for locally buying and selling electricity among plug-in hybrid electric vehicles in smart grids. Wu *et al.* in [4] proposed the corresponding algorithm to solve the optimal transaction problem, and found the optimal transaction price effectively, as well as the optimal energy scheduling for each consumer and seller. Asfia *et al.* in [33] proposed a novel electric vehicles participation charging scheme for a decentralized blockchain using smart contracts to maximize utility for each individual.

To clarify the main difference between other papers and this paper, a comprehensive comparison has been shown in Tab. I. For V2V electricity trading schemes, existing researches are mostly based on modeling analysis of complete information. Each participant has accurate knowledge of the characteristics, strategic space and payment function of all other participants. However, it is all entities are not trivial to acquire the full information in the decentralized IoV network timely, due to that communication and computation load grow exponentially with network size. Therefore, the Bayesian game based V2V electricity trading scheme is proposed in the distributed BIoV with incomplete information sharing.

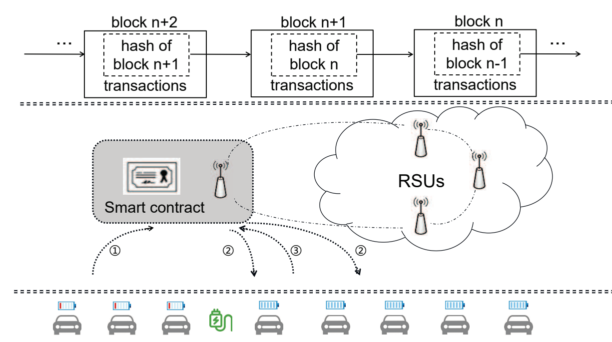

Fig. 1: Architectural description of electricity trading in BIoV.

III. System Description

Fig. 1 gives the schematic illustration of the electricity trading in BIoV. Two entities in the BIoV are concerned, i.e., electric vehicles and roadside units (RSUs). Electric vehicles, as mobile electricity storage carriers, are equipped with a “charge-discharge” two-way system. Specifically, there are two roles for vehicles, i.e., electricity buyer and electricity seller. One vehicle that needs to buy electricity from others is called electricity buyer. When one vehicle has enough electricity for its own use and a certain volume of surplus electricity, it can choose to be an electricity seller and trade electricity with buyers. RSUs coordinate charging and discharging between electric vehicles. With the blockchain technology, electric vehicles can trade the electricity in a decentralized but trustful way. Simultaneously, the smart contract, as the virtual agency, writes the Bayesian-game-based pricing mechanism. When a transaction occurs, the system will execute the deployed smart contract to obtain the optimal trading scheme.

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A. System Initialization

Each electric vehicle or RSU in BIoV becomes legitimate node after registration with the certificate authority (CA) by binding their identities in the real world, e.g., the license plate of each electric vehicle user. Assume that there are Q entity nodes in the system, each legitimate node $q \in \{1, 2, ..., Q\}$ in the blockchain gets its public/private key pair (PK_q , SK_q). Here, the public key PK_q can be seen as the pseudonym of node q and can be known by all the nodes in the blockchain, while the private key SK_q should be secretly kept by the node itself. Blockchain technology uses asymmetric cryptography to encrypt data, the personal information and transaction data of transaction users are securely protected. Specifically, the public key is used to encrypt data. Data encrypted with the public key can only be decrypted using the private key. After CA signs with its private key SK_{CA}, node q obtains its digital certificate DC_q, which can prove the authenticity of the user's identity. Each electric vehicle user has an account A_q, which is given as $A_q = (PK_q, SK_q, DC_q, E_q, B_q)$, where E_q is the total available electricity volume that node q possesses, B_q is the account balance of node q. When an electric vehicle user sells electricity as an electricity seller, E_q will decrease and B_q will increase in the account of the electricity seller. When an electric vehicle user requests to buy electricity as an electricity buyer, E_q will increase and B_q will decrease in the account of the electricity buyer. Smart meters built into each node calculate and record the volume of electricity traded in real time, and electricity buyers pay electricity sellers based on smart meter records.

B. Electricity Trading in BIoV

1) Electricity trading process: There are three roles in the BIoV we studied, i.e., electricity sellers, electricity buyers and RSUs as auctioneers. More details about operation steps of the electricity trading scheme are given as follows.

Step 1: As shown in Fig. 1, node q generate an electricity request $Req = \{role_q||ElecMsg_q||T_{stamp}\}$, where $role_q = (-1, 1)$ represents the role of electric vehicles in electricity trading, if $role_q = -1$, it means that the electric vehicle need to purchase electricity. Otherwise, $role_q = 1$ means that it has surplus electricity could sell to other electric vehicles. Here, $role_q = -1$. $ElecMsg_q$ contains the electricity demand information of electric vehicle user, which will be explained in detail in Section IV. T_{stamp} is the time stamp of the request message generation. Then the electric vehicle user signs Req with its private key SK_q and sends the request message $ReqMsg_q = \{Sign_{PK_q}(Req)||DC_q\}$ to the near RSU.

Step 2: When receiving electricity purchase request $ReqMsg_q$ from vehicle user, RSU checks the validity of the digital certificate by using CA's public key PK_{CA}. Firstly, check whether the certificate is out-of-date or not. Secondly, the public key PK_q can be obtained to verify the identity of the request sender. Finally, RSU gets the message contents by decrypting the Req with its private key.

Step 3: If the validation is successful, as shown in Fig. 1, RSU will broadcast the request message $Msg = \{ReqElec_q||T_{stamp}||T_{limit}\}$ to nearby electric vehicles, where $ReqElec_q$ contains electricity demand information which will be explained in detail in Section IV. Furthermore, in order to improve the efficiency of electricity transactions, T_{limit} denotes the time that RSU wait for the response of other electric vehicles, which limited the waiting time for a response.

Step 4: The nearby electric vehicle users received the broadcast message from the nearby RSU, as shown in Fig. 1, similar to the RSU authentication request message, the vehicle user verifies the message that RSU broadcast, and decides whether to sell its electricity, and generates a reply $Reply = \{role_{q^{'},q^{'} \neq q}||SupplyMsg_{q^{'}}||T_{stamp}\}$. Here $role_q^{'} = 1$, $SupplyMsg_{q^{'}}$ contains the electricity supply information, which will be explained in detail in Section IV. Finally, the electric vehicles who decide to sell electricity will send a message $ReqMsg_{q^{'}} = \{Sign_{PK_{q^{'}}}(Reply)||DC_{q^{'}}\}$ to the RSU.

Step 5: When received the response of the nearby electric vehicle, similar to the authentication request message, RSU receives the message contents by decrypting the $Reply$. Simultaneously, the RSU will check the current time t satisfies $t \leq T_{stamp} + T_{limit}$, if not satisfies, the reply of electric vehicle will be discarded.

When the RSU receives and validates the information submitted by the electricity buyers and the electricity sellers, it matches the transaction and obtains the optimal transaction scheme by triggering the pricing mechanism we designed in the smart contract. Electric vehicle users will conduct electricity trading according to the transaction results.

2) Building Blocks in BIoV: RSUs collect all local transaction records during a certain period, and then encrypt and digitally sign these records to guarantee the authenticity and accuracy of transactions. As shown in Fig. 1, the transaction records are structured into blocks. For traceability and verification, blocks are arranged in time-stamp order, and each block contains a cryptographic hash to the prior blocks in the blockchain.

3) Carrying Out Consensus Process: In this work, the Proof-of-Authority (PoA) [34] is chosen as the consensus mechanism. Unlike traditional Proof-of-Work (PoW), PoA does not require a lot of computation. With PoA, a preset set of signers in the system take turns generating blocks. Even if a malicious node is added to the signer list, it can only attack one of the block signatures each height. Simultaneously, the nodes in the authorization group can also vote to add new nodes or remove malicious nodes. Specifically, signer initiates a proposal through the API interface, which is broadcast to other nodes through the coinbase and nonce fields of the reuse block header. All authorized signers vote "join" for the new signer. When the affirmative vote exceeds 50% of the total number of authorized signers, the signer is allowed to join. Similarly, if an old signer needs to be kicked out, all authorized signers will vote "kick out" for the old signer. When the affirmative vote exceeds 50% of the total number of authorized signers, the signer will be kicked out. This greatly guarantees the security of blockchain network.

In our BIoV, the default authorized RSUs are responsible for generating blocks as signers. Each height has a signer in the IN-TURN state and other signers in the OUT-OF-TURN

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state. The signer signed block whose state is IN-TURN will be broadcast immediately, and the signer signed block whose state is OUT-OF-TURN will be broadcast after a little random time delay, so as to ensure that the in-turn signed block has a higher priority to generate blocks. The remaining RSUs verify and decide whether to add the current block to the blockchain.

C. Security and Reliability Analysis

Unlike traditional transactions based on intermediaries, within the blockchain environment, distributed nodes in the network jointly maintain and store transaction data, which makes the system operate at low cost and high reliability. In our V2V electricity trading scheme, blockchain technology helps to ensure the reliability of electricity trading and the data privacy security of vehicle users. Specifically, the security and reliability performances of BIoV are listed as follows.

1) *Not relying on a third party:* With the advent of blockchain technology, trust can be built on mathematics, technology and algorithms, instead of relying on third parties. In our BIoV, the authorized RSUs work together as distributed nodes to maintain transaction data on the network. Even if one node is under malicious attack, the rest can still guarantee the normal operation of the network. Therefore, the reliability of the system is ensured while the maintenance cost is reduced.
2) *Data encryption:* In the blockchain network, asymmetric encryption is performed using public/private key pairs. The public key is public to others, the private key is secretly kept by self, and no one else can deduce the corresponding private key from the public key. The message sender uses its private key to sign the message and sends it to the message receiver, who uses the public key of the message sender to decrypt the signature so as to ensure that the message is sent by information sender. Furthermore, the message receiver can use his private key to decrypt the message. In our BIoV, electric vehicle users communicate with RSU in this way to ensure that message content is not disclosed.
3) *Transaction validation:* In our BIoV, all transaction data is publicly reviewed and verified by all authorized RSUs. Due to the overwhelming cost, it is impossible to harm all entities in the blockchain. Even if a RSU is compromised, other RSUs will still find and correct problematic transaction data before constructing blocks. Furthermore, transaction records are permanently recorded in the blockchain ledger in the order of timestamp, which makes transactions traceable. For our decentralized electricity trading system, it provides a more secure and reliable trading platform.

IV. Bayesian-Game-Based Trading Scheme

In practical trading application, both RSUs and vehicles are not trivial to acquire the full information of the whole IoV network timely, due to communication and computation load exponentially related to network size. In such scenario, the Bayesian game has the potential to solve the V2V electricity pricing problem with incomplete information. The electricity buyers and the electricity sellers in the transaction have no accurate information about each other, and they hope that their expected utility can be maximized. The electricity pricing problem we need to solve is the final transaction price and volume. In this section, firstly, the Bayesian game based pricing mechanism is designed to maximize the utility of electricity buyers and electricity sellers. Next, the transaction volume under the maximized social welfare condition according to the pricing can be obtained. These mechanisms are integrated in smart contracts. When an electricity trading occurs, the smart contracts will be executed to complete the transaction.

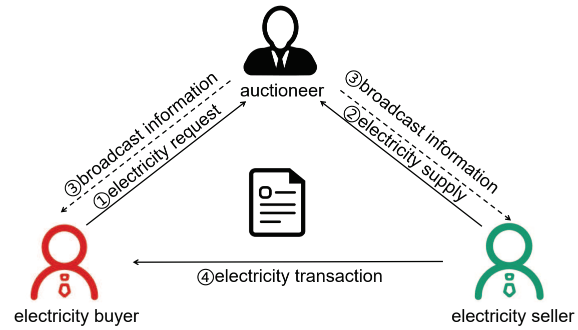

Fig. 2: The process of electricity trading.

A. V2V Electricity Trading Problem Formulation

Consider the IoVs consisting of two kinds of vehicles, i.e., electricity buyers and electricity sellers, and RSUs as auctioneers. For each buyer i, it requests electricity b_i, where $b_i \in [b_i^{\min}, b_i^{\max}]$. It means buyer i requires minimum electricity $b_i^{\min}$ for the necessary trip and can accept maximum electricity $b_i^{\max}$. For seller j, it has electricity s_j^{t} currently and would reserve electricity s_j^{r} for the necessary trip itself. It can provide electricity no more than s_j^{t} for trading. Furthermore, in our designed electricity trading scheme, for the sake of simplicity, the electricity sellers need to go to the place that the electricity buyer requests to make the electricity trading. d_{ji} is the distance between the electricity seller j and the electricity buyer i. When the electricity buyer receives the replies from multiple electricity sellers, the buyer can choose the vehicles close to itself to conduct the electricity trading, e.g.,1km, so as to meet the electricity demand more quickly.

In the transaction between electricity buyers and electricity sellers, b_{ij} is the electricity volume demand of electricity buyer i for electricity seller j. s_{ji} is the electricity volume supply from electricity seller j to electricity buyer i. As the demand from electricity buyers matches the supply from electricity sellers, therefore, b_{ij}=s_{ji}. Note that symbols used in this paper are summarized in Table. 1.

Fig. 2 shows the transaction process between electricity buyer and electricity buyer. First, to adapt to market price level, auctioneer needs to impose price restrictions on both the electricity buyer and the electricity seller to make the transactions more efficient. $v^{\min}$ declared by auctioneer, denotes the lower bound of electricity price for buyers. $c^{\max}$ indicates the upper bound of electricity price for sellers.

TABLE II: Symbol definition

Symbol	Definition
b_i	The demand vector of electricity buyer i, $i = 1, \ldots, N$, $b_i \in [b_i^{\text{min}}, b_i^{\text{max}}]$
s_j	The supply vector of electricity seller j $j = 1, \ldots, M$, $s_j \in [0, s_j^{\text{t}}]$
b_{ij}	The electricity volume demand of electricity buyer i from electricity seller j
s_{ji}	the electricity volume supply from electricity seller j to electricity buyer i
ρ_j	The electricity loss rate of electricity seller j during the trading
v_i	Electricity price proposed by electricity buyer i, where $v_i \in [v_i^{\text{min}}, v_i^{\text{max}}]$
c_j	Electricity price proposed by electricity seller j, where $c_j \in [c_j^{\text{min}}, c_j^{\text{max}}]$
v^{min}	The lower bound of electricity price for buyers declared by auctioneer, where $v^{\text{min}} \leq v_i^{\text{min}}$ for $i = 1, \ldots, N$
c^{max}	The upper bound of electricity price for sellers declared by auctioneer, where $c^{\text{max}} \geq c_j^{\text{max}}$ for $j = 1, \ldots, M$
T_{ij}	The transaction price between the electricity buyer i and the electricity seller j
$U(b_i)$	The utility function of electricity buyer i
$C(s_j)$	The cost function of electricity seller j
$P_{ij}(v_i)$	The price function of buyer i bid for seller j
$R_{ji}(c_j)$	The price function of seller j ask for buyer i

Electricity request: Electricity buyer i sends a request to auctioneer and submits the unit electricity value v_i, where $v_i \in [v_i^{\text{min}}, v_i^{\text{max}}]$. At the same time, electricity buyers need to submit their own minimum and maximum electricity demand, which is denoted by b_i^{min} and b_i^{max}, respectively.

Electricity supply: Electricity sellers receive electricity demand message from auctioneer. When a seller j chooses to sell its surplus electricity, it will submit the unit value c_j to auctioneer, where $c_j \in [c_j^{\text{min}}, c_j^{\text{max}}]$.

Broadcast information: After receiving the purchase demand information from the electricity buyer and the supply information from the electricity seller, The smart contract designed for the transaction will execute to get the optimal trading scheme. The auctioneer will broadcast the information to the sellers and buyers.

Electricity transaction: When the electricity buyers and electricity sellers receive the trading scheme, they will start to execute electricity trading according to the scheme.

B. *Bayesian game based pricing mechanism*

In this trading scheme, electricity sellers and buyers submit their electricity information to the auctioneer. The smart contract will be executed to calculate the bid price of the two parties to maximize their revenue. If the electricity buyer offers no more than the electricity seller's asking price, the transaction will be cancelled.

Here, assuming that the pricing of both parties satisfies the linear strategic equilibrium, then the price function of electricity buyer i bid for electricity seller j is assumed to be

$$P_{ij}(v_i) = \alpha_b + \beta_b v_i. \tag{1}$$

The price function of electricity seller j ask for electricity buyer i is assumed to be

$$R_{ji}(c_j) = \alpha_s + \beta_s c_j. \tag{2}$$

In this transaction scheme, both sides of the transaction are in the situation of incomplete information. Electricity buyers only know their unit electricity value of v_i. Similarly, electricity sellers only know their unit electricity value of c_j. Therefore, for electricity buyer, the optimal bidding scheme is to

$$\begin{aligned}\max_{P_{ij}} \ & [v_i - \frac{1}{2}(P_{ij} + E[R_{ji}(c_j)|P_{ij} \geq R_{ji}(c_j)])] \\ & \cdot Prob\{P_{ij} \geq R_{ji}(c_j)\},\end{aligned} \tag{3}$$

where $E[R_{ji}(c_j)|P_{ij} \geq R_{ji}(c_j)]$ means that under the condition that the electricity buyer's bid is not lower than the electricity seller's bid, the electricity buyer expects the electricity seller's bid. For electricity buyer, the optimal bidding scheme is to

$$\begin{aligned}\max_{R_{ji}} \ & [\frac{1}{2}(R_{ji} + E[P_{ij}(v_i)|P_{ij}(v_i) \geq R_{ji}]) - c_j] \\ & \cdot Prob\{P_{ij}(v_i) \geq R_{ji}\},\end{aligned} \tag{4}$$

where $E[P_{ij}(v_i)|P_{ij}(v_i) \geq R_{ji}]$ means that under the condition that the electricity buyer's bid is not lower than the electricity seller's bid, the electricity seller expects the electricity buyer's bid. Based on the bidding scheme, we have following theorem.

Theorem 1: In the Bayesian game based trading scheme, when the bid price of electricity buyers and electricity sellers satisfy formulas (5) and (6) respectively, the strategic combination $\{P_{ij}^*, R_{ji}^*\}$ is a Bayesian equilibrium, i.e.,

$$P_{ij}^* = \frac{1}{12}v_i^{\text{max}} + \frac{1}{4}c_j^{\text{min}} + \frac{2}{3}v_i, \tag{5}$$

$$R_{ji}^* = \frac{1}{12}c_j^{\text{min}} + \frac{1}{4}v_i^{\text{max}} + \frac{2}{3}c_j. \tag{6}$$

Proof: Assuming that c_j, v_i are evenly distributed over their respective intervals, then $Prob\{P_{ij} \geq R_{ji}(c_j)\}$ in (3) can be obtained as

$$\begin{aligned}Prob\{P_{ij} \geq R_{ji}(c_j)\} &= Prob\{P_{ij} \geq \alpha_s + \beta_s c_j^{\text{min}}\} \\ &= \frac{P_{ij} - \alpha_s - \beta_s c_j^{\text{min}}}{\beta_s(c_j^{\text{max}} - c_j^{\text{min}})},\end{aligned} \tag{7}$$

and $E[R_{ji}(c_j)|P_{ij} \geq R_{ji}(c_j)]$ in (3) can be obtained as

$$\begin{aligned}E[R_{ji}(c_j)|P_{ij} \geq R_{ji}(c_j)] &= \int_{\alpha_s+\beta_s c_j^{\text{min}}}^{P_{ij}} \frac{xdx}{P_{ij} - \alpha_s - \beta_s c_j^{\text{min}}} \\ &= \frac{1}{2}(\alpha_s + \beta_s c_j^{\text{min}} + P_{ij}).\end{aligned} \tag{8}$$

Similarly, $Prob\{P_{ij}(v_i) \geq R_{ji}\}$ and $E[P_{ij}(v_i)|P_{ij}(v_i) \geq R_{ji}]$ in (4) can be respectively obtained as

$$\begin{aligned}Prob\{P_{ij}(v_i) \geq R_{ji}\} &= Prob\{\alpha_b + \beta_b v_i^{\text{max}} \geq R_{ji}\} \\ &= \frac{\alpha_b + \beta_b v_i^{\text{max}} - R_{ji}}{\beta_b(v_i^{\text{max}} - v_i^{\text{min}})},\end{aligned} \tag{9}$$

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$$
\begin{aligned}
E[P_{ij}(v_i)|P_{ij}(v_i) \geq R_{ji}] &= \int_{R_{ji}}^{\alpha_b+\beta_b v_i^{\max}} \frac{xdx}{\alpha_b+\beta_b v_i^{\max}-R_{ji}} \\
&= \frac{1}{2}(\alpha_b+\beta_b v_i^{\max}+R_{ji}).
\end{aligned} \tag{10}
$$

Substitute the (7), (8) and (9), (10) into (3) and (4) respectively. Combine them with the (1) and (2), P_{ij}^* and R_{ji}^* are derived. The proof is finished. ∎

When the pricing equilibrium (P_{ij}^*, R_{ji}^*) is obtained, if the price P_{ij}^* of the electricity buyer i is not lower than the price R_{ji}^* of the electricity seller j, the transaction price $T_{ij} = \frac{P_{ij}^*+R_{ji}^*}{2}$. Otherwise, the transaction is not valid.

C. Optimization of electricity trading volume

From the perspective of social welfare, the V2V electricity trading scheme should maximize social welfare and effectively achieve market equilibrium. In our trading scheme, when electricity buyers and electricity sellers decide to trade electricity, the smart contract calculates the optimal transaction volume between electricity buyers and electricity consumers under the condition of maximizing social welfare. Here, the objective function of social welfare problem is expected as follows:

$$
\mathcal{P}1: \quad \max_{b_i,s_j} \sum_{i=1}^{I} U(b_i) - \sum_{j=1}^{J} C(s_j), \tag{11}
$$

$$
s.t. \quad b_i^{\min} \leq \sum_{j=1}^{J} b_{ij} \leq b_i^{\max}, \tag{12}
$$

$$
s_j^{\mathrm{t}} - \sum_{i=1}^{I}(1+\rho_j)s_{ji} \leq s_j^{\mathrm{r}}, \tag{13}
$$

$$
b_{ij} = s_{ji} \geq 0, \tag{14}
$$

where

$$
U(b_i) = w_i ln(\sum_{j=1}^{J} b_{ij} - b_i^{\min} + 1), \tag{15}
$$

$$
C(s_j) = l_1 \sum_{i=1}^{I} \rho_j (s_{ji})^2 + l_2 \sum_{i=1}^{I} \rho_j s_{ji}. \tag{16}
$$

Suppose that the willingness w_i of each electricity buyer with each electricity seller falls in [0, 5]. $l_1 > 0$ and $l_2 > 0$ are cost factor. Substitute (15) and (16) into (11). Then, the second-order partial derivatives satisfy $\frac{d^2(b_i)}{{db_i}^2} < 0$, $\frac{d^2C(s_j)}{{ds_j}^2} > 0$. Accordingly, the objective function (11) is strictly concave and the restriction conditions are also convex. The objective function has a unique optimal solution.

When electricity buyers and electricity sellers submit their respective quotations to the auctioneer, it needs to calculate the optimal transaction volumes according to their different needs. Referring to [35], the following optimization function is set for auctioneer to determine the transaction volumes, by which the maximum utility of traded energies can be achieved, i.e.,

$$
\mathcal{P}2: \quad \max_{b_i,s_j} \sum_{i=1}^{I}\sum_{j=1}^{J}[T_{ij}\ln b_{ij} - T_{ij}s_{ji}], \tag{17}
$$

$$
s.t. \quad (12),\ (13),\ \text{and}\ (14).
$$

It can be seen that $\mathcal{P}2$ is also a strictly concave function. In the following, the optimal transaction volume $\{b_{ij}^*, s_{ji}^*\}$ that satisfy both the social welfare in $\mathcal{P}1$ and electricity utility in $\mathcal{P}2$ are pursued. The results are presented in followed Theorem 2.

Theorem 2: The optimal transaction volume $\{b_{ij}^*, s_{ji}^*\}$ achieving the maximum social welfare can be derived by

$$
b_{ij}^* = s_{ji}^* = \frac{Tr_{ji} - l_2\rho_j}{2l_1\rho_j}. \tag{18}
$$

Proof: Since that $\mathcal{P}1$ and $\mathcal{P}2$ together with their constraints are all convex, the Karush-Kuhn-Tucher condition can be used to solve the both optimization problems. Specifically, $\alpha = \{\alpha_i|i=1,\ldots,I\}$, $\beta = \{\beta_i|i=1,\ldots,I\}$, $\gamma = \{\gamma_i|i=1,\ldots,I\}$, $\lambda = \{\lambda_{ij}|i=1,\ldots,I; j=1,\ldots,J\}$, $\mu = \{\mu_{ij}|i=1,\ldots,I; j=1,\ldots,J\}$ as Lagrange multipliers for constraints, the dual function of $\mathcal{P}1$ is

$$
\begin{aligned}
&F_1(b_i,s_j,\alpha,\beta,\gamma,\delta,\lambda,\mu) = \sum_{i=1}^{I} U(b_i) - \sum_{j=1}^{J} C(s_j) \\
&+ \sum_{i=1}^{I}\alpha_i(b_i^{\min} - \sum_{j=1}^{J} b_{ij}) + \sum_{i=1}^{I}\beta_i(\sum_{j=1}^{J} b_{ij} - b_i^{\max}) \\
&+ \sum_{j=1}^{J}\gamma_i[s_j^{\mathrm{t}} - \sum_{i=1}^{I}(1+\rho_j)s_{ji} - s_j^{\mathrm{r}}] \\
&+ \sum_{i=1}^{I}\sum_{j=1}^{J}\lambda_{ij}(b_{ij}-s_{ji}) - \sum_{i=1}^{I}\sum_{j=1}^{J}\mu_{ij}b_{ij},
\end{aligned} \tag{19}
$$

The partial derivatives of (19) are

$$
\begin{aligned}
\nabla_{b_{ij}} F_1(b_i,s_j,\alpha,\beta,\gamma,\lambda,\mu) =& \frac{w_i}{\sum\limits_{j=1}^{J} b_{ij} - b_i^{\min} + 1} \\
&- \alpha_i + \beta_i - \lambda_{ij} - \mu_{ij} = 0.
\end{aligned} \tag{20}
$$

$$
\begin{aligned}
\nabla_{s_{ji}} F_1(b_i,s_j,\alpha,\beta,\gamma,\lambda,\mu) =& -2l_1\rho_j s_{ji} - l_2\rho_j \\
&- (1+\rho_j)\gamma_j - \lambda_{ij} = 0.
\end{aligned} \tag{21}
$$

Similarly, suppose $F_2(b_i,s_j,\alpha,\beta,\gamma,\lambda,\mu)$ as the dual function of $\mathcal{P}2$. Then, its partial derivatives are

$$
\nabla b_{ij} F_2(b_i,s_j,\alpha,\beta,\gamma,\lambda,\mu) = \frac{T_{ij}}{b_{ij}} - \alpha_i + \beta_i - \lambda_{ij} - \mu_{ij} = 0. \tag{22}
$$

$$
\nabla s_{ji} F_2(b_i,s_j,\alpha,\beta,\gamma,\delta,\lambda,\mu) = -Tr_{ji} - (1+\rho_j)\gamma_j - \lambda_{ij} = 0. \tag{23}
$$

Combining (20), (21), (22), and (23), the optimal transaction volume can be obtained. The proof is finished. ∎

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Algorithm 1 V2V Electricity Trading Algorithm

Input: $\{b_i^{\min}, b_i^{\max}, v_i^{\min}, v_i^{\max}, v_i\}_{i=1}^{N}$, $\{s_j^{\min}, s_j^{\max}, c_j^{\min}, c_j^{\max}, c_j\}_{j=1}^{M}$
Initialization: $c^{\max}$, $v^{\min}$
Output: $\{T_{ij}, b_{ij}\}$

for $i = 1 \to N$ **do**
  for $j = 1 \to M$ **do**
    if $c^{\max} \leq c_j^{\max}$ or $c_j \notin [c_j^{\min}, c_j^{\max}]$ **then**
      seller j needs to resubmit the bid.
    end if
    if $v_i^{\min} \leq v^{\min}$ or $v_i \notin [v_i^{\min}, v_i^{\max}]$ **then**
      buyer i needs to resubmit the bid.
    end if
    if $c^{\max} \geq c_j^{\max}$ and $v_i^{\min} \geq v^{\min}$ **then**
      Solve (3) and (4), the optimal biding prices $\{P_{ij}^*, R_{ji}^*\}$ that achieve the Bayesian equilibrium can be obtained.
      if $P_{ij} \geq R_{ji}$ **then**
        $T_{ij} = (P_{ij} + R_{ji})/2$
      else
        The transaction between buyer i and seller j is not valid.
      end if
    end if
    Solve the problem $\mathcal{P}1$ and $\mathcal{P}2$ according to T_{ij} to get the optimal trading volume $\{b_{ij}^*, s_{ji}^*\}$.
  end for
end for
return $\{T_{ij}, b_{ij}\}$

In summary, with Theorem 1, the optimal biding prices $\{P_{ij}^*, R_{ji}^*\}$ that achieve the Bayesian equilibrium has been obtained. Then, with Theorem 2, the optimal transaction volumes $\{b_{ij}^*, s_{ji}^*\}$ between the buyers and sellers are obtained, which achieve the maximum social welfare.

D. Complexity Analysis

In our designed electricity trading mechanism, as shown in Algorithm 1, assuming there are N electricity buyers and M electricity sellers. Firstly, the price equilibrium is solved in the pricing mechanism based on Bayesian game, and then the optimal electricity trading volume under the constraint condition is solved according to the designed social welfare maximization objective function. For the time complexity of convex optimization problem $\mathcal{O}(max(n^3, n^2m, F))$, where n is the number of input data, m is the number of constraints and $m = N + M + NM$, F is the computational cost of solving the first and second derivatives of the objective function and the constraint function.

V. Experimental Results

A. Simulation settings

A blockchain-based parking prototype has been established. A Fabric blockchain network with version 1.4 was deployed on 4 servers. Golang is used as the development language of smart contract. Applications access multiple resources in Fabric blockchain network through SDK, including ledger, transaction, chaincode, event, and permission management.

In our electricity trading experiment, as shown in Fig. 3, we chose Jinhua city as the experimental scenario. Specifically, we selected some electric vehicles which can carry out electricity trading in a region as the electricity sellers and the electricity buyers. According to the different transaction needs proposed by vehicle users, the optimal transaction scheme will be obtained by implementing the smart contract based on BIoV designed in this paper. As shown in Algorithm 2, Function BuyerSubmit is the input of demand information of the electricity buyer, and function SellerSubmit is the

Algorithm 2 Smart Contract Implementation Algorithm

func (t *TradingChaincode) BuyerSubmit(stub shim.ChaincodeStubInterface, args []string) peer.Response {
  var buyer BuyerInfo
  $\{v_i^{\min}, v_i^{\max}, v_i, b_i^{\min}, b_i^{\max}\} \leftarrow$ args
  buyerInfoAsJSONBytes, err $\leftarrow$ json.Marshal(buyer)
  err = stub.PutState(buyer.BuyerID, buyerInfoAsJSONBytes)
  return shim.Success(buyerInfoAsJSONBytes)
}
func (t *TradingChaincode) SellerSubmit(stub shim.ChaincodeStubInterface, args []string) peer.Response {
  var seller SellerInfo
  $\{c_j^{\min}, c_j^{\max}, c_j, s_j^{\text{t}}, s_j^{\text{r}}\} \leftarrow$ args
  sellerInfoAsJSONBytes, err $\leftarrow$ json.Marshal(seller)
  err = stub.PutState(seller.SellerID, sellerInfoAsJSONBytes)
}
func (t *TradingChaincode) TradingScheme(stub shim.ChaincodeStubInterface, args []string) peer.Response {
  var buyer BuyerInfo
  var seller SellerInfo
  var transaction TransactionInfo
  var l_1, l_2, ρ_j float64
  buyerResult, err $\leftarrow$ stub.GetState(args[0])
  err = json.Unmarshal(buyerResult, &buyer)
  sellerResult, err $\leftarrow$ stub.GetState(args[1])
  err = json.Unmarshal(sellerResult, &seller)
  for $i = 1; i < N; i++$ {
    for $j = 1; i < M; j++$ {
      $P_{ij}(v_i)$ = $v_i^{\min}$/12 + $c_j^{\min}$/4 + (2*v_i)/3
      $R_{ji}(c_j)$ = $c_j^{\min}$/12 + $v_i^{\max}$/4 + (2*c_j)/3
      if $P_{ij}(v_i)$ <$R_{ji}(c_j)$ {
        return shim.Error("Transaction failed!")
      }
      T_{ij} = ($P_{ij}(v_i)$ + $R_{ji}(c_j)$) / 2
      s_{ji} = $Tr_{ji} - l_2\rho_j/2l_1\rho_j$
    }
  }
  err = stub.PutState(transaction.TxID, transactionAsJSONBytes)
  return shim.Success(transactionAsJSONBytes)
}

Fig. 3: Experimental scenario: the traffic map of Jinhua city.

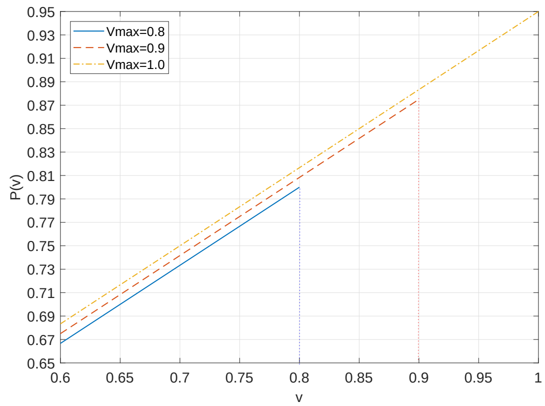

Fig. 4: The pricing strategy of electricity buyer.

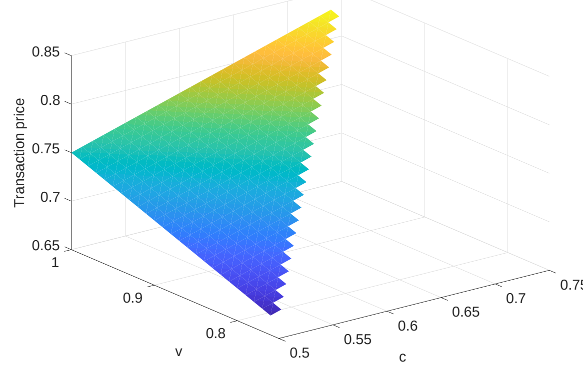

Fig. 6: The transaction price based on Bayesian game.

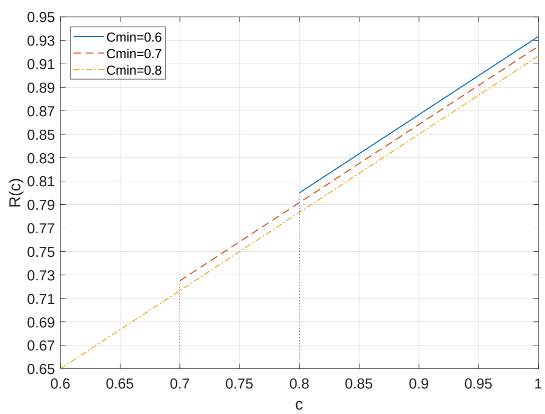

Fig. 5: The pricing strategy of electricity seller.

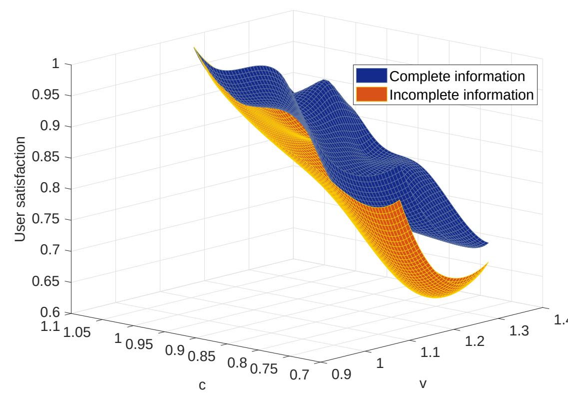

Fig. 7: User satisfaction with incomplete information and complete information.

input of supply information of the electricity seller, which will be encrypted and saved on the blockchain to ensure the security of user information. According to the information submitted by the electricity buyers and electricity sellers, the function TradingScheme uses the Bayesian game pricing scheme designed in this paper to distribute the electricity. The transaction records will be recorded in the blockchain ledger, and the electricity buyers and electricity sellers must conduct the electricity trading in strict accordance with the result, so as to ensure the traceability and non-tamper of the transaction.

B. Results and analysis

1) Transaction price based on Bayesian game: In the studied BIoV, we consider Bayesian game based on linear strategy for transaction pricing. Fig. 4 shows the relationship between electricity buyer's bid price P_{ij} and unit electricity value v_i. The bid price of electricity buyer has a linear relationship with v_i. The price offered by the electricity buyer is influenced by the minimum electricity value $c_j^{\min}$ of the electricity seller and the maximum electricity value $v_i^{\max}$ of the electricity seller. Assuming that the $c_j^{\min}$ is determined, the electricity buyer hopes to lower its bid by lowering the $v_i^{\max}$, thereby lowering the transaction price. However, for market equilibrium, the system have limited the v_i of the electricity buyer, i.e., $v^{\min}$. In addition, it can be found that when the electricity buyer reduces $v_i^{\max}$, the probability of unsuccessful transaction will increase due to the lower price.

Similarly, as shown in Fig. 5, the bid price of the electricity seller s_{ji} has a linear relationship with unit electricity value c_j proposed by electricity seller j. When electricity seller adds $c_j^{\min}$ to raise its asking price, the probability of success in electricity trading will also decrease. In the electricity trading scheme designed in this paper, when the bid price of the electricity buyer is lower than the asking price of the electricity seller, the transaction is invalid. As shown in Fig. 6, when c_j and v_i satisfy $v_i \geq c_j + \dfrac{1}{4}v_i^{max} - \dfrac{1}{4}c_j^{min}$, electricity buyers and electricity sellers can trade successfully, otherwise the transaction will fail.

2)Comparison with complete information: In contrast to incomplete information, complete information game means that each user has accurate information about the characteristics, strategies and benefit functions of all other users. Under complete information, the two sides of the transaction know each other's pricing strategy. Under incomplete information, the pricing strategy is formulated by estimating the expected price of both sides of the transaction. User satisfaction is defined as the ratio of transaction price to its own bid, that

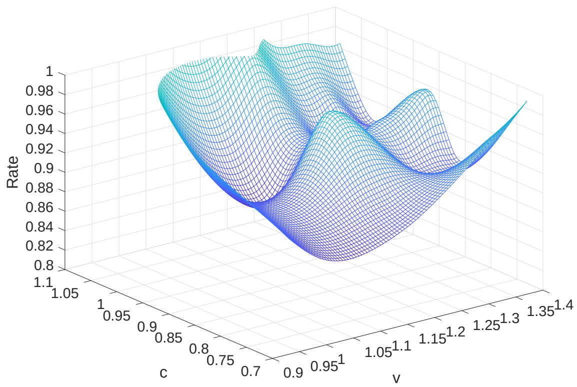

Fig. 8: Comparison of user satisfaction with incomplete information versus complete information.

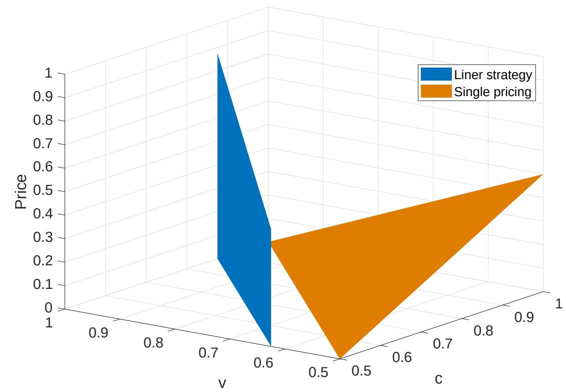

Fig. 10: The benefit based on Bayesian game and single price.

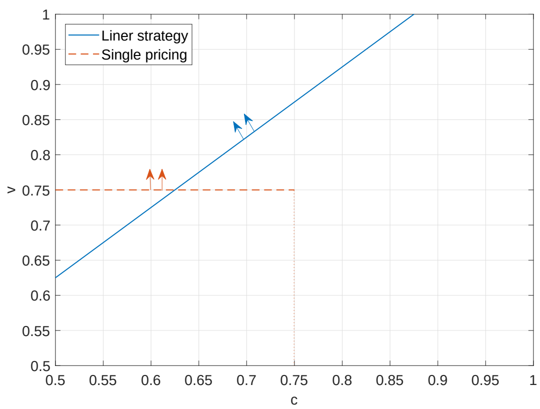

Fig. 9: A Bayesian game based price versus a single price.

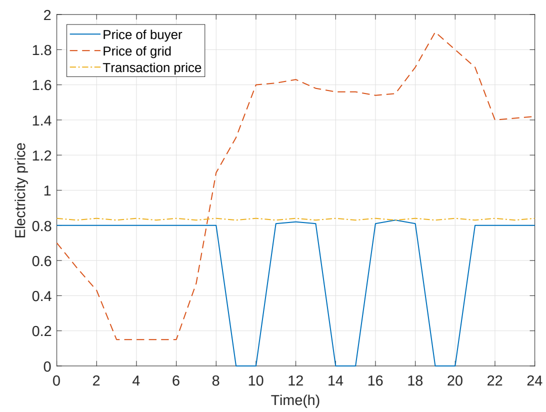

Fig. 11: The electricity price of the grid and vehicles.

is, the closer the transaction price is to its own bid, the higher the satisfaction is. As shown in Fig. 7, the user satisfaction under incomplete information and complete information are simulated. Furthermore, the user satisfaction of Bayesian game pricing strategy with incomplete information is compared with that of static game pricing strategy with complete information, as shown in Fig. 8.

The pricing of complete information and incomplete information has been simulated in different bid ranges. Referring to the benchmark of static game with complete information, the proposed Bayesian game with incomplete information can achieve approximate satisfaction of users. The degree of approximation is basically higher than 80% and can reach to 98% when the pricing ranges of buyers and sellers are close. Moreover, the Bayesian game with incomplete information has great advantages over the static game with complete information in terms of communication overhead and timeliness in the decentralized IoVs.

3)Bayesian game based price versus the single price: As shown in Fig. 9, the single price is a given market price. If the unit electricity value considered by the buyer is higher than the single price, and the unit electricity value considered by the seller is lower than the single price, both parties would trade according to the price. Compared with a single price, there is a certain relationship between the electricity value v proposed by the electricity buyer and the electricity value c proposed by the electricity seller under the linear strategy based on Bayesian game.

Assuming that $v \in [0.5, 1]$, $c \in [0.5, 1]$, it can be seen that the trading area is above $v = c + \frac{1}{8}$, that is, when $v \geq c + \frac{1}{8}$, the transaction is successful. However, for a single price strategy, trading is established in the area of $c \leq 0.75$ and $v \geq 0.75$. Furthermore, the single price missed some valuable transactions, e.g., $c = 0$ and $v = 0.75 - \epsilon$, where ϵ is small enough. In contrast, pricing equilibrium under a linear strategy loses transactions of little value, i.e., $0 \leq v - c < \frac{1}{8}$. From the perspective of maximizing the expected benefit available to participants, as shown in Fig. 10, the user benefit of the linear strategic equilibrium based on Bayesian games is better than a single price.

4) Electricity prices under different conditions: In the traditional P2P electricity trading system, electricity buyers optimize their daily charging cost individually by programming when and where charge their vehicles, taking into account the day-ahead electricity price provided by the electric market operator. Fig. 11 compares the electricity prices of the

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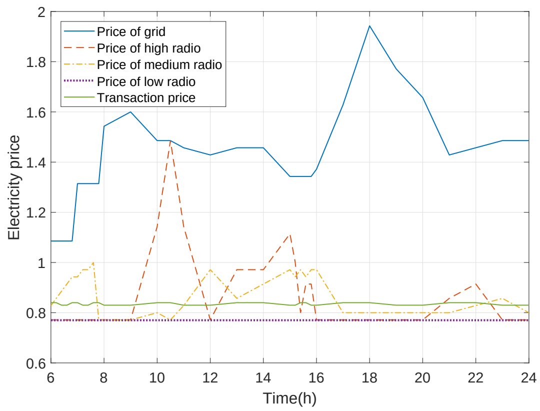

Fig. 12: The electricity price of different radio of vehicles.

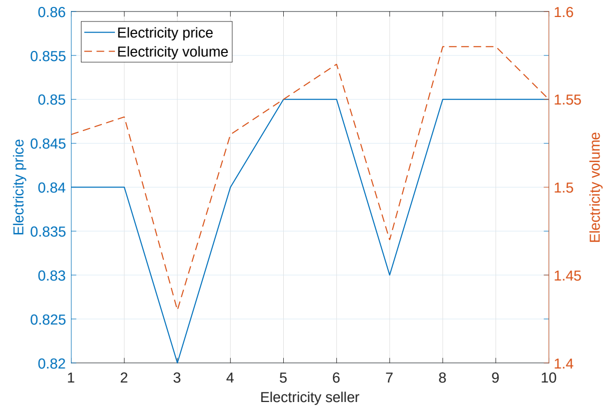

Fig. 14: The electricity trading price and volume.

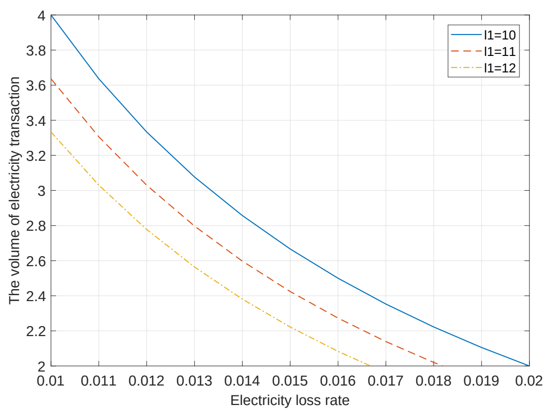

Fig. 13: The relationship between the volume and loss rate.

grid and vehicles in the P2P electricity trading system with the transaction prices in our proposed Bayesian-game-based electricity trading scheme. In the traditional P2P electricity trading system, when the electricity price is lower than the seller's asking price, the electricity buyer will choose to purchase electricity from the grid. Instead, they will choose to buy electricity from electricity sellers. Therefore, electricity buyers need to make their own charging plan. However, in our electricity trading scheme based on Bayesian game, when users need to purchase electricity, they only need to send a message to RSU and submit the electricity demand, and the optimal transaction price and volume can be obtained with smart contract calculation. In addition, electricity trading can take place at any time and place. Therefore, the V2V electricity trading scheme proposed in this paper is more convenient for electricity buyers.

Fig. 12 compares electricity prices from different proportions of electricity buyers and electricity sellers in the P2P electricity trading system with the transaction prices in our proposed Bayesian-game-based electricity trading scheme. In the P2P electricity trading system, electricity prices are relatively high when there are more buyers than sellers. Conversely, electricity is relatively cheaper. In our Bayesian-game-based electricity trading scheme, the price of electricity does not change with the number of electricity buyers and sellers. From the user's point of view, our electricity trading scheme can make more efficient use of electricity and improve trading efficiency.

5) Electricity transaction volume: For simplicity, there considers the loss rate as a factor to affect the seller's electricity. As shown in Fig. 13, the electricity trading volume is negatively correlated with the electricity loss rate. The higher the electricity loss rate, the lower the electricity trading volume. Furthermore, in the social welfare objective function, the satisfaction of the electricity buyer minus the consumption cost of the electricity seller as social welfare, in order to maximize the social welfare, it is necessary to reduce the consumption cost. Specifically, the power transaction of a group of electric vehicles is simulated. As shown in Fig. 14, the electricity trading volume is positively correlated with the price. Moreover, it can be found that when the price of electricity is the same, due to the impact of power loss rate, the transaction volume appears different.

VI. Conclusion

In this paper, a V2V electricity trading scheme based on blockchain technology has been designed for IoVs. In particular, the Bayesian game based pricing scheme has been designed to deal with the incomplete information sharing in distributed IoVs. The optimal pricing under the linear strategic equilibrium is obtained which maximizes the utilities of both sides of electricity transaction. The transaction volume is determined from the formulated convex problem that maximizes the social welfare. For implementation, the pricing game is conducted by the dedicated smart contract. Blockchain is leveraged to guarantee its trustworthiness, security, and reliability. Numerical results have demonstrated the feasibility and validity of the proposed V2V electricity trading scheme. In future, the blockchain technology based vehicle energy trading schemes in a more general scenario will be considered, such as mixed V2X electricity trading.

References

[1] S. S. Gill, S. Tuli, M. Xu, I. Singh, K. V. Singh, D. Lindsay, S. Tuli, D. Smirnova, M. Singh, U. Jain, H. Pervaiz, B. Sehgal,

S. S. Kaila, S. Misra, M. S. Aslanpour, H. Mehta, V. Stankovski, and P. Garraghan, "Transformative effects of IoT, blockchain and artificial intelligence on cloud computing: Evolution, vision, trends and open challenges," *Internet of Things*, vol. 8, Dec. 2019.

[2] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," White Paper, 2008, [Online]. Available: https://bitcoin.org/bitcoin.pdf.

[3] Y. Wang, Z. Su, Q. Xu, T. Yang, and N. Zhang, "A novel charging scheme for electric vehicles with smart communities in vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 9, pp. 8487–8501, Sep. 2019.

[4] Y. Wu, X. Tan, L. Qian, D. H. K. Tsang, W. Song, and L. Yu, "Optimal pricing and energy scheduling for hybrid energy trading market in future smart grid," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 6, pp. 1585–1596, Dec. 2015.

[5] C. M. Martinez, X. Hu, D. Cao, E. Velenis, B. Gao, and M. Wellers, "Energy management in plug-in hybrid electric vehicles: Recent progress and a connected vehicles perspective," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 6, pp. 4534–4549, Jun. 2017.

[6] J. Mohammadi, G. Hug, and S. Kar, "A fully distributed cooperative charging approach for plug-in electric vehicles," *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3507–3518, Jul. 2018.

[7] S. Zou, Z. Ma, X. Liu, and I. Hiskens, "An efficient game for coordinating electric vehicle charging," *IEEE Transactions on Automatic Control*, vol. 62, no. 5, pp. 2374–2389, May 2017.

[8] C. Liu, K. K. Chai, X. Zhang, E. T. Lau, and Y. Chen, "Adaptive blockchain-based electric vehicle participation scheme in smart grid platform," *IEEE Access*, vol. 6, pp. 25 657–25 665, 2018.

[9] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 6, pp. 3154–3164, Dec. 2017.

[10] S. Sicari, A. Rizzardi, L. Grieco, and A. Coen-Porisini, "Security, privacy and trust in Internet of Things: The road ahead," *Computer Networks*, vol. 76, pp. 146–164, 2015.

[11] C. Xu, W. Quan, H. Zhang, and L. A. Grieco, "GrIMS: Green information-centric multimedia streaming framework in vehicular ad hoc networks," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 28, no. 2, pp. 483–498, Feb. 2018.

[12] O. Kaiwartya, A. H. Abdullah, Y. Cao, A. Altameem, M. Prasad, C. Lin, and X. Liu, "Internet of vehicles: Motivation, layered architecture, network model, challenges, and future aspects," *IEEE Access*, vol. 4, pp. 5356–5373, 2016.

[13] F. Yang, S. Wang, J. Li, Z. Liu, and Q. Sun, "An overview of Internet of vehicles," *China Communications*, vol. 11, no. 10, pp. 1–15, Oct. 2014.

[14] W. Zhang and X. Xi, "The innovation and development of Internet of vehicles," *China Communications*, vol. 13, no. 5, pp. 122–127, May 2016.

[15] A. Singh, L. Gaba, and A. Sharma, "Internet of vehicles: Proposed architecture, network models, open issues and challenges," in *Proc. Amity International Conference on Artificial Intelligence*, Dubai, United Arab Emirates, Feb. 4-6 2019, pp. 632–636.

[16] S. Ahmed, S. Al-Rubeaai, and K. Tepe, "Novel trust framework for vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 10, pp. 9498–9511, Oct. 2017.

[17] S. Tanwar, Q. Bhatia, P. Patel, A. Kumari, P. K. Singh, and W. Hong, "Machine learning adoption in blockchain-based smart applications: The challenges, and a way forward," *IEEE Access*, vol. 8, pp. 474–488, 2020.

[18] P. Bhattacharya, S. Tanwar, U. Bodke, S. Tyagi, and N. Kumar, "BinDaaS: Blockchain-based deep-learning as-a-service in healthcare 4.0 applications," *IEEE Transactions on Network Science and Engineering*, pp. 1–1, 2019.

[19] I. Mistry, S. Tanwar, S. Tyagi, and N. Kumar, "Blockchain for 5G-enabled IoT for industrial automation: A systematic review, solutions, and challenges," *Mechanical System and Signal Processing*, vol. 135, Jan. 2020.

[20] Y. Yuan and F. Wang, "Towards blockchain-based intelligent transportation systems," in *Proc. IEEE 19th International Conference on Intelligent Transportation Systems*, Rio de Janeiro, Brazil, Nov. 1-4 2016, pp. 2663–2668.

[21] L. Li, J. Liu, L. Cheng, S. Qiu, W. Wang, X. Zhang, and Z. Zhang, "CreditCoin: A privacy-preserving blockchain-based incentive announcement network for communications of smart vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 7, pp. 2204–2220, Jul. 2018.

[22] T. Jiang, H. Fang, and H. Wang, "Blockchain-based Internet of vehicles: Distributed network architecture and performance analysis," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 4640–4649, Jun. 2019.

[23] M. Liu, Y. Teng, F. R. Yu, V. C. M. Leung, and M. Song, "Deep reinforcement learning based performance optimization in blockchain-enabled Internet of vehicle," in *Proc. IEEE International Conference on Communications*, Shanghai, China, May 20-24 2019, pp. 1–6.

[24] C. Chen, J. Wu, H. Lin, W. Chen, and Z. Zheng, "A secure and efficient blockchain-based data trading approach for Internet of vehicles," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 9, pp. 9110–9121, Sep. 2019.

[25] Z. Li, J. Kang, R. Yu, D. Ye, Q. Deng, and Y. Zhang, "Consortium blockchain for secure energy trading in industrial Internet of things," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 8, pp. 3690–3700, Aug. 2018.

[26] Y. Wang, Z. Su, and N. Zhang, "BSIS: Blockchain-based secure incentive scheme for energy delivery in vehicular energy network," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 6, pp. 3620–3631, Jun. 2019.

[27] J. Kang, Z. Xiong, D. Niyato, D. Ye, D. I. Kim, and J. Zhao, "Toward secure blockchain-enabled Internet of vehicles: Optimizing consensus management using reputation and contract theory," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 2906–2920, Mar. 2019.

[28] N. Z. Aitzhan and D. Svetinovic, "Security and privacy in decentralized energy trading through multi-signatures, blockchain and anonymous messaging streams," *IEEE Transactions on Dependable and Secure Computing*, vol. 15, no. 5, pp. 840–852, Sep. 2018.

[29] X. Huang, C. Xu, P. Wang, and H. Liu, "LNSC: A security model for electric vehicle and charging pile management based on blockchain ecosystem," *IEEE Access*, vol. 6, pp. 13 565–13 574, 2018.

[30] R. Alvaro-Hermana, J. Fraile-Ardanuy, P. J. Zufiria, L. Knapen, and D. Janssens, "Peer to peer energy trading with electric vehicles," *IEEE Intelligent Transportation Systems Magazine*, vol. 8, no. 3, pp. 33–44, Fall 2016.

[31] C. Lin, D. Deng, C. Kuo, and Y. Liang, "Optimal charging control of energy storage and electric vehicle of an individual in the Internet of energy with energy trading," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 6, pp. 2570–2578, Jun. 2018.

[32] P. Tedeschi, G. Piro, J. A. S. Murillo, N. Ignjatov, M. Pilc, K. Lebloch, and G. Boggia, "Blockchain as a service: Securing bartering functionalities in the H2020 symbIoTe framework," *Internet Technology Letters*, vol. 2, no. 1, pp. 1–6, Aug. 2018.

[33] U. Asfia, V. Kamuni, A. Sheikh, S. Wagh, and D. Patel, "Energy trading of electric vehicles using blockchain and smart contracts," in *Proc. 18th European Control Conference*, Naples, Italy, Jun. 25-28 2019, pp. 3958–3963.

[34] D. Puthal and S. P. Mohanty, "Proof of authentication: Iot-friendly blockchains," *IEEE Potentials*, vol. 38, no. 1, pp. 26–29, Jan. 2019.

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[35] F. P. Kelly, A. K. Maulloo, and D. K. H. Tan, "Rate control for communication networks: shadow prices, proportional fairness and stability," *Journal of the Operational Research Society*, vol. 49, no. 3, pp. 237–252, 1998.

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