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A Secure and Efficient Blockchain-based Data Trading Approach for Internet of Vehicles

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***Abstract*—In this paper, we propose a secure and efficient blockchain-based data trading approach for the Internet of Vehicles (IoV). First, we apply consortium blockchain technologies to ensure secure and truthful data trading, and propose a general blockchain-based data trading framework for IoV. Second, to improve the efficiency of data trading and encourage more participants to trade data, we propose an iterative double auction mechanism with the purpose of achieving social welfare maximization, in which pricing rules of buyers and sellers are designed to induce participants to submit bids and to decide the amount of traded data and its price among buyers and sellers. In particular, in our algorithm, the hidden information of individuals can be extracted gradually so that the privacy of participants in data trading can be protected well. Finally, the experimental results show the efficiency of our proposed algorithm. Moreover, the correctness of social welfare maximization, incentive compatibility, individually rationality, and weakly budget balance of our auction mechanism are verified in the experiments.**

***Index Terms*—Blockchain, Internet of Vehicles, Industrial Internet of Things, data trading.**

I. Introduction

Internet of Vehicles (IoV) is attracting increasing attention from academic and industry because of its huge research values and commercial interests. In particular, data exchange in IoV has been considered to benefit business entities, creating new revenue sources [1] [2]. Since more and more entities have joined the business chain along the lifecycle of cars, the data exchange in IoV has the following characteristics [3] [4]: 1) Involvement of multiple parties during the data exchange (e.g. data providers, data buyers, data transmitters, and insurance companies); 2) Conflicting interests among these parties so that no single party can be really trusted; 3) Data exchange only depends on the guarantees and credits of both parties, increasing the joining threshold for more business entities. Because of these characteristics, data exchange in IoV is facing the challenges of low information transparency and illegal data tampering therefore its applications to real-world are limited.

On the other hand, blockchain technologies, which allow IoV to maintain information transparency and build trust among participants via blockchain's decentralized, tamper-proof, secure, and traceable characteristics, are considered to promote the substantial and sustainable growth of data exchange ecosystem for IoV [5] [6]. Detailed data exchange and verification scope, information on data ownership, as well as the processes of data collection, distribution, exchange, storage, and data analytics, can be recorded in the blockchain [7] [8]. Thus, data trading can be traceable based on blockchain and thereby the quality of the data can be further ensured in global large-scale data exchange for IoV [9]. Although blockchain-based decentralized data exchange networks can support the secure data exchange, more efforts are increasingly needed in blockchain-based data exchange efficiency (e. g. social welfare maximization, the exchange costs and benefits, and the delay reduction of data exchange) to accelerate the successful commercialization of the large-scale data exchange market for IoV.

In this paper, we study the security and efficiency of the blockchain-based data trading for IoV. The main challenges here are: 1) how to design a general secure and trustful data trading system using blockchain technologies? And 2) how to achieve the social welfare maximization meanwhile protecting the privacy of buyers and sellers? To address the first challenge, we propose a realistic and general P2P data trading framework based on the consortium blockchain technologies in which the consensus process is controlled by a preselected set of authorized nodes, considering the scalability of data trading system. In our scenarios, authorized nodes are the local aggregators gathering data trading information, over which the verification of transactions is executed without relying on a trusted third party. Besides, a broker is introduced to manage the data trading market for agreement establishment among the buyers and sellers via smart contract applications. To address the second challenge, we propose an efficient, individually rational, and weakly budget balanced double auction to achieve the desired economic benefits and protect the privacy of buyers and sellers. The iterative double auction mechanism is to design pricing rules of the buyers and the sellers to induce them to submit bids, so that the hidden participators' information can be extracted gradually and meanwhile the social welfare can be maximized by determining how much data of sellers will be sold to each buyer and at what price.

To our best knowledge, we are the first to study the consortium blockchain-based data trading problem for IoV based on the iterative double auction scheme with the goal of maximizing the social welfare and protecting the privacy of the buyers and sellers. The contributions of this paper are summarized as follows.

- We propose a consortium blockchain-based data trading framework in which the consortium blockchain based on

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local aggregators is established to audit and verify transaction records among data traders, the purpose being to provide a secure and truthful way for data trading in IoV.

- To optimize data pricing and the amount of traded data among users, an iterative double auction mechanism is proposed to maximize social welfare, in which the privacy of the buyers and sellers can be protected and the data transmission cost is taken into consideration to improve system stability.
- Numerical simulations are conducted to evaluate the performance of the proposed algorithm, and the experimental results verify that the desirable economic properties (e.g. social welfare maximization, individually rational, and weakly budget balanced) in our double auction mechanism can be fully satisfied.

The remainder of this paper is structured as follows. In Section II, we discuss related researches. In Section III, we introduce our blockchain-based data trading framework. In Section IV, we propose an iterative double auction mechanism. Then we evaluate our proposed solution in Section V, and conclude the paper in Section VI.

II. Related Work

In the area of blockchain-based IoT, most of existing studies focus on the architectures and protocols [10] [11] [12]. For example, Novo [5] proposed a fully distributed scalable access control architecture for arbitrating roles and permissions in IoT based on blockchain technology. Li et al. [8] designed a secure and accountable large-scale IoT storage and protection system using blockchain and certificateless cryptography. Zou et al. [12] proposed proof-of-trust consensus protocol for enhancing accountability in the crowdsourcing services in particular and online services in general.

More recently, some work started to develop various applications of blockchain-based IoT [13] [14] [15]. In the energy trading domain, Li et al. [16] proposed a secure energy trading system by employing the consortium blockchain technology to address the security challenges in energy markets. Kang et al. [17] proposed a localized P2P electricity trading system based on the consortium blockchain to improve the transactional security. In the computation resources trading domain, Jiao et al. [18] proposed a social welfare maximization auction for mobile blockchain in edge computing resource allocation to release the use of blockchain in mobile IoT environments. Xiong et al. [19] proposed an edge computing resource management and pricing strategy using game theory for mobile blockchain to support offloading mobile blockchain process. Xu et al. [20] proposed a blockchain-based decentralized resource management framework to reduce the cost of energy consumption from request scheduling and migration among data centers. In the Sensing-as-a-Service domain, Ferrer et al. [21] proposed a blockchain-based decentralized framework for robotic swarm systems to provide sensing services. In the smart home domain, Dorri et al. [22] outlined the various core components of the blockchain-based smart home and designed various transactions and procedures associated with it.

Finally, in the data trading domain, Yu et al. [23] introduced a brokerage-based mobile data trading market to match the market supply and demand. Jiao et al. [24] designed a data market model and pricing mechanism to solve the profit maximization problem and provide useful strategies for the data analytics service provider. However, the trusty issues (such as illegal data tampering) among different participants remain unsolved. To enhance the trusty issues, Wang et al. [25] designed and implemented a blockchain-based information resource sharing system using the techniques of blockchain structure and consensus algorithms. Xu et al. [26] developed a blockchain-based big data sharing framework to support various applications across resource-limited edges. Xia et al. [27] proposed MeDShare, a system that used blockchain to address the issue of medical data sharing among medical big data custodians in a trust-less environment. However, the efficiency of the data trading mechanism based on blockchain is yet discussed [28] [29] [30]. Comparing with the above-mentioned studies, our approach focus on the efficient consortium blockchain-based data trading mechanism, in which the latency factor and the data transfer fee are considered. In particular, we consider that the trading information can be hidden and unknown in real-world scenarios to further protect the privacy of data trading parties.

III. Consortium Blockchain-based Data trading for Internet of Vehicle

A. Framework of Consortium Blockchain-based Data Trading

Data trading is a ubiquitous scenario on a variety of IoV applications. As shown in Fig. 1, to guarantee security and privacy of P2P data transactions, we design a consortium blockchain-based data trading framework consisting of the following common entities.

1) *Vehicles*: The vehicles in the system exchange their data as commodity, and a vehicle that requires some particular data needs to pay the data provider a virtual token, which is referred to as *data coins*. In this way, the vehicles in the IoV play different roles in the process of P2P data exchange, including data sellers which provide collected data, data buyers which ask for data, and idle nodes which neither sell nor buy data. The role of each node may switch according to its current state and data requirements.
2) *Edge Layer*: Edge servers in the edge layer of the IoV framework work as data brokers to manage the process of data trading and exchange by utilizing smart contracts. In this consortium blockchain, each data buyer sends its data requirement to the nearest data broker, and then the broker announces this requirement to local sellers. After that, the vehicles with required data submit selling prices to the broker, and the data broker will carry out an iterative double auction among the vehicles, and match the data trading pairs.
3) *Blockchain Layer*: The core mechanisms of blockchain layer are blockchain, smart contracts, and miners. Blockchain is used to ensure high credibility and high security, smart contracts support various user-designed algorithms, and mining brings superior robustness. In our framework, the edge layer and blockchain layer

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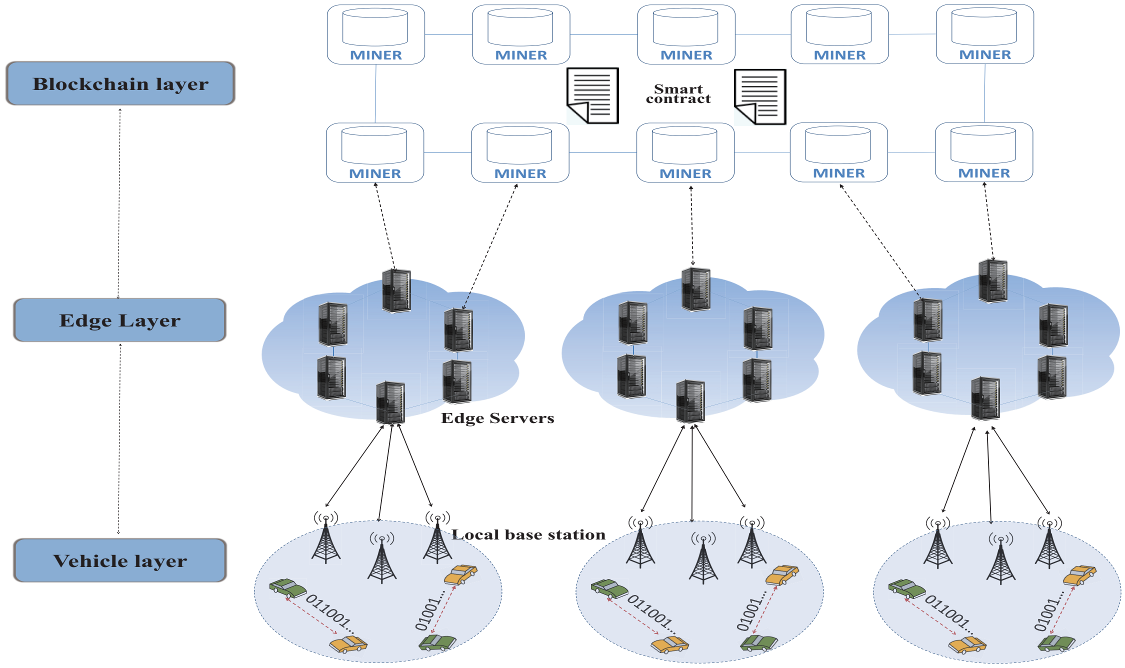

Figure 1. Framework of consortium blockchain-based data trading.

can collaborate with each other in two ways. First, the edge layer provides blockchain layer powerful storage and computational resources for ledger storage and blockchain consensus process. Second, the blockchain layer supports the edge layer for building trust and ensuring security.

In order to maintain information transparency and security for P2P data trading, we establish a consortium blockchain which contains three core components as follows.

1) *Transactional Data*: In the consortium blockchain, information and records of data trading among the vehicles include raw transactional data, data type, metadata tags, index history, timestamps for transaction generation, and the vehicles' pseudonyms used for privacy protection. To ensure authenticity, the transactional data are signed and encrypted with digital signatures. As mentioned above, here we adopt a digital cryptocurrency called data coin as the digital asset for data trading.
2) *Blockchain Architecture*: All the information and records of the data are broadcasted, stored, and audited in the blockchain, which consists of a series of blocks. Each block consists of two components, namely, transactional data and hash values. Details about the transaction data have been given above, and the hash value can be regarded as a link from the current block to its previous block. The first block is referred to as the genesis block, and newly generated blocks are validated and sequentially added in a linear chronological order to the genesis block or the prior blocks.
3) *Consensus Process*: For blockchain-based trading systems, a consensus process should be performed before appending a newly generated block to the blockchain. The consensus process is usually carried out by a mechanism called proof of work (PoW) for its higher security and stability guarantee (Other consensus protocols, e.g. PoS or PBFT, based trading system remains to be the future work). In this work, the authorized edge computing servers can perform the consensus process for the vehicles and write the transactional data into the next block. After that, the transactional data are publicly audited among all servers in the edge layer and no other intermediary involves in the process of data trading. Therefore, the data trading model based on consortium blockchain can achieve the security and privacy of the P2P data trading in IoVs.

B. Key Operations of Consortium Blockchain-based Data Trading

In this blockchain for data trading, we adopt the Boneh–Franklin digital signature scheme for system initialization. After registration on a trusted authority, each vehicle is regarded as a legitimate entity in the consortium blockchain. The detailed process of the data trading based on consortium blockchain is depicted in Fig. 2 and can be described as follows:

Step 1: The data sellers first need to register the data service to the data pools managed by the brokers.

Step 2: Then the data buyers will broadcast its data requirements and ask for a list of sellers that can provide the required data from the brokers.

Step 3: The brokers then search for the required data from the data pools and select the optimal. In this work, we adopt a double auction mechanism to execute the biding process of data trading among the vehicles. Details of the auction mechanism will be explained in Section IV.

Step 4: After selecting the data as well as the seller, the buyer sends an order for the required data to the seller.

Step 5: The seller verifies the order and the identity of the buyer, and sends the required data to the buyer directly or via the edge servers.

Step 6: After the data transmission, the data buyer will check and confirm whether the transaction is successful. A data transaction is successful if and only if the received data is valid and meets all the requirements. After confirming all the details of the received data and the validity of the transaction, the buyer then sends the corresponding data coins to the public wallet address of the seller.

Step 7: After the payment, both the seller and the buyer broadcast the transaction data to the broker for validation and audit purposes. Moreover, to encourage data exchange and sharing, we give an extra reward to the broker with the greatest contribution of data sharing during a certain period as an incentive to solve PoW.

Step 8: The brokers record the data of transactions within a certain time period, and then pack them into blocks after encryption and digitally signing. To form a chain of blocks, each block contains a hash value pointing to its previous block. Moreover, each broker can work as a miner to calculate the hash value of a block according to the hash value of the previous block, random nonce value, timestamp, the Merkel root of transactions, etc. [5]. After finding a valid PoW, the fastest miner will become a leader of the current consensus process and broadcast the result to other miners for the purpose of validation. New blocks will be successfully added to the blockchain in a linear and chronological order if the majority or all of the minors reach consensus on the block, and the fastest minor gets some data coins as the mining reward.

It should be noted that, unlike public blockchains, the consensus process of the consortium blockchain discussed here is conducted by a small number of data brokers. In this way, this consortium blockchain-based p2p trading mechanism has good scalability and can be utilized in a large scale IoV system. On the other hand, since the blockchain layer is built upon the distributed and authorized edge servers and the whole trading process requires only demand and supply limit from each participant, security guarantee for the privacy protection can be provided by the proposed P2P trading mechanism.

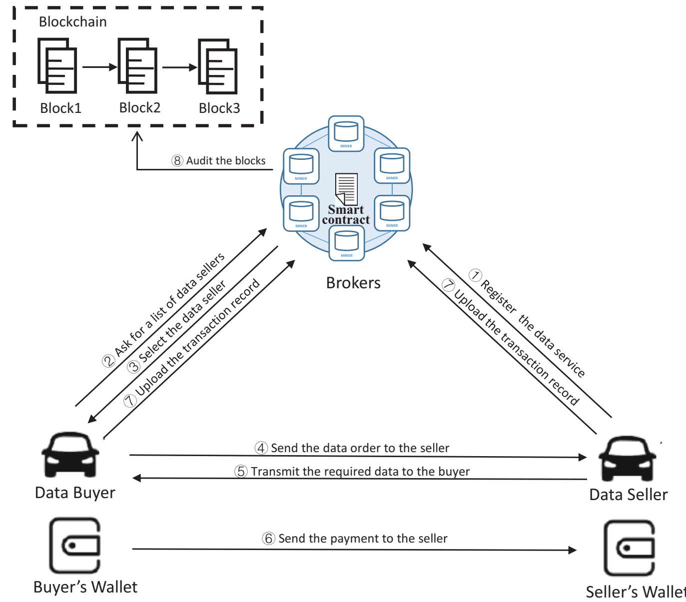

Figure 2. Consortium blockchain-based P2P data trading process.

IV. Problem Description and Double Auction Model for Blockchain-based Data trading

In this section, based on the proposed framework, we propose an iterative double auction mechanism with the goal of achieving the desirable economic benefit and protecting the privacy of buyers and sellers, to ensure the efficiency of data trading and encourage more participants to trade data.

A. Problem Description

The problem definition for optimizing both the amount of traded data and data pricing is presented in this section, aiming to maximize the overall welfare among individuals. In this work, we consider a data trading scenario with N individuals, where each individual can either be a data seller or a data buyer. Let us denote the number of buyer individuals as N_B and the number of seller individuals as N_S where $N = N_B + N_S$. Each buyer is indexed as $i \in \{1, 2, ..., N_B\}$ and each seller is indexed as $j \in \{1, 2, ..., N_S\}$. The i-th buyer is assumed to demand a data amount $d_{i,j} \geq 0$ from the j-th seller. Depending on the network topology and considering the communicating quality between any two individuals, each buyer can request different demands from different sellers. We define the $1 \times N_S$ demand vector of the i-th buyer as $\mathbf{d_i}$ and a positive, increasing and strictly concave function $U_i(\mathbf{d_i})$ to be the utility of the i-th buyer. Each buyer i is assumed to have demands range between D_i^{min} and D_i^{max}, respectively, where $D_i^{min} \leq \mathbf{d}_i^T \mathbf{1} \leq D_i^{max}$.

As an individual in the trading market, the information of the network topology is known to both buyers and sellers (announced by the broker through the blockchain), hence it will demand in such a way to minimize the transmission loss including transmission delay and cost. For example, a buyer which is topologically located near to a seller in the network, will evidently demand most of or even all its data from that particular seller than those located farther. The transmission loss between two individuals denoted as $t_{i,j}$ is assumed to incorporate both the transmission delay and transmission fee between them. Detailed definition of $t_{i,j}$ will be given in the next section.

Alternatively, consider the j-th seller with supply availability for the i-th buyer as $s_{j,i} \geq 0$ and define the $1 \times N_B$ supply vector of the j-th seller as $\mathbf{s}_j$. Since the whole data trading process will incur the time cost associated with the transmission fee. We assume a cost function $C_j(\mathbf{s}_j)$ which reflects the drop in the utility of the j-th seller delivering data vector $\mathbf{s}_j$, assumed to be a positive, increasing and strictly convex function of $\mathbf{s}_j$. We further assume each seller has a maximum limit of supply (limited by its capacity), defined as S_j^{max} where $\mathbf{s_j^T 1} \leq \mathbf{S_j^{max}}$.

It is certain that the market equilibrium, will be attained when both demand and supply matches between a buyer and a seller, i.e., $s_{j,i} = d_{i,j}$ for $i \in \{1, 2, ..., N_B\}$ and

Table I
NOTATIONS

Symbol	Definition
N, N_B, N_S	The number of total individuals, buyer individuals, and seller individuals, respectively, N = N_B + N_S
N_i	Each buyer is indexed as $i \in \{1, 2, ..., N_B\}$
N_j	Each seller is indexed as $j \in \{1, 2, ..., N_S\}$
$\mathbf{d_i}$	The $1 \times N_S$ demand vector of the i-th buyer
$\mathbf{s_j}$	The $1 \times N_B$ supply vector of the j-th seller
$d_{i,j}$	The amount of data that the i-th buyer wants from the j-th seller
$U_i(\mathbf{d_i})$	The utility of the i-th buyer
D_i^{min} , D_i^{max}	The minimum and maximum data demand of buyer i respectively, $D_i^{min} \leq \mathbf{d}_i^T\mathbf{1} \leq D_i^{max}$
$t_{i,j}$	The transmission loss between i-th buyer and j-th seller
$s_{j,i}$	The available supply of the j-th seller for the i-th buyer
$C_j(\mathbf{s}_j)$	The cost function which reflects the drop in utility of the j-th seller delivering data vector $\mathbf{s}_j$
S_j^{max}	The maximum limit of supply of the j-th seller, $\mathbf{s_j^T 1} \leq \mathbf{S_j^{max}}$
w_i	The trading willingness of buyer i
$v_{i,j}$, $f_{i,j}$	The transmission speed and the transmission fee between i-th buyer and j-th seller per data unit, respectively
C	A constant which refers to the congestion status of the network
α_i, β_i, γ_j, λ_{ij}, μ_{ij}	The Lagrange multipliers for the inequality and equality constrains whose corresponding vectors are denoted by $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}$, and $\boldsymbol{\mu}$
$P_i(\mathbf{bd}_i)$	The settlement pricing rules for i-th buyer
$R_j(\mathbf{bs}_j)$	The rewarding rules for j-th seller

$j \in \{1, 2, ..., N_B\}$. To establish a real–time data trading market, the brokers in the blockchain are assumed to be capable to communicate with any individuals and able to facilitate the data trading between any buyer and seller in the network. Note that the symbols used in this paper are summarized in Table I.

B. Problem Formulation

Due to the conflict objectives of buyers and sellers, i.e., buyers try to maximize their utilities while sellers try to minimize their incurred cost, the broker should maximize this social welfare and achieve effective market equilibrium. In this way, to allocate data for each buyer and seller for trading, the objective function ($Objective\ 1$) is expressed as follows:

$$Objective\ 1 : \max_{\mathbf{d}_i, \mathbf{s}_j} \sum_{i=1}^{N_B} U_i(\mathbf{d}_i) - \sum_{j=1}^{N_S} C_j(\mathbf{s}_j), \tag{1}$$

$$\begin{aligned} s.t.\quad & D_i^{min} \leq \mathbf{d}_i^T\mathbf{1} \leq D_i^{max},\ i \in \{1, 2, ..., N_B\}, \\ & \mathbf{s}_j^T\mathbf{1} \leq S_j^{max},\ j \in \{1, 2, ..., N_S\}, \\ & d_{i,j} = s_{j,i},\ i \in \{1, 2, ..., N_B\},\ j \in \{1, 2, ..., N_S\}, \\ & s_{i,j} \geq 0,\ i \in \{1, 2, ..., N_B\},\ j \in \{1, 2, ..., N_S\}, \end{aligned}$$

where the utility function of buyer i, denoted by $U_i(\mathbf{d}_i)$, and the cost function of seller j, denoted by $C_j(\mathbf{s}_j)$, are defined as follows:

$$U_i(\mathbf{d}_i) = w_i ln(\sum_{j=1}^{N_S} t_{i,j} d_{i,j} - D_i^{min} + 1), \tag{2}$$

$$C_j(\mathbf{s}_j) = \sum_{i=1}^{N_B} t_{i,j}(l_1 s_{j,i}^2 + l_2 s_{j,i}), \tag{3}$$

where $t_{i,j}$ refers to the transmission loss between two individuals i and j, w_i refers to the trading willingness of buyer i, and l_1 and l_2 are two cost factors. According to (2), the utility of a buyer is a strictly concave function of the data amount $d_(i,j)$, and a buyer with a higher trading willingness is expect to obtain a higher utility value. Besides, in (3), $C_j(\mathbf{s}_j)$ is a positive, increasing and strictly convex function of s_j.

Since $t_{i,j}$ incorporates both the transmission delay and transmission fee, it can be formulated as

$$t_{i,j} = e^{d_{i,j}/v_{i,j}} + f_{i,j} d_{i,j} + C, \tag{4}$$

where $v_{i,j}$ refers to the transmission speed and $f_{i,j}$ refers to the transmission fee per unit, and C is a constant which refers to the congestion status of the network. This means, either the increase of the delay $d_{i,j}/v_{i,j}$ or the cost $f_{i,j}d_{i,j}$ will result in a lower transmission gain. In our framework, the calculation of $t_{i,j}$ is done by the broker according to $\mathbf{d}_i$ and $\mathbf{s}_j$ in the previous iteration. After that, a new set of $\{t_{i,j}\}$ associated with $\mathbf{d}_i$ and $\mathbf{s}_j$ will be announced to all individuals in the blockchain. It is easy to verify that $t_{i,j} \geq 1$ which guarantees that $U_i(\mathbf{d}_i) \geq 0$.

By such setting, the objective function is strictly concave with compact, convex constrains, hence possesses a unique optimal solution which can be described using KKT conditions. Let $\mathbf{d} = \{\mathbf{d}_1, ..., \mathbf{d}_{N_B}\}$, $\mathbf{s} = \{\mathbf{s}_1, ..., \mathbf{s}_{N_S}\}$, the relaxation of constrains yields the following Lagrangian L_1,

$$\begin{aligned} L_1(\mathbf{d}, \mathbf{s}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}, \boldsymbol{\mu}) &= \sum_{i=1}^{N_B} U_i(\mathbf{d}_i) - \sum_{j=1}^{N_S} C_j(\mathbf{s}_j) \\ &+ \sum_{i=1}^{N_B} \alpha_i (D_i^{min} - \sum_{j=1}^{N_S} d_{i,j}) + \sum_{i=1}^{N_B} \beta_i (\sum_{j=1}^{N_S} d_{i,j} - D_i^{max}) \\ &+ \sum_{j=1}^{N_S} \gamma_j (\sum_{j=1}^{N_B} s_{j,i} - S_j^{max}) + \sum_{i=1}^{N_B}\sum_{j=1}^{N_S} \lambda_{ij}(d_{i,j} - s_{j,i}) \\ &- \sum_{i=1}^{N_B}\sum_{j=1}^{N_S} \mu_{ij} s_{j,i}, \end{aligned} \tag{5}$$

where $\alpha_i \geq 0$, $\beta_i \geq 0$, $\gamma_j \geq 0$, λ_{ij}, and $\mu_{ij} \geq 0$ are Lagrange multipliers for the inequality and equality constrains whose corresponding vectors are denoted by $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\lambda}$, and $\boldsymbol{\mu}$. Considering the stationary conditions, the optimal of $Objective\ 1$ should meet the following equalities:

$$\nabla_{d_{i,j}} L_1 = \frac{w_i t_{i,j}}{\sum_{j=1}^{N_S} t_{i,j} d_{i,j} - D_i^{min} + 1} - \alpha_i + \beta_i + \lambda_{ij}, \tag{6}$$

$$\nabla_{s_{j,i}} L_1 = -2 l_1 t_{i,j} s_{j,i} - l_2 t_{i,j} + \gamma_j - \lambda_{ij} - \mu_{ij}. \tag{7}$$

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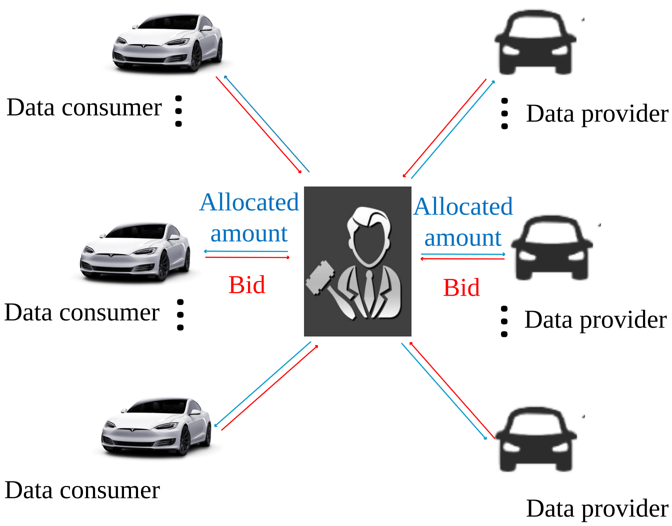

Figure 3. The information flow for data trading based on the double auction mechanism.

In a such system, the information of all individuals' utilities and cost functions are required to enable the broker to solve the problem using (6) and (7). However, due to the limitation of complete information, the broker needs to design a mechanism to extract hidden information from the individuals. Proposing an efficient (maximizes social welfare), individually rational (bidders will bid truthfully according to their private information), weakly budget balanced (broker would not lose money to conduct the mechanism) double auction, the elicitation of hidden information can be done in a real, perfect, and competitive market with a large number of vehicle participants having limited computational capabilities.

As each individual tries to maximize its own welfare, their pricing strategy will make the data trading market competitive.

C. Double Auction Model

In this section, we present the concept of iterative double auction (IDA) used to elicit hidden information of individuals to the broker. Fig. 3 shows the information flow for data trading based on the double auction mechanism. On the basis of IDA, we further design the pricing rules for both buyers and sellers.

1) Broker's Auction Mechanism: Assuming that a reliable communication link that facilitates flow of information between individuals and the broker exists, broker will perform an IDA that can meet the desirable social welfare maximization. The i-th buyer will submit a bid price for each demand as $bd_{i,j} \geq 0$ to each j-th seller, i.e., $1 \times N_S$ bid vector $\mathbf{bd}_i$, likewise, the j-th seller will also submit a bid $bs_{j,i} \geq 0$ for its supply to each i-th buyer, i.e., $1 \times N_B$ bid vector $\mathbf{bs}_j$, to the broker. These bids will reflect demand and supply of buyers and sellers respectively along with their preferences. After submission of bids, the broker will solve an optimal data allocation problem based on the bids from all individuals, to achieve effective market equilibrium. Other than $Objective$ 1, it is called Broker Allocation Problem ($Objective$ 2).

Solving $Objective$ 2 will result in new optimal allocations $\mathbf{d}_j$ and $\mathbf{s}_j$ for an announcement to the individuals for trading. It would have been possible to attain the effective market equilibrium by performing the auction for once if all individuals have the complete network information, which is not the case. This obliges performing the double auction mechanism for multiple iterations where each individual will solve its own utility maximization problem, namely Optimal Data Buying Problem (DBP) and Data Selling Problem (DSP) at each iteration to update their bid vectors according to the newly transmission loss, allocated demand and supply by the broker. As individuals are selfish and non-cooperative, they are not concerned about the social objectives and try to maximize their own profit. Therefore, it is also the brokers' role to design some pricing rules for buyers and sellers respectively, which will be discussed in the next subsection. Therefore, $Objective$ 2 can be formulated using the following objective function as

$$Objective\ 2: \max_{\mathbf{d}_i,\mathbf{s}_j} \sum_{i=1}^{N_B}\sum_{j=1}^{N_S}(bd_{i,j}logd_{i,j} - \frac{1}{2}bs_{j,i}s_{j,i}^2), \quad (8)$$

$$\begin{aligned} s.t.\quad & D_i^{min} \leq \mathbf{d}_i^T\mathbf{1} \leq D_i^{max},\ i \in \{1,2,...,N_B\},\\ & \mathbf{s}_j^T\mathbf{1} \leq S_j^{max},\ j \in \{1,2,...,N_S\},\\ & d_{i,j} = s_{j,i},\ i \in \{1,2,...,N_B\},\ j \in \{1,2,...,N_S\},\\ & s_{i,j} \geq 0,\ i \in \{1,2,...,N_B\},\ j \in \{1,2,...,N_S\}, \end{aligned}$$

The $Objective$ 2 has the same constraint set as the $Objective$ 1, yet with a different strictly concave objective function which ensures existence of a unique optimal solution. The constraint relaxation of (8) by Lagrangian L_2 generates

$$\begin{aligned} L_2(\mathbf{d},\mathbf{s},\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\lambda},\boldsymbol{\mu}) = & \sum_{i=1}^{N_B}\sum_{j=1}^{N_S}(bd_{i,j}logd_{i,j} - \frac{1}{2}bs_{j,i}s_{j,i}^2) \quad (9)\\ & + \sum_{i=1}^{N_B}\alpha_i(D_i^{min} - \sum_{j=1}^{N_S}d_{i,j}) + \sum_{i=1}^{N_B}\beta_i(\sum_{j=1}^{N_S}d_{i,j} - D_i^{max})\\ & + \sum_{j=1}^{N_S}\gamma_j(\sum_{j=1}^{N_B}s_{j,i} - S_j^{max}) + \sum_{i=1}^{N_B}\sum_{j=1}^{N_S}\lambda_{ij}(d_{i,j} - s_{j,i})\\ & - \sum_{i=1}^{N_B}\sum_{j=1}^{N_S}\mu_{ij}s_{j,i}. \end{aligned}$$

To ensure that the optimal solution of $Objective$ 2 also solve $Objective$ 1, it is necessary that all KKT conditions along with the stationary conditions need to be matched for both $Objective$ 1 and $Objective$ 2. Therefore L_1 and L_2 share the same Lagrange multipliers. Applying the stationary conditions yields

$$\nabla_{d_{i,j}}L_2 = \frac{bd_{i,j}}{d_{i,j}} - \alpha_i + \beta_i + \lambda_{ij}, \quad (10)$$

$$\nabla_{s_{i,j}}L_2 = -bs_{j,i}s_{j,i} + \gamma_j - \lambda_{ij} - \mu_{ij}. \quad (11)$$

As the KKT conditions are the same, by comparing (6) and (7) with (10) and (11), we further have

$$bd_{i,j} = \frac{w_i t_{i,j} d_{i,j}}{\sum_{j=1}^{N_S} t_{i,j}d_{i,j} - D_i^{min} + 1}, \quad (12)$$

$$bs_{j,i} = 2l_1 t_{i,j} + \frac{l_2 t_{i,j}}{s_{j,i}}, \quad (13)$$

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which means if each buyer and seller submit their bids according to (12) and (13) respectively, then for broker solving $Objective$ 2 will be equivalent to solving $Objective$ 1, which will elicit the hidden information from the market. So, the broker has to design settlement rule for buyers and rewarding rule for sellers in such a manner that each individual will be induced to submit his bids according to (12) and (13).

2) Buyers and Sellers' Pricing Rules: Now we define the settlement pricing rules for i-th buyer as $P_i(\mathbf{bd}_i)$ which depends on the allocated demand vector $\mathbf{d}_i$ of that buyer. Similarly, a rewarding rule for j-th seller is defined as $R_j(\mathbf{bs}_j)$, which depends on the allocated supply vector $\mathbf{s}_j$ for that seller. Since each individual is a non-cooperative and price-taking entity, it will try to maximize its overall utility which now depends upon its settlement or earning rule.

Thus, the i-th buyer will solve its own DBP to obtain his optimal bids vector $\mathbf{bd}_i$:

$$\max_{\mathbf{bd}_i} U_i(\mathbf{d}_i) - P_i(\mathbf{bd}_i). \tag{14}$$

Similarly, the j-th seller will solve its own DSP in order to otain his optimal bid vector $\mathbf{bs}_j$:

$$\max_{\mathbf{bs}_j} R_j(\mathbf{bs}_j) - C_j(\mathbf{s}_j). \tag{15}$$

The bid price based on (12) and (13) will hold if the pricing rule are chosen as follows:

$$P_i(\mathbf{bd}_i) = \sum_{j=1}^{N_S} bd_{i,j}, \tag{16}$$

$$R_j(\mathbf{bs}_j) = \sum_{i=1}^{N_B} \frac{(\gamma_j - \lambda_{ij} - \mu_{ij})^2}{bs_{j,i}}. \tag{17}$$

Theorem 1. *The optimal buying and selling price satisfy Eqn. (12) and (13) if the pricing and rewarding rules are set to be Eqn. (16) and (17) respectively.*

Proof. For each i-th buyer, the optimal buying price satisfies the following condition from (14)

$$\frac{\partial U_i(\mathbf{d}_i)}{\partial bd_{i,j}} - \frac{\partial P_i(\mathbf{bd}_i)}{\partial bd_{i,j}} = 0. \tag{18}$$

According to (16), we have

$$\frac{\partial U_i(\mathbf{d}_i)}{\partial bd_{i,j}} = \frac{\partial U_i(\mathbf{d}_i)}{\partial d_{i,j}} \frac{\partial d_{i,j}}{\partial bd_{i,j}} = \frac{\partial P_i(\mathbf{bd}_i)}{\partial bd_{i,j}} = 1. \tag{19}$$

Hence, by Taylor's theorem,

$$bd_{i,j} = \frac{\partial U_i(\mathbf{d}_i)}{\partial d_{i,j}} d_{i,j} = \frac{w_i t_{i,j} d_{i,j}}{\sum_{j=1}^{N_S} t_{i,j} d_{i,j} - D_i^{min} + 1}. \tag{20}$$

which is the same as (12).

For each j-th seller, the optimal buying price satisfies the following condition from (15)

$$\frac{\partial R_j(\mathbf{bs}_j)}{\partial bs_{j,i}} - \frac{\partial C_j(\mathbf{s}_j)}{\partial bs_{j,i}} = 0, \tag{21}$$

which can be further expanded as

$$\frac{\partial C_j(\mathbf{s}_j)}{\partial s_{j,i}} \frac{\partial s_{j,i}}{\partial bs_{j,i}} = \frac{\partial R_j(\mathbf{bs}_j)}{\partial bs_{j,i}} = -\frac{(\gamma_j - \lambda_{ij} - \mu_{ij})^2}{(bs_{j,i})^2}. \tag{22}$$

Hence, we have

$$\frac{\partial s_{j,i}}{\partial bs_{j,i}} = -\frac{(\gamma_j - \lambda_{ij} - \mu_{ij})}{(bs_{j,i})^2}. \tag{23}$$

By considering (7), we have

$$s_{j,i} = \frac{2l_1 t_{i,j} s_{j,i} + l_2 t_{i,j}}{bs_{j,i}}. \tag{24}$$

This formula can be further written as

$$bs_{j,i} = 2l_1 t_{i,j} + \frac{l_2 t_{i,j}}{s_{j,i}}, \tag{25}$$

which is the same as (13). Then, we proved that the optimal buying and selling price satisfy Eqn. (12) and (13) if the pricing and rewarding rules are set to be Eqn. (16) and (17) respectively. □

In another word, the pricing rules following (16) and (17) guarantee that the optimal bid of each vehicle will aid the broker to obtain the socially optimal welfare which is nothing but the optimal solution of $Objective$ 1.

D. Double Auction Procedure

The proposed double auction model comprises the following steps.

1) In the first iteration, each buyer will submit his initial bid vector for all sellers to the broker. On the other side, each seller will submit his bid vector for all buyers. Note that, each buyer will submit his initial bids based on the transmission loss factor, with specific seller preferences. Each buyer and seller will also specify his maximum demand-supply limits respectively.
2) Then, by using this initial information, the broker will solve $Objective$ 2 in order to allocate the demand and supply based on their individual bids. After that, the broker will compute the new transmission loss based on the new allocations. In turn, these new allocations associated with transmission loss will be announced to the buyers and sellers.
3) Based on this new information, buyers and sellers solve their own BDP and BSP respectively to obtain their optimal bids for the next iteration. These new bids will be submitted to the broker by themselves. The whole procedure will terminate until the termination condition is meet, checked by the broker.

Based on the above procedure, we present the iterative double auction algorithm, as shown in Alg. 1.

In such a setting, a truthful, individually rational, weakly budget balanced iterative double auction mechanism can attain a socially optimal data allocation between buyers and sellers during an outage with incomplete information to the broker. Due to the nature of the algorithm, only the demand and supply limits from each individual (data buyer or seller) are required and thus data security and user privacy of each participant can be well preserved by using pseudonyms.

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Algorithm 1 Iterative Double Auction Algorithm

Input: ϵ,

Individuals submit demand and supply limit D_i^{max}, D_i^{min}, and S_j^{max} to the broker;
Individuals place initial bid vector $\mathbf{bd}^{(0)}$, $\mathbf{bs}^{(0)}$, $t \longleftarrow 0$;
while $||\mathbf{bd}^{(t)} - \mathbf{bd}^{(t-1)}||_2 \geq \epsilon$ or $||\mathbf{bs}^{(t)} - \mathbf{bs}^{(t-1)}||_2 \geq \epsilon$ **do**
  $t \longleftarrow t + 1$;
  Broker obtains $\mathbf{d}^{(t)}$, $\mathbf{s}^{(t)}$, $\{\gamma_j\}$, $\{\lambda_{ij}\}$, $\{\mu_{ij}\}$ by solving $Objective$ 2;
  Broker computes $t_{i,j}$ using (4), compute $P_i(\mathbf{bd}_i)$ and $R_j(\mathbf{bs}_j)$ using (16) and (17);
  Broker announces $\mathbf{d}^{(t)}$, $\mathbf{s}^{(t)}$ through the blockchain;
  Individuals compute the new bid prices:
Buyers solve BDP to update bid vector $\mathbf{bd}^{(t)}$ using (12);
Sellers solve BSP to update bid vector $\mathbf{bs}^{(t)}$ using (13);
  Individuals submit bid vector $\mathbf{bd}^{(t)}$, $\mathbf{bs}^{(t)}$;
end while

Output: $\mathbf{d}^{(t)}$, $\mathbf{s}^{(t)}$, $\mathbf{bd}^{(t)}$, $\mathbf{bs}^{(t)}$.

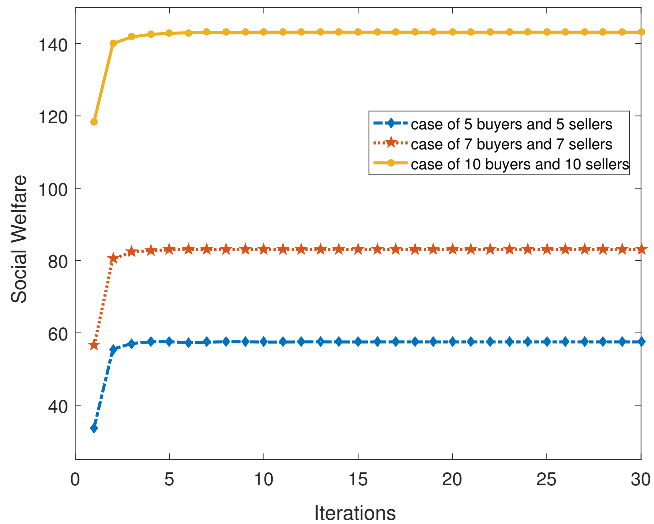

Figure 4. The convergence of the social welfare function.

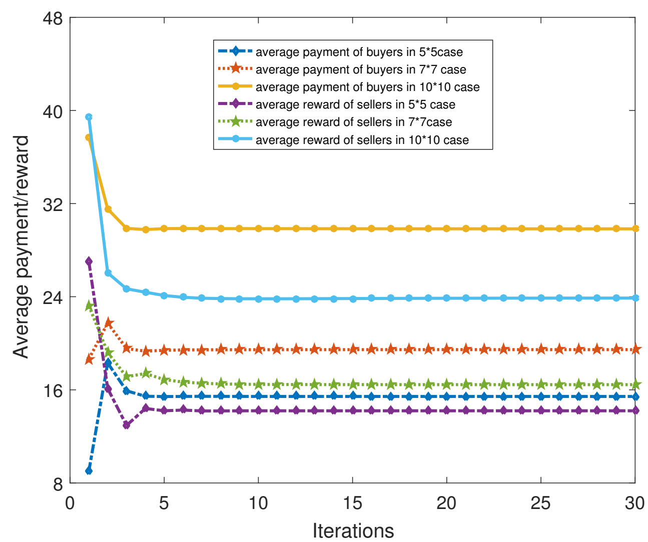

Figure 5. The relationship between the payments of all buyers and the rewards of all sellers.

V. Evaluation

To evaluate the performance of our approach, we study the convergence of social welfare function, the broker's profits, the utilities of buyers and sellers, and the relation of amounts/bids. Finally we study the impact of the data transmission lose.

A. Experimental Setting

In our experiments, B_i ($i \in \{1, 2, ..., N_B\}$) is denoted as the i-th buyer and S_j ($j \in \{1, 2, ..., N_S\}$) is denoted as the j-th seller. The maximal and minimal demands of data buyers are set to be $[12, 18]$ and $[5, 10]$, respectively. And the maximum limit of sellers' supply is set to $[15, 30]$. The cost factors l_1 and l_2 in Eq. (3) are adjusted to 0.015 and 0.01. In addition, the transmission delay $d_{i,j}/v_{i,j}$ randomly ranges from 0 ms to 18 ms [31], and the transmission fee f per data unit varies from 0.02 dollars/GB to 0.2 dollars/GB [32]. Accordingly, the willingness w of each buyer with each seller is set to [0,5]. The experimental results are averaged over 100 independent trials.

B. Experimental Results

We evaluate the performances of the proposed iterative double auction algorithm with different $N_B * N_S$ settings. In our experiments, we use three different settings $5*5$, $7*7$ and $10*10$, to answer the following research questions (RQs).

RQ1: How effectively can our social welfare function converge? Fig. 4 shows the social welfare of the proposed algorithm with iterations under different models. We can see that the maximal social welfare can be achieved quickly by the proposed algorithm in no matter which model. Furthermore, the larger the scale of $B * S$ is, the larger the maximal social welfare is, and the larger the iteration number of convergence is. These results verify that the proposed iterative double auction algorithm is efficient, since the social welfare can be maximized quickly.

RQ2: How much benefit can the brokers gain in our approach? Fig. 5 shows the relationship between the payments of all buyers and the rewards of all sellers under different models. The rewards and the payments can converge to stable values quickly. Furthermore, the payments of all data buyers are larger than the rewards of all data sellers in different models, which ensures that the broker will not undertake any loss and can obtain a certain earning. Note that the difference between the payments by all data buyers and the rewards by all data sellers is the benefit of the broker. Our experimental results demonstrate that the proposed iterative double auction algorithm satisfies weakly budget balance, i.e., the rewards should not less than the payments.

RQ3: How effectively can our approach encourage the buyers and sellers to trade data? We study the maximum utilities of buyers and sellers, i.e. DBP and DSP defined in Eqs.

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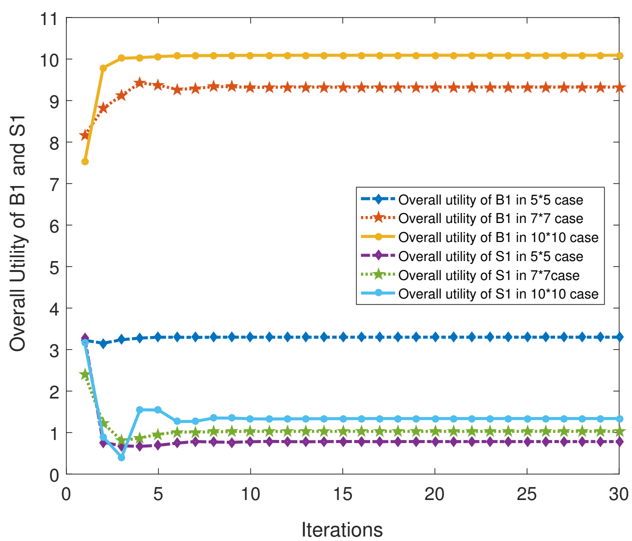

Figure 6. The maximum utility of the buyer and the seller.

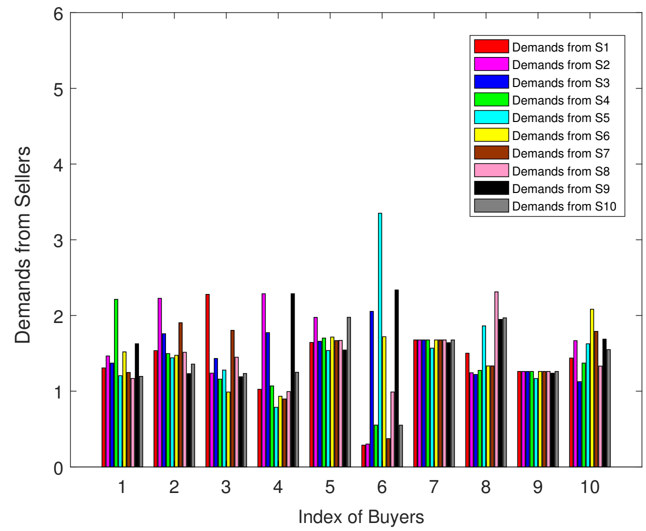

Figure 7. The allocated amount of data for buyers from sellers.

(14) and (15), respectively. We randomly choose the maximum utilities of B_1 and S_1 under different models, as shown in Fig. 6. Note that the other pairs between buyers and sellers also show similar results. It can be seen that the maximum utilities of buyers and sellers can converge to stable values quickly and increase with the numbers of buyers and sellers. Furthermore, the maximum utility of buyers is always greater than that of sellers under any model in our proposed algorithm. Hence, the proposed iterative double auction algorithm satisfies the property of incentive compatibility, i.e. utilities of the buyers and the sellers are at least nonnegative when participating in data trading. In other words, the buyers and sellers are willing to trade data in our approach.

RQ4: How much can our approach follow the law of the market? The allocated amounts of 10 buyers from 10 sellers are shown in Fig. 7 and the bids from 10 buyers to 10 sellers are shown in Fig. 8, respectively. The vertical scale represents the allocated amount or the bids, and the horizontal scale represents the buyer's index. The results show that our approach follows the law of the market well. For example, the buyer B_6 trends to buy more amount of data from S_5 than from other sellers, accordingly the bid of the buyer B_6 to S_5 is higher compared to other sellers. This demonstrates that if a buyer's data demand is larger, the price he has to pay is higher, which matches the market discipline well.

RQ5: Does our approach perform well in different data transmission loss? We evaluate the impact of the data transmission loss of t for the data trading amount by varying the parameter C. Note that the smaller value of C represents the high heterogeneity of data transmission loss among buyers and sellers. Fig. 9 shows the data trading amount between buyer and seller with different constant C. Here, we choose B1 and S1 randomly as an example (note that the other pairs between buyers and sellers show similar results). From Fig. 9, we can see that the smaller C can lead to a larger amount of traded data provided by the seller S_1 to the buyer B_1 in our approach. These experimental results indicate that

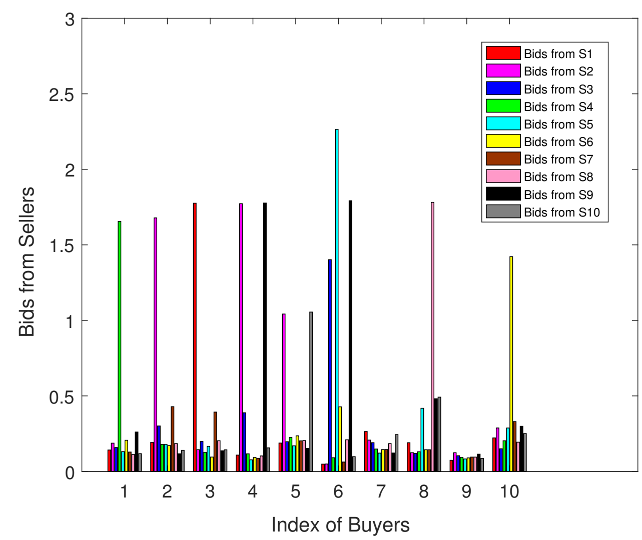

Figure 8. The bids from buyers to sellers.

our approach can perform well in environments with higher heterogeneity, e.g. the huge difference of data transmission speed and transmission fee among buyers and sellers.

RQ6: Does our proposed algorithm scale well for blockchain-based data trading? To further validate the efficiency of our proposed approach, we evaluate the performance of our approach in terms of the algorithm running time. Fig. 10 shows the running time of our proposed algorithm under different scales. Note that the number of buyer-seller pairs grows exponentially as the scale of B * S increases. We can see that the running time of the proposed algorithm increases linearly rather than exponentially as the scale of B * S increases. This result verifies that our proposed double auction algorithm has high scalability for large-scale blockchain-based data trading systems.

In summary, according to the above experimental results, we

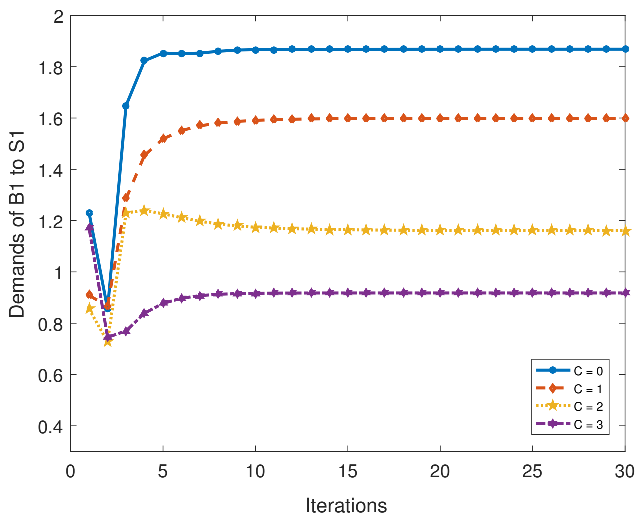

Figure 9. The effect of data transmission loss function t on data trading amount from S_1 to B_1.

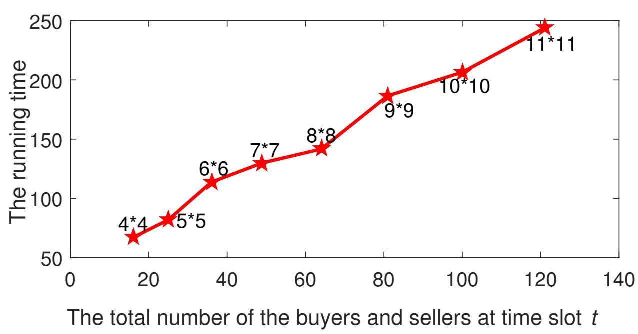

Figure 10. The running time of our proposed algorithm with different scales.

can see that the proposed iterative double auction algorithm can gradually reveal the hidden information and also obtain the optimal solutions quickly, meanwhile achieving the maximum social welfare. Besides, our approach can effectively encourage the buyers and sellers to participate in data trading, promise the benefit of the broker via following the law of the market, and perform well in different data transmission loss.

VI. Conclusion

In this paper, we proposed a consortium blockchain-based data trading framework and an iterative double auction mechanism to enable secure and efficient data trading for IoV. To address the issues of low information transparency and illegal data tampering in the process of data trading, we proposed a consortium blockchain-based data trading framework in which data trading can be traceable based on blockchain. In addition, to improve data trading efficiency, we developed an iterative double auction mechanism in which the maximum social welfare can be achieved quickly and the privacy of data trading parties can be protected. Our approach can ensure the benefits of the broker and encourage both the buyers and sellers to participate in the data trading. Experimental results showed the efficiency of our proposed algorithm and demonstrated that data trading in our approach matches the market discipline well (e.g. a buyer's data demand is larger, the price it has to pay is higher). In future work, we will consider more detailed incentive mechanisms for the process of data transmission in the data trading scenarios of IoV, and introduce trusted computing or the role of mediator to tackle the possible disputes between buyers and sellers.

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References

[1] Y. Hu, C. Chen, J. He, B. Yang and X. Guan, "IoT Based Proactive Energy Supply Control for Connected Electric Vehicles," *IEEE Internet of Things Journal*, doi: 10.1109/JIOT.2019.2899928, 2019.

[2] K. Christidis and M. Devetsikiotis, "Blockchains and Smart Contracts for the Internet of Things," *IEEE Access*, vol. 4, pp. 2292-2303, 2016.

[3] W. Liao, J. He, S. Zhu, C. Chen and X. Guan, "On the Tradeoff Between Data-Privacy and Utility for Data Publishing," *IEEE 24th International Conference on Parallel and Distributed Systems (ICPADS)*, Singapore, pp. 779-786, 2018.

[4] Z. Hong, H. Huang, S. Guo, W. Chen and Z. Zheng, "QoS-Aware Cooperative Computation Offloading for Robot Swarms in Cloud Robotics," *IEEE Transactions on Vehicular Technology*, doi: 10.1109/TVT.2019.2901761, 2019.

[5] O. Novo, "Blockchain Meets IoT: An Architecture for Scalable Access Management in IoT," *IEEE Internet of Things Journal*, vol. 5, no. 2, pp. 1184-1195, Mar. 2018.

[6] A. Ouaddah, A. A. Elkalam, A. A. Ouahman, Towards a Novel Privacy-Preserving Access Control Model Based on Blockchain Technology in IoT, *Cham, Switzerland: Springer*, pp. 523-533, 2017.

[7] P. K. Sharma, M. Y. Chen and J. H. Park, "A Software Defined Fog Node Based Distributed Blockchain Cloud Architecture for IoT," *IEEE Access*, vol. 6, pp. 115-124, 2018.

[8] R. Li, T. Song, B. Mei, H. Li, X. Cheng and L. Sun, "Blockchain For Large-Scale Internet of Things Data Storage and Protection," *IEEE Transactions on Services Computing*, doi: 10.1109/TSC.2018.2853167, 2018.

[9] A. Lei, H. Cruickshank, Y. Cao, P. Asuquo, C. P. A. Ogah and Z. Sun, "Blockchain-Based Dynamic Key Management for Heterogeneous Intelligent Transportation Systems," *IEEE Internet of Things Journal*, vol. 4, no. 6, pp. 1832-1843, Dec. 2017.

[10] P. K. Sharma, S. Singh, Y. S. Jeong and J. H. Park, "DistBlockNet: A Distributed Blockchains-Based Secure SDN Architecture for IoT Networks," *IEEE Communications Magazine*, vol. 55, no. 9, pp. 78-85, 2017.

[11] 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. 13565-13574, 2018.

[12] J. Zou, B. Ye, L. Qu, Y. Wang, M. A. Orgun and L. Li, "A Proof-of-Trust Consensus Protocol for Enhancing Accountability in Crowdsourcing Services," *IEEE Transactions on Services Computing*, doi: 10.1109/TSC.2018.2823705, 2018.

[13] M. Liu, R. Yu, Y. Teng, V. C. M. Leung and M. Song, "Computation Offloading and Content Caching in Wireless Blockchain Networks with Mobile Edge Computing," *IEEE Transactions on Vehicular Technology*, doi: 10.1109/TVT.2018.2866365, 2018.

[14] D. Chatzopoulos, M. Ahmadi, S. Kosta and P. Hui, "FlopCoin: A Cryptocurrency for Computation Offloading," in *IEEE Transactions on Mobile Computing*, vol. 17, no. 5, pp. 1062-1075, 1 May 2018.

[15] G. Zizzo, E. Riva Sanseverino, M. G. Ippolito, M. L. Di Silvestre and P. Gallo, "A Technical Approach to P2P Energy Transactions in Microgrids," *IEEE Transactions on Industrial Informatics*, doi: 10.1109/TII.2018.2806357, 2018.

[16] 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*, doi: 10.1109/TII.2017.2786307, 2017.

[17] 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.

[18] Y. Jiao, P. Wang, D. Niyato, and Z. Xiong. Social welfare maximization auction in edge computing resource allocation for mobile blockchain, arXiv:1710.10595, 2017.

[19] Z. Xiong, S. Feng, D. Niyato, P. Wang, and Z. Han, Edge Computing Resource Management and Pricing for Mobile Blockchain, arXiv:1710.01567, 2018.

[20] C. Xu, K. Wang and M. Guo, "Intelligent Resource Management in Blockchain-Based Cloud Datacenters," *IEEE Cloud Computing*, vol. 4, no. 6, pp. 50-59, November/December 2017.

[21] E. C. Ferrer, The blockchain: a new framework for robotic swarm systems, arXiv:1608.00695, 2017.

[22] A. Dorri, S. S. Kanhere, R. Jurdak and P. Gauravaram, "Blockchain for IoT security and privacy: The case study of a smart home," in *Proc. 2017 IEEE International Conference on Pervasive Computing and Communications Workshops*, pp. 618-623, 2017.

[23] J. Yu, M. H. Cheung, J. Huang and H. V. Poor, "Mobile Data Trading: Behavioral Economics Analysis and Algorithm Design," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 4, pp. 994-1005, 2017.

[24] Y. Jiao, P. Wang, S. Feng and D. Niyato, "Profit Maximization Mechanism and Data Management for Data Analytics Services," in *IEEE Internet of Things Journal*, vol. 5, no. 3, pp. 2001-2014, June 2018.

[25] L. Wang, W. Liu and X. Han, "Blockchain-Based Government Information Resource Sharing," in *Proc. 2017 IEEE 23rd International Conference on Parallel and Distributed Systems*, pp. 804-809, 2017.

[26] C. Xu, K. Wang, P. Li, S. Guo, J. Luo, B. Ye, and M. Guo, "Making Big Data Open in Edges: A Resource-Efficient Blockchain-based Approach," in *IEEE Transactions on Parallel and Distributed Systems*, doi: 10.1109/TPDS.2018.2871449, 2018.

[27] Q. Xia, E. B. Sifah, K. O. Asamoah, J. Gao, X. Du and M. Guizani, "MeDShare: Trust-Less Medical Data Sharing Among Cloud Service Providers via Blockchain," in *IEEE Access*, vol. 5, pp. 14757-14767, 2017.

[28] Z. Su, Y. Wang, Q. Xu, M. Fei, Y. Tian and N. Zhang, "A Secure Charging Scheme for Electric Vehicles with Smart Communities in Energy Blockchain," in *IEEE Internet of Things Journal*, doi: 10.1109/JIOT.2018.2869297, 2018.

[29] T. Salman, M. Zolanvari, A. Erbad, R. Jain and M. Samaka, "Security Services Using Blockchains: A State of the Art Survey," *IEEE Communications Surveys and Tutorials*, doi: 10.1109/COMST.2018.2863956, 2018.

[30] T. T. A. Dinh, R. Liu, M. Zhang, G. Chen, B. C. Ooi and J. Wang, "Untangling Blockchain: A Data Processing View of Blockchain Systems," in *IEEE Transactions on Knowledge and Data Engineering*, vol. 30, no. 7, pp. 1366-1385, 1 July 2018.

[31] J. Liu, N. Kato, J. Ma and N. Kadowaki, "Device-to-Device Communication in LTE-Advanced Networks: A Survey," *IEEE Communications Surveys Tutorials*, vol. 17, no. 4, pp. 1923-1940, 2015.

[32] H. Guo, J. Liu, J. Zhang, W. Sun and N. Kato, "Mobile-Edge Computation Offloading for Ultradense IoT Networks," *IEEE Internet of Things Journal*, vol. 5, no. 6, pp. 4977-4988, Dec. 2018.