A Novel Debt-Credit Mechanism for Blockchain-Based Data-Trading in Internet of Vehicles

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***Abstract*—With the advancement and emergence of diverse network services in Internet of Vehicles (IoV), large volume of data are collected and stored, making data important properties. Data will be one of the most important commodities in the future blockchain-based IoV systems. However, efficiency challenges have been commonly found in blockchain-based data markets, which is mainly caused by transaction confirmation delays and the cold-start problems for new users. To address the efficiency challenges, we propose a secure, decentralized IoV data-trading system by exploiting the blockchain technology, and design an efficient debt-credit mechamism to support efficient data-trading in IoV. In the debt-credit mechanism, a vehicle with loan demand could loan from multivehicles by promising to pay interest and reward. In particular, we encourage loaning among vehicles by a motivation-based investing and pricing mechanism. We formulate a two-stage Stackelberg game to maximize the profits of borrower vehicle and lender vehicles jointly. In the first stage, the borrower vehicle set the interest rate and reward for the loan as its pricing strategies. In the second stage, the lender vehicles decide on their investing strategies. We apply backward induction to analyze the subgame perfect equilibrium at each stage for both independent and uniform pricing schemes. We also validate the existence and uniqueness of Stackelberg equilibrium. The numerical results illustrate the efficiency of the proposed pricing schemes.**

***Index Terms*—Blockchain, data-trading, debt-credit, Internet of Vehicles (IoV), Stackelberg game.**

I. Introduction

ALONG with the continuing development of intelligent vehicular equipments and wireless access technology, the concept of the Internet of Vehicles (IoV) has attracted widespread attentions by industry and academia [1], [2]. An universal network framework of vehicles includes all existing heterogeneous networks and vehicle-related mobile devices. This concept is strongly shaped due to highly growing number of vehicles and mobile devices, such as smartphones, laptops, wearable smart devices, and other sensor enabled devices [3]. With the development of diverse network services, the data collected, and stored in IoV are explosive increasing, and are becoming non-negligible resources [4], [5]. The current IoV framework usually adopt cyber-physical system (CPS) as a centralized information infrastructure [6], [7]. In the CPS framework, vehicle–vehicle interactions such as data exchanging and trading are conducted via a management center, which has high performance and reliability requirements for data storage and computation-intensive tasks. Under the background of big data and cloud storage technology, data exchanging and trading will become important in future IoV. However, under the current cloud-based centralized IoV framework, the loss of control over users' data has became a very serious challenge, making it difficult to protect privacy, boost innovation, and guarantee data sovereignty.

Recently, blockchain technology has emerged with its advantages of decentralization, security, and trust [8]–[10]. Blockchain technology has been considered as a feasible solution for addressing the challenges of trusty and security in Internet of Things (IoT) [11]–[13]. With the assistance of blockchain, IoT devices could trade energy or resources with other un-trusted peers securely [14]–[16]. Especially, researchers have also study applying blockchain in IoV scenarios for enhancing data security [17], which motivate us to take a further study of establishing an efficient, peer-to-peer (P2P) data-trading system for IoV. Li *et al.* [18] proposed a blockchain-based secure scheme for IoT data storage and protection, and exploited this scheme for data-trading. Liu *et al.* [19] investigated the security issues of the data interactions in the electric vehicles cloud and edge (EVCE) computing, and proposed blockchain-inspired "data coins" to support secure data interactions.

In the scenario of IoV, data interactions frequently occur among multiple participating roles, such as vehicle-vehicle, vehicle-roadside, and vehicle-infrastructure interactions [3]. Data commodities in IoV usually contain sensitive personal information, thus the guarantee of security and privacy is

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crucial for users involving data-trading [20]. The blockchain-based trading system has the advantages of decentralization and security, thus can provide security and privacy protection for IoV data-trading. In the other hand, blockchain-based trading system still faces many challenges. First, the mobility of vehicles makes the connections of IoV instability and frequently changes. The orders of IoV data commodities are frequently interrupted and repricing is necessary. This poses challenges of efficiency to IoV data-trading. Second, IoV data usually represent high perishability. The perishable IoV data suffer a greater loss in value with the trading time gap getting larger [8]. For example, the smart vehicle navigation system needs the latest nearby traffic and environmental information to avoid traffic jams. The consensus process in a blockchain-based system increases the transaction confirmation delays, which affects trading efficiency and funds turnover of data-requester. During frequently data-trading of IoV, data requesters usually do not have enough funds to support their next transaction immediately due to the transaction confirmation delays. Third, in IoV scenario there are many occasional users. It is difficult for such new users to participate in data-trading before they get data tokens by selling their data, which reduces the trading willingness of new users. Such "cold-start" problem also increases the barriers for new users. To overcome the above challenges in data-trading, the blockchain-based IoV system needs a flexible P2P debt-credit mechanism to help data requesters pay for their transactions immediately even if there are not enough funds in their accounts. The debt-credit mechanism can improve trading efficiency and solve the cold-start problem.

In this paper, we design an auxiliary debt-credit mechanism for the blockchain-based IoV data-trading system. We first describe typical P2P data-trading and loaning scenarios in IoV. Then, we present an unified data-trading IoV framework including buyer vehicles, seller vehicles, borrower vehicles, and lender vehicles. To improve trading efficiency, we propose a motivation-based debt-credit mechanism. The proposed debt-credit system adopts a multiple-multiple, pure P2P debt-credit mechanism. We encourage debt-credit businesses by providing both interests and rewards to the lender vehicles. To the best of our knowledge, we are the first to introduce debt-credit mechanism into IoV data-trading system. The main contributions of this paper are summarized as following.

1) In this paper, we establish a blockchain-based data-trading system for IoV. To support efficient data-trading, we design an auxiliary debt-credit mechanism for the data-trading system.
2) We formulate an investing and pricing model for the debt-credit transaction, and adopt a two-stage Stackelberg game to maximize the utility of the borrower vehicle. In this game, the borrower vehicle acts as leader and determines the loan rate for each lender vehicle. The lender vehicles act as followers and determine their investing amount.
3) We derive an unique Nash equilibrium point among lender vehicles in the second stage. We investigate the independent pricing as well as uniform pricing schemes in the first stage. We prove that for both the independent and uniform pricing schemes, the Stackelberg equilibrium is derived analytically.
4) We conduct simulation in a virtual map to evaluate the performance of the proposed pricing schemes. The numerical results show that our proposed pricing schemes are effective and efficient. The independent pricing scheme performs better than uniform pricing scheme for maximizing the profit of the borrower vehicle, and can better encourage data-trading and loaning.

The rest of this paper is organized as follows. Section II is the research work related to this paper. In Section III, we introduce the system components of the data-trading framework as well as the debt-credit system. We propose a new architecture for the blockchain-based IoV system. We also describe the key operations of debt-credit business. In Section IV, we formulate the two-stage Stackelberg game for the investing and pricing problem. We analyze the optimal investing amount of lender vehicles as well as the profit maximization of the borrower vehicle by using backward induction for both the independent and uniform pricing schemes. In Section V, we give the performance evaluation with simulation and results. In Section VI, we give the conclusions of this paper with future directions.

II. Related Works

With the development of intelligent vehicles and vehicular networks, the sharing and interaction of vehicular data have also been focused by both academia and industry. Vehicular data includes data generated from vehicular network and the data required by vehicle users. How to securely and efficiently share vehicular data is a challenge issue. Ko *et al.* [21] presented an efficient data dissemination system in vehicular networks via the cooperation of infrastructure-to-vehicle and vehicle-to-vehicle communication. More *et al.* [22] proposed a cooperative data sharing with secure framework for voluntary services in vehicular networks. Ito *et al.* [23] proposed a road alert information sharing system with multiple vehicles considering various communication network environments by using vehicle-to-vehicle communication. Moreover, Feng and Wang [24] proposed and analyzed a selective sharing scheme for vehicular data owners to share their sensitive data with some authorized data users in a vehicular social network. The above works expanded the application of vehicular data in various IoV scenarios. However, the security challenge and privacy risk exist in the sharing of vehicular data.

In the last few years, the application of the blockchain has been extended to IoT. Ferrag *et al.* [25] gave an overview of the blockchain protocols and applications for IoT, and discussed the existing issues and challenges in blockchain-based IoT framework. Moreover, many researchers have investigated the potential of blockchain for establishing a trusted and secure trading system for IoV. Kang *et al.* [26] exploited a consortium blockchain to design a localized P2P energy-trading system in which electric vehicles can trade energy. This motivates us to study how to establish a blockchain-based data-trading system for IoV. Singh and Kim [27] proposed a blockchain-based crypto Trust point (cTp) mechanism to build a secure trusted decentralized environment for vehicular data-sharing. Yang *et al.* [17] proposed a decentralized trust management system for IoV based on blockchain. The above systems did not consider the efficiency issue of data-trading. Vehicular data are characterized by perishability [4]. Data requesters in IoV usually urgently need the desired data, such as real-time road conditions data for trip time prediction. Transaction efficiency becomes a bottleneck problem for blockchain-based data-trading system.

In blockchain-based data-trading system, users are usually short of funds due to the transaction confirmation delays and cold-start problem, which significantly influences the transaction efficiency. Li *et al.* [28] designed a credit-based payment scheme to overcome the efficiency issue of blockchain-based energy-trading system in IIoT. This scheme depends on authorized "Credit Bank" which makes it not a pure P2P mechanism. User privacy is still facing security risks. In this paper, we exploit the blockchain technology to propose an efficient data-trading and loan system for IoV. In particular, we design a motivation-based investing and pricing mechanism for the debt-credit system to address the efficiency challenge of data-trading in IoV.

III. Blockchain-Based Data-Trading and Debt-Credit System

In this section, we introduce the entities and core components of the blockchain-based data-trading and debt-credit system. We propose a blockchain-enhanced five layered architecture for IoV based on the legacy architecture. We also describe the key operations of the debt-credit process.

A. Entities in the Data-Trading and Debt-Credit System

The explosive increase of data generated in IoV makes it impossible to store and manage all data in the local vehicular devices. Our proposed data-trading and debt-credit system includes multi-interface-based station as aggregators which provide high-speed communication and ledge storage service for vehicles. Fig. 1 illustrates the data-trading and loan system we consider. This system consists of the following components.

1) Vehicles: Vehicles in our proposed system can exchange their private data as commodities. Meanwhile, the vehicles can also borrow and lend their data tokens, which we call "data coins," with other peers. Vehicles can gain data coins by selling their private data, or borrowing data coins from other vehicles. Vehicles which lend their data coins to others can also get revenue of data coins as interests. Thus, in the proposed data-trading and debt-credit system, vehicles play multiple roles: seller vehicles, buyer vehicles, borrower vehicles, and lender vehicles. Each vehicle chooses its role according to its data requirement and economic state.

2) Aggregators: In the data-trading and debt-credit system, aggregators work as brokers to manage trading-related activities and provide edge-computing services. The aggregators also support high-speed communication among vehicles. In a typical IoV system, the communication infrastructure (i.e., base stations) usually act as the aggregators [29]. Aggregators also provide storage and backup for vehicular data, especially when the local storage space is limited. Vehicles can transmit their data via vehicle-to-vehicle communication directly or via the aggregators.

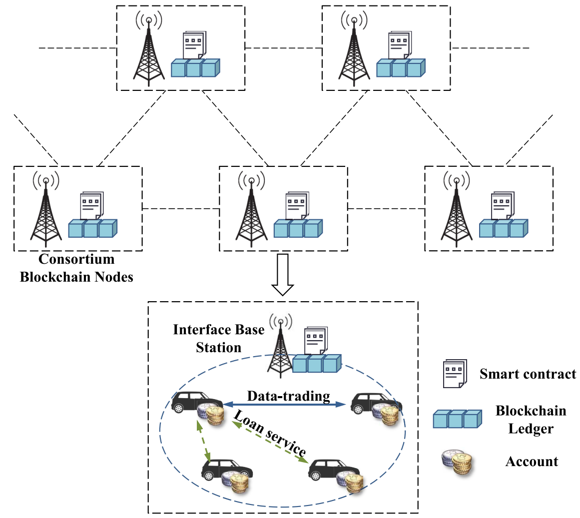


Fig. 1. Blockchain-based data-trading and loaning system in IoV.

B. Unified Blockchain for Data-Trading and Debt-Credit System

In the proposed data-trading and debt-credit system, we exploit a consortium blockchain for secure P2P data-trading and loan services. Based on the five layered legacy IoV architecture proposed in [3], we designed a new blockchain-enhanced layered architecture for IoV, which includes the following layers: perception layer, coordination layer, artificial intelligence layer, application layer, and business layer. The proposed five layered architecture with the related protocol stack is shown in Fig. 2.

1) Data Layer: The first layer of our architecture is data layer, which is consisted of the IoV perception sublayer and blockchain data sublayer. IoV perception sublayer is mainly responsible to gather vehicular data via vehicular sensors and personal devices. The blockchain data sublayer is represented by a series of connected blocks. Each block contains a hash pointing to the previous block such that all blocks comprise the blockchain. The transactional data stored in the blocks are visible to all vehicles. Transactional data are encrypted and signed with the digital signature for security.

2) Network Layer: The second layer of the architecture is network layer, which is consisted of a network coordination module and P2P network sublayer of blockchain. The network coordination module is involving heterogeneous networks including IEEE 802.11p, 802.11, and WAVE-1609.4. In our system, we exploit a consortium blockchain to support secure and efficient data-trading and loan services. The aggregators are selected as the authorized blockchain nodes. Therefore, the P2P connections are actually built among the authorized aggregators.

3) Artificial Intelligence Layer: The third layer is artificial intelligence layer, which is consisted of the blockchain

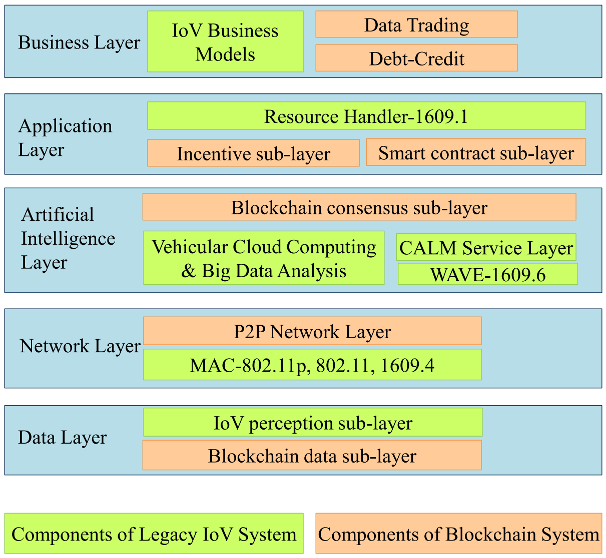


Fig. 2. Blockchain-enhanced five-layered IoV architecture.

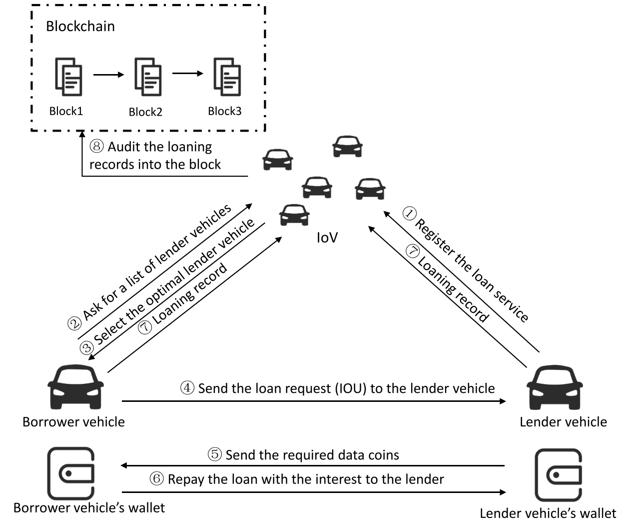


Fig. 3. Key operations of debt-credit process.

consensus sublayer, and vehicular-oriented computing and analysis services. The protocols in this layer include CALM service sublayer, WAVE-1609.6 service related protocols, vehicular cloud computing and big data analysis related protocols, and the consensus protocol of blockchain. In our system, the authorized aggregators perform the proof-of-work (PoW) consensus algorithm for vehicles and write the blocks with transactional data. Transactional data are publicly audited by all authorized aggregators [29].

4) Application Layer: The fourth layer is application layer, which is consisted of resource handler protocol WAVE-1609.1, blockchain intensive sublayer, and blockchain smart contract sublayer. The resource handler protocol could manage resource among IoV applications. Blockchain intensive sublayer is responsible for rewarding the miner that first provides valid PoW with digital tokens. Smart contracts are a series of predefined protocols operated by all peers in a blockchain-based system for specific service requirements. Blockchain smart contract sublayer defines the smart contracts involving trading and debt-credit business.

5) Business Layer: The topmost layer is business layer, which is consisted of IoV business models, data-trading business, and debt-credit business. As defined in [3], four types of business models are considered in IoV, i.e., insurance, sale, service and advertisement. Data-trading business and debt-credit business are guaranteed by the blockchain system with security.

C. Operations of Debt-Credit Business

We now discuss the key operations of the proposed debt-credit mechanism. The key operations of debt-credit process are illustrated in Fig. 3.

1) System Initialization: In the proposed system, each vehicle will become a legitimate entity by registration with a trusted authority. Smart contracts deployed in the system ensure the authority of vehicles. When joining the system, each vehicle obtains an unique identity, its public and private keys, and its encrypted signature. The authority also allocates a wallet address for each vehicle as its account. After registration, the authority generates a mapping list for each vehicle and stores the list in each aggregator.

2) Choosing Different Roles: In the debt-credit scenario, vehicles are divided into borrower vehicles and lender vehicles. Vehicles without enough funds become the borrower vehicles, and vehicles with surplus funds become the lender vehicles. Lender vehicles should register their loan services into the service pools. The borrower vehicle asks for a list of lender vehicles from the service pools and select the appropriate lender vehicles.

3) Borrowing and Lending: Our proposed debt-credit mechanism supports a multiple-multiple borrowing and lending model. A borrower vehicle can get its loans from multiple lender vehicles, and a lender vehicle can also provide loans to multiple borrower vehicles. In this debt-credit machanism, the loan amount and rate of each borrower-lender pairs are derived by a motivation-based investing and pricing mechanism. More details are given in Section IV. After determining the loan amount and interest rate, the borrower vehicle will send an IOU (i.e., a promise to pay a debt) to each lender vehicle. After verifying the IOU as well as the identity of the borrower vehicle, the lender vehicles send corresponding data coins to the public wallet address of the borrower vehicle. In the repayment process, the borrower vehicle sends the repayments, including both capital and interest, to the wallet address of each lender vehicle. The lender vehicles confirm the amount of repayments and whether the repayments are overdue. Finally, both the lender vehicles and borrower vehicle will update their credit rate and broadcast the transactional data to aggregators for public audit.

4) Building Blocks and Carrying Out Consensus Process: Authorized aggregators will collect all transactional data for a certain period with encrypted signatures, and structure them into blocks. Each block contains a cryptographic hash for its prior block, thus form the blockchain. The authorized aggregators that first gives a valid PoW in the consensus process will be selected as the blockchain leader. The blockchain leader broadcasts block data, a timestamp, and its PoW to other peers for verification and audit. Other peers then reply with their audit results for mutual supervision and verification. If all the auditors agree on the block data, the blockchain leader will add its block into the blockchain and obtain its mining rewards.

IV. Motivation-Based Investing and Pricing Mechanism for Debt-Credit System

In the scenario of data-trading, buyer vehicles obtain the required data by paying data coins to the seller vehicles. The perishability of digital goods requires an efficient trading and payment manner [4]. However, due to the transaction confirmation delays, some buyer vehicles may not have enough data coins for their required data. The cold-start problem for new users also increases the barriers for new participants joining the trading. In this section, we present a debt-credit system to address the challenge of efficiency, and solve the cold-start problem of new users. We propose a motivation-based investing and pricing mechanism for the debt-credit system. In particular, we formulate a two-stage Stackelberg game to solve the pricing problem in the debt-credit process. In this game, the borrower vehicle acts as the leader and sets its loan rate for each lender. The lender vehicles act as followers and decide their optimal investing strategies.

A. Problem Formulation

The proposed loan system is similar with a bond-based investment system. In this system, the borrower vehicle raise the required funds by issuing bonds with a given repayment term. The lender vehicles act as investors. Each investor will purchase some bonds from the borrower vehicle. The borrower vehicle has the duty to repay both capital and interest to the investors within the prescribed repayment term.

We consider that there are a group of N lender vehicles, the set of which is denoted by $\mathcal{N} = \{1, \ldots, N\}$, that can provide lending services to the borrower vehicle. The borrower vehicle obtains its required data coins by issuing bonds with a certain interest rate to each lender vehicle. The lender vehicles purchase the bonds by paying data coins to the borrower vehicle. In this model, the borrower vehicle determines its loan rate from each lender vehicle $i \in \mathcal{N}$, which is denoted by r_i. Lender vehicle i determines its investing amount, i.e., the lending amount, which is denoted by x_i. The minimum loan requirement of the borrower vehicle is denoted by X. The maximum investing amount, i.e., the maximum lending amount, of i is denoted by $x_i^{\max}$. The minimum lending rate of i is denoted as $r_i^{\min}$. The maximum loan rate the borrower vehicle can give is denoted by $r^{\max}$. Let $\mathbf{x} \triangleq (x_1, \ldots, x_N)$ and $\mathbf{x}^* \triangleq (x_1^*, \ldots, x_N^*)$ represent the investing amount profile and optimal investing amount profile of the lender vehicles, respectively. Similarly, let $\mathbf{r} \triangleq (r_1, \ldots, r_N)$ and $\mathbf{r}^* \triangleq (r_1^*, \ldots, r_N^*)$ represent the loan rate profile and the optimal loan rate profile of the borrower vehicle for each lender vehicle. The major notations used in this paper are listed in Table I.

TABLE I
NOTATIONS

Symbol	Definition
$\mathcal{N}$	Set of lender vehicles
N	The number of lender vehicles
x_i	The investing amount of lender vehicle i
x_i^{max}	The maximum investing amount of lender vehicle i
r_i	The loan rate from lender vehicle i
r_i^{min}	Minimum lending rate of lender vehicle i
r^{max}	Maximum loan rate of the borrower vehicle
$\mathbf{x}$	The investing amount profile of all the lender vehicles
$\mathbf{x}_{-i}$	The investing amount profile of all other lender vehicles except lender vehicle i
$\mathbf{r}$	The loan rate profile of all the lender vehicles
$\mathbf{r}_{-i}$	The loan rate profile of all other lender vehicles except lender vehicle i
R	The unstable reward
ϕ_i	The investment willing of lender vehicle i for the unstable reward
w	The investment willing factor for the unstable reward
X	The minimum loan demand of the borrower vehicle
η	The greedy factor of borrower vehicle for the loan

The interactions among borrower vehicle and lender vehicles can be modeled as a two-stage Stackelberg game [28]. In this game, the borrower vehicle acts as the leader and sets its loan rate profile $\mathbf{r}$ in Stage I. The lender vehicles act as the followers and decide their investing amount profile $\mathbf{x}$ in Stage II. Fig. 4 illustrates this two-stage Stackelberg game. In this model, we design a motivation-based investing and pricing mechanism to provide economic incentives for the lender vehicles. In this mechanism, the revenue of each lender vehicle i consists a steady interest income, i.e., $x_i r_i$, and an unstable reward R. In a loan transaction, all the lender vehicles can obtain their interest incomes, but only one lender vehicle can obtain the unstable reward R. In our model, the lender vehicle with more investment should be more likely to win the unstable reward. Thus, we define the probability that lender vehicle i successfully wins the unstable reward as

$$P_i(x_i, \mathbf{x}_{-i}) = \frac{x_i}{\sum_{j \in \mathcal{N}} x_j}. \quad (1)$$

Considering the economic risks of investing for the unstable reward, which is a discouragement to the investors, we define the investment willingness of i for the unstable reward as

$$\phi_i = w\big(x_i^{\max} + R - x_i\big)/x_i^{\max} \quad (2)$$

where w is a predefined investment willing factor for R. Therefore, the expected utility of lender vehicle i can be given as

$$LU_i(x_i, \mathbf{x}_{-i}, r_i) = \frac{x_i}{\sum_{j \in \mathcal{N}} x_j} \phi_i R + \left(r_i - r_i^{\min}\right) x_i. \quad (3)$$

The satisfaction of the borrower vehicle is related to total raised funds, i.e., the investing amount from all lender vehicles. We denote the satisfaction function of the borrower vehicle as

$$BU_{\text{sat}}(\mathbf{x}) = \eta \ln\left(\sum_{i \in \mathcal{N}} x_i - X + 1\right) \quad (4)$$

where $\eta > 0$ is a predefined greedy factor of the borrower vehicle, indicating the willingness of the borrower vehicle for raising more loans.

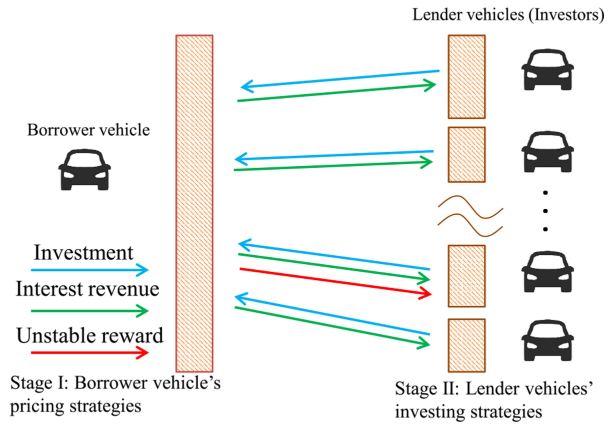


Fig. 4. Two-stage Stackberg game model of loan pricing problem.

The profit of the borrower vehicle is its satisfaction minus the interest and the reward it will pay. Thus, the expected profit of the borrower vehicle is represented as

$$\begin{aligned} BU(\mathbf{x},\ \mathbf{r}) &= BU_{\text{sat}}(\mathbf{x}) - \sum_{i\in\mathcal{N}}\left(r_i x_i + \frac{x_i}{\sum_{j\in\mathcal{N}} x_j}R\right) \\ &= BU_{\text{sat}}(\mathbf{x}) - \sum_{i\in\mathcal{N}} r_i x_i - R. \end{aligned} \tag{5}$$

By using backward induction, we formulate the optimization problem for borrower vehicle and lender vehicles as follows.

Problem 1 (Lender Vehicle i Subgame):

$$\begin{aligned} &\underset{x_i}{\text{maximize}} \ \ LU_i(x_i, \mathbf{x}_{-i}, r_i) \\ &\text{subject to} \ \ x_i \in [0,\ x_i^{\mathbf{max}}], \forall i \in \mathcal{N}. \end{aligned} \tag{6}$$

Problem 2 (Borrower Vehicle Subgame):

$$\begin{aligned} &\underset{\mathbf{r}}{\text{maximize}} \ \ BU(\mathbf{x},\ \mathbf{r}) \\ &\text{subject to} \ \ r_i \in \left[r_i^{\min},\ r^{\max}\right], \forall i \in \mathcal{N}. \end{aligned} \tag{7}$$

Problems 1 and 2 together form the two-stage Stackelberg game. The objective of this game is to find the Stackelberg equilibrium in which the profit of the leader is maximized given that the followers adopt their best responses.

Definition 1: Let $\mathbf{x}^*$ and $\mathbf{r}^*$ denote the optimal investing amount profile of the lender vehicles and the optimal loan rate profile of the borrower vehicle for each lender vehicle, respectively. The point $(\mathbf{x}^*, \mathbf{r}^*)$ is the Stackelberg equilibrium if the following conditions:

$$BU\left(\mathbf{x}^*,\ \mathbf{r}^*\right) \geq BU\left(\mathbf{x}^*,\ \mathbf{r}\right) \tag{8}$$

and

$$LU_i\left(x_i^*, \mathbf{x}_{-i}^*, r_i^*\right) \geq LU_i\left(x_i, \mathbf{x}_{-i}^*, r_i^*\right), \forall x_i \geq 0, \forall i \in \mathcal{N} \tag{9}$$

are satisfied, where $\mathbf{x}_{-i}^*$ is the optimal investing amount profile of other lender vehicles except i.

In this Stackelberg game, the borrower vehicle can apply two types of pricing schemes to the lender vehicles: 1) the independent pricing scheme and 2) the uniform pricing scheme. These two types of pricing schemes focus on the profit of the borrower vehicle and the profit of the lender vehicles, respectively. In the independent pricing mode, the borrower vehicle set different loan rate for each lender vehicle independently to maximize its profit and minimize the cost. In the uniform pricing mode, the borrower vehicle set the same loan rate for each lender vehicle. Each lender vehicle impartially get their interest income based on an uniform loan rate. This mode embodies the principle of fairness for the investments of the lender vehicles. We investigate these two pricing schemes, and conduct equilibrium analysis in the following.

B. Independent Pricing Scheme

We first investigate the independent pricing scheme. The Stackelberg game between the borrower vehicle and the lender vehicles can be divided into a series of subgames between the borrower vehicle and each lender vehicle. Therefore, we can solve the pricing problem by deriving the Stackeberg equilibrium, i.e., the Nash equilibrium, of each subgame independently. We use backward induction to analyze the two-stage Stackelberg game.

1) Lender Vehicles' Investing Strategies in Stage II: Given the loan rate of the borrower vehicle for each lender vehicle $i \in \mathcal{N}$, i.e., $\{r_i\}_{i\in\mathcal{N}}$, the lender vehicles maximize their utilities by determining their optimal investing strategies. This forms the noncooperative Lender vehicles' investing game (LIG), which is presented as: $\mathcal{G} = \{\mathcal{N}, \{x_i\}_{i\in\mathcal{N}}, \{LU_i(x_i, \mathbf{x}_{-i}, r_i)\}_{i\in\mathcal{N}}\}$, where $\{x_i\}_{i\in\mathcal{N}}$ is the set of investing strategies, and $LU_i(x_i, \mathbf{x}_{-i}, r_i)$ is the utility of lender vehicle i corresponding to r_i and $\mathbf{x}$. Each lender vehicle sets its investing strategy to maximize its utility. We next investigate the Nash equilibrium in the LIG.

Definition 2: The investing mount vector $\mathbf{x}^* \triangleq (x_1^*, \ldots, x_N^*)$ is the Nash equilibrium of $\mathcal{G} = \{\mathcal{N}, \{x_i\}_{i\in\mathcal{N}}, \{LU_i(x_i, \mathbf{x}_{-i}, r_i)\}_{i\in\mathcal{N}}\}$, *if* $LU_i(x_i^*, \mathbf{x}_{-i}^*, r_i^*) \geq LU_i(x_i, \mathbf{x}_{-i}^*, r_i^*)$ is satisfied for each lender vehicle $i \in \mathcal{N}$ and for all $x_i \in [0, x_i^{\max}]$.

Theorem 1: An unique Nash equilibrium exists in $\mathcal{G} = \{\mathcal{N}, \{x_i\}_{i\in\mathcal{N}}, \{LU_i(x_i, \mathbf{x}_{-i}, r_i)\}_{i\in\mathcal{N}}\}$.

Proof: The strategy space for i is defined to be $[0, x_i^{\max}]$, which is a nonempty, convex, compact subset of the Euclidean space. From (3), $LU_i(x_i, \mathbf{x}_{-i}, r_i)$ is apparently continuous in $[0, x_i^{\max}]$. We define $\alpha = \sum_{i\in N} x_i$ as the loan amount of the borrower vehicle from all lender vehicles. Similarly, we define $\beta_i = \alpha - x_i = \sum_{j\neq i} x_j$ as the loan amount of the borrower vehicle from other lender vehicles except i, and assume that $\beta_i > x_i, \forall i \in \mathcal{N}$. We take the first- and second-order derivatives of (3) with respect to x_i to prove its concavity, which can be written as follows:

$$\begin{aligned} \frac{\partial LU_i}{\partial x_i} = \frac{wR}{x_i^{\max}\alpha^2}\Bigg[&\left(r_i - r_i^{\min}\right)\frac{x_i^{\max}\alpha^2}{wR} \\ &+ \left(x_i^{\max} + R\right)\beta_i - 2x_i\alpha + x_i^2\Bigg] \end{aligned} \tag{10}$$

and

$$\frac{\partial^2 LU_i}{\partial x_i^2} = -\frac{2wR}{x_i^{\max}\alpha^2}\left[2x_i^{\max} + 2R - 3x_i + \beta_i\right] < 0. \tag{11}$$

$$\begin{aligned}\lambda\mathcal{F}_i(\mathbf{x})-\mathcal{F}_i(\lambda\mathbf{x})&=\lambda\sqrt{\frac{wR\Big[\Big(\sum_{j\neq i}x_j\Big)^2+\big(x_i^{\max}+R\big)\sum_{j\neq i}x_j\Big]}{wR-x_i^{\max}\big(r_i-r_i^{\min}\big)}}-\lambda\sum_{j\neq i}x_j\\&\quad-\sqrt{\frac{wR\Big[\Big(\sum_{j\neq i}\lambda x_j\Big)^2+\big(x_i^{\max}+R\big)\sum_{j\neq i}\lambda x_j\Big]}{wR-x_i^{\max}\big(r_i-r_i^{\min}\big)}}+\sum_{j\neq i}\lambda x_j\\&=\frac{\big(\sqrt{\lambda}-1\big)\sqrt{\frac{wR(x_i^{\max}+R)\sum_{j\neq i}x_j}{wR-x_i^{\max}(r_i-r_i^{\min})}}}{\sqrt{\lambda\Big(\sum_{j\neq i}x_j\Big)^2+\lambda\big(x_i^{\max}+R\big)\sum_{j\neq i}x_j}+\sqrt{\lambda\Big(\sum_{j\neq i}x_j\Big)^2+\big(x_i^{\max}+R\big)\sum_{j\neq i}x_j}}>0,\forall\lambda>1\end{aligned}\tag{18}$$

Therefore, we proved that $LU_i(x_i, \mathbf{x}_{-i}, r_i)$ is strictly concave with respect to x_i. Accordingly, a Nash equilibrium exists in this noncooperative LIG.

Next, we prove the uniqueness of the Nash equilibrium in LIG. We investigate the optimal investing strategies $\{x_i^*\}_{i\in\mathcal{N}}$ of lender vehicles.

Based on $[(\partial LU_i)/(\partial x_i)] = 0$, we have

$$\frac{\alpha^2 x_i^{\max}\big(r_i-r_i^{\min}\big)}{wR}+\big(x_i^{\max}+R\big)\beta_i-2x_i\alpha+x_i^2=0.\tag{12}$$

Therefore, we obtain the best response function for lender vehicle i by solving (12) as following:

$$x_i^*=\mathcal{F}_i(\mathbf{x})=\begin{cases}x_i^{\max} & z_i>x_i^{\max}\\ z_i & 0<z_i\le x_i^{\max}\\ 0 & z_i\le 0\end{cases}\tag{13}$$

where $z_i=\sqrt{([wR(\beta_i^2+x_i^{\max}\beta_i+R\beta_i)]/[wR-x_i^{\max}(r_i-r_i^{\min})])}$ $-\beta_i$, $\mathcal{F}_i(\mathbf{x})$ is the best response function of lender vehicle i.

Let $\mathbf{x}^*$ denote the Nash equilibrium of LIG. This Nash equilibrium must satisfy $\mathbf{x}^* = \mathcal{F}(\mathbf{x})$, where $\mathcal{F}(\mathbf{x}) = (\mathcal{F}_1(\mathbf{x}), \ldots, \mathcal{F}_N(\mathbf{x}))$. $\mathcal{F}_i(\mathbf{x})$ is the best response function of lender vehicle i as shown in (13). The uniqueness of the Nash equilibrium in LIG can be proved by showing that the best response function of i is a standard function [30].

Definition 3: A function $\mathcal{F}(\mathbf{x})$ is a standard function when the following properties are guaranteed.

1) *Positivity:* $\mathcal{F}(\mathbf{x}) > 0$.
2) *Monotonicity:* If $\mathbf{x} \le \mathbf{x}'$, then $\mathcal{F}(\mathbf{x}) \le \mathcal{F}(\mathbf{x}')$.
3) *Scalability:* For all $\lambda > 1$, $\lambda\mathcal{F}(\mathbf{x}) > \mathcal{F}(\lambda\mathbf{x})$.

We will prove that $\mathcal{F}_i(\mathbf{x})$ satisfies the three properties of a standard function.

First, for the positivity, we have

$$\begin{aligned}\mathcal{F}_i(\mathbf{x})&=\sqrt{\frac{wR\big(\beta_i^2+x_i^{\max}\beta_i+R\beta_i\big)}{wR-x_i^{\max}\big(r_i-r_i^{\min}\big)}}-\beta_i\\&>\sqrt{\big(\beta_i^2+x_i^{\max}\beta_i+R\beta_i\big)}-\beta_i>0,\forall i\in\mathcal{N}.\end{aligned}\tag{14}$$

Therefore, we prove the positivity of $\mathcal{F}(\mathbf{x})$.

Then, we prove the monotonicity of $\mathcal{F}(\mathbf{x})$ with respect to $\mathbf{x}$. We first prove the monotonicity of $\mathcal{F}(\mathbf{x})$ with respect to β_i. By differentiating (13) with respect to β_i, we have

$$\begin{aligned}\frac{\partial\mathcal{F}_i(\mathbf{x})}{\partial\beta_i}&=\sqrt{\frac{wR\big[\beta_i+\big(x_i^{\max}+R\big)/2\big]^2}{\big[wR-x_i^{\max}\big(r_i-r_i^{\min}\big)\big]\big[\beta_i^2+\big(x_i^{\max}+R\big)\beta_i\big]}}\\&\quad-1>\sqrt{1+\frac{\big(x_i^{\max}+R\big)^2}{4\big[\beta_i^2+\big(x_i^{\max}+R\big)\beta_i\big]}}-1>0.\end{aligned}\tag{15}$$

Let $\mathbf{x}' > \mathbf{x}$, we have the following inequality for lender vehicle i:

$$\beta_i'=\sum_{j\neq i}x_j'>\sum_{j\neq i}x_j=\beta_i.\tag{16}$$

Based on (15) and (16), we have

$$\mathcal{F}(\mathbf{x})-\mathcal{F}\big(\mathbf{x}'\big)>0.\tag{17}$$

Therefore, the best response function $\mathcal{F}(\mathbf{x})$ is always monotone increasing with $\mathbf{x}$.

Finally, for scalability, we must prove that $\lambda\mathcal{F}(\mathbf{x}) - \mathcal{F}(\lambda\mathbf{x}) > 0$, for all $\lambda > 1$. The steps of proving the positivity of $\lambda\mathcal{F}(\mathbf{x}) - \mathcal{F}(\lambda\mathbf{x})$ are shown in (18), at the top of this page.

So far, we have proved that the best response function $\mathcal{F}(\mathbf{x})$ satisfies the three properties of a standard function. Therefore, an unique Nash equilibrium exists in LIG. The proof is completed. ■

In the following, we will analyze the profit maximization of the borrower vehicle in Stage I under independent pricing scheme to further investigate the Stackelberg equilibrium.

2) Borrower Vehicle's Pricing Strategies in Stage I: Based on the Nash equilibrium of the lender vehicles' investing strategies in Stage II, the borrower vehicle maximizes its profit by optimizing its pricing strategies in Stage I. Therefore, the optimal pricing strategies of the borrower vehicle can be formulated as an optimization problem. Based on (5), the profit maximization problem of the borrower vehicle in Stage I is simplified as follows:

$$\begin{aligned}&\underset{\mathbf{r}}{\text{maximize}}\;\; \mathrm{BU}(\mathbf{x},\ \mathbf{r})=\eta\ln\Big(\sum_{i\in\mathcal{N}}x_i-X+1\Big)\\&\qquad\qquad-\sum_{i\in\mathcal{N}}r_ix_i-R\\&\text{subject to}\;\; r_i\in\Big[r_i^{\min},\ r^{\max}\Big],\forall i\in\mathcal{N}.\end{aligned}\tag{19}$$

Theorem 2: In the borrower vehicle's pricing game, the convergence of borrower vehicle's profit $BU(\mathbf{x}, \mathbf{r})$ is guaranteed if there are sufficient funds in the loan market, and the parameter η satisfies the following condition:

$$\eta < \frac{(\alpha - X + 1)^2 \left(4wR - x_i^{\max} r_i + 4x_i^{\max} r_i^{\min}\right)}{x_i^{\max}(2\alpha - 3X + 3)}, \forall i \in \mathcal{N}. \tag{20}$$

Proof: In the independent pricing scheme, we assume that the borrower vehicle sets the loan rate r_i for each lender vehicle independently. On the other hand, each lender vehicle i gives its investing strategy mainly based on r_i and other lender vehicles' investing strategies $\mathbf{x}_{-i}$. In this model, we assume the investing strategy of i is independent with the borrower vehicle's loan rate for other lender vehicles. Thus, we have the following relations:

$$\frac{\partial x_i}{\partial r_j} = 0, \forall j \neq i \tag{21}$$

and

$$\frac{\partial \beta_i}{\partial r_i} = 0, \forall i \in \mathcal{N}. \tag{22}$$

Based on (13), the loan amount of the borrower vehicle from all lender vehicles is represented as

$$\alpha = \sqrt{\frac{wR\left(\beta_i^2 + x_i^{\max}\beta_i + R\beta_i\right)}{wR - x_i^{\max}\left(r_i - r_i^{\min}\right)}}, \forall i \in \mathcal{N}. \tag{23}$$

We derive the first- and second-order derivatives of α with respect to r_i by substituting (21) and (22) into (23), which can be written as follows:

$$\frac{\partial \alpha}{\partial r_i} = \frac{\partial x_i}{\partial r_i} = \frac{x_i^{\max}\sqrt{wR\left(\beta_i^2 + x_i^{\max}\beta_i + R\beta_i\right)}}{2\left[wR - x_i^{\max}\left(r_i - r_i^{\min}\right)\right]^{3/2}} \tag{24}$$

and

$$\frac{\partial^2 \alpha}{\partial r_i^2} = \frac{\partial^2 x_i}{\partial r_i^2} = \frac{3\left(x_i^{\max}\right)^2\sqrt{wR\left(\beta_i^2 + x_i^{\max}\beta_i + R\beta_i\right)}}{4\left[wR - x_i^{\max}\left(r_i - r_i^{\min}\right)\right]^{5/2}} \tag{25}$$

$$\psi_i = \frac{\partial x_i}{\partial r_i} = \frac{x_i^{\max}\sqrt{wR\left(\beta_i^2 + x_i^{\max}\beta_i + R\beta_i\right)}}{2\left[wR - x_i^{\max}\left(r_i - r_i^{\min}\right)\right]^{3/2}}. \tag{26}$$

We define $\psi_i = [(\partial x_i)/(\partial r_i)] > 0$ and $\varphi_i = [(\partial^2 x_i)/(\partial r_i^2)] > 0$ for convenience. Based on (23)–(25) we can obtain the following relation:

$$3\psi_i^2 = \alpha\varphi_i. \tag{27}$$

Based on (19) and (26), the first- and second-order derivative of borrower vehicle's profit with respect to r_i is given as follows:

$$\frac{\partial BU}{\partial r_i} = \frac{\psi_i \eta}{\alpha - X + 1} - (x_i + \psi_i r_i) \tag{28}$$

and

$$\begin{aligned}\frac{\partial^2 BU}{\partial r_i^2} &= \frac{\eta\varphi_i}{\alpha - X + 1} - \frac{\eta\psi_i^2}{(\alpha - X + 1)^2} - 2\psi_i - \varphi_i r_i \\ &= \frac{\eta\varphi_i\left(\frac{2}{3}\alpha - X + 1\right)}{(\alpha - X + 1)^2} - 2\psi_i - \varphi_i r_i \\ &= \varphi_i \frac{\frac{2}{3}\alpha - X + 1}{(\alpha - X + 1)^2}(\eta - \gamma_i)\end{aligned} \tag{29}$$

where $\gamma_i = [((\alpha - X + 1)^2(4wR - x_i^{\max} r_i + 4x_i^{\max} r_i^{\min}))/(x_i^{\max}(2\alpha - 3X + 3))]$.

Since there are sufficient funds in the market, we assume that $(2/3)\alpha - X + 1 > 0$. It is easy to derive that $[(\partial^2 BU)/(\partial r_i^2)] < 0$ if the condition $\eta < \gamma_i$ is satisfied. The convergence of $BU(\mathbf{x}, \mathbf{r})$ is guaranteed. The proof is completed. ■

The profit maximization of the borrower vehicle defined in (19) is a convex optimization problem. We can apply a low-complexity gradient-based search algorithm to achieve the maximized profit of the borrower vehicle, as well as the optimal strategies of both the borrower vehicle and lender vehicles. We adopt Algorithm 1 to obtain the unique Stackelberg equilibrium and solve the optimal loan pricing problem. The basic description is explained as follows. First, the leader, i.e., the borrower vehicle, offer its initial pricing strategies to the lender vehicles. Then, the subgame of each follower (lender vehicle) is solved based on the given pricing strategies. Next, each lender vehicle offers its optimal investing strategy to the borrower vehicle. After substituting the best response of the follower's subgame into the leader's subgame, we find the leader's corresponding pricing strategies which are fed back to the follower's subgame. Therefore, the leader's optimal pricing strategies can be obtained by a gradient-based algorithm.

C. *Uniform Pricing Scheme*

Then, we investigate the uniform pricing scheme. In this scheme, the borrower vehicle treats all the lender vehicles equally with an uniform loan rate, i.e., $r_i = r, \forall i \in \mathcal{N}$. We use the backward induction to analyze the optimal investing strategies of lender vehicles and the profit maximization of the borrower vehicle.

1) Lender Vehicles' Strategies in Stage II: In the uniform pricing scheme, the strategy space of the borrower vehicle becomes $r \in [\,\mathbf{max}\{r_i^{\min}\}_{i\in\mathcal{N}}, r^{\max}]$. The best response function of lender vehicle i is similar with (13), which is represented as follows:

$$x_i^* = \mathcal{F}_i(\mathbf{x}) = \begin{cases} x_i^{\max} & z_i > x_i^{\max} \\ z_i & 0 < z_i \le x_i^{\max} \\ 0 & z_i \le 0 \end{cases} \tag{30}$$

where $z_i = \sqrt{([wR(\beta_i^2 + x_i^{\max}\beta_i + R\beta_i)]/[wR - x_i^{\max}(r - r_i^{\min})])} - \beta_i$.

Since in the above section, we have proved the existence and uniqueness of Nash equilibrium in LIG given the independent pricing scheme, under the uniform pricing scheme the existence and uniqueness of Nash equilibrium is also guaranteed. To further investigate the Stackelberg game, we next analysis the profit maximize of the borrower vehicle.

Algorithm 1 Iterative Gradient Algorithm to Find the Stackelberg Equilibrium of the Independent Pricing Scheme

Initialization:
Set the initial input $\mathbf{r}^{(0)} = [r_i^{(0)}]_{i\in\mathcal{N}}$ and $\mathbf{x}^{(0)} = [x_i^{(0)}]_{i\in\mathcal{N}}$, where $r_i^{(0)} \in [r_i^{min}, r^{max}]$ and $x_i^{(0)} \in [0, x_i^{max}]$, $1 \leftarrow t$, $1 \leftarrow \tau$, a precision threshold $\varepsilon \ll 1$;
while $(\tau > \varepsilon)$ **do**
  for all $i \in N$ **do**
    i decides its investing strategy $x_i^{(t)}$ by $x_i^{(t-1)}$ using (13);
  end for
  for all $i \in N$ **do**
    The borrower vehicle updates its pricing strategies for each lender vehicle using a gradient-assisted search algorithm:

$$r_i^{(t)} = r_i^{(t-1)} + \mu \frac{\partial BU(\mathbf{x}^{(t)},\ \mathbf{r}^{(t-1)})}{\partial r_i},$$

    where μ is the step size of the price update. $r_i^{(t)}$ is subject to $[r_i^{\min}, r^{max}]$.
  end for
  $t \leftarrow t + 1$,
  $\tau \leftarrow \frac{\sum_{i\in\mathcal{N}} \|r_i^{(t)} - r_i^{(t-1)}\|}{\sum_{i\in\mathcal{N}} \|r_i^{(t-1)}\|}$,
end while
Output: $BU(\mathbf{x}^{(t)},\ \mathbf{r}^{(t)})$,$\mathbf{r}^{(t)} = [r_i^{(t)}]_{i\in\mathcal{N}}$,$\mathbf{x}^{(t)} = [x_i^{(t)}]_{i\in\mathcal{N}}$

Algorithm 2 Borrower Vehicle's Optimal Pricing Searching Algorithm of the Uniform Pricing Scheme

Initialization:
Set the initial input $r^* = \mathbf{max}\{r_i^{min}\}_{i\in\mathcal{N}}$, $BU^* = 0$ and $\mathbf{x}^{(0)} = [x_i^{(0)}]_{i\in\mathcal{N}}$, where $x_i^{(0)} \in [0, x_i^{max}]$, $\tau \leftarrow 1$, a predefined ascending factor δ, and a precision threshold $\varepsilon \ll 1$;
for $r = \mathbf{max}\{r_i^{min}\}_{i\in\mathcal{N}}$; $r \le r^{max}$; $r = r + \delta$ **do**
  $0 \leftarrow t$
  while $(\tau > \varepsilon)$ **do**
    $t \leftarrow t + 1$
    for all $i \in N$ **do**
      i decides its investing strategy $x_i^{(t)}$ by (29);
    end for
    $\tau \leftarrow \frac{\sum_{i\in\mathcal{N}} \|x_i^{(t)} - x_i^{(t-1)}\|}{\sum_{i\in\mathcal{N}} \|x_i^{(t-1)}\|}$,
  end while
  Obtain the borrower vehicle's profit $BU(\mathbf{x}^{(t)},\ r)$ by (30).
  if $BU^* < BU(\mathbf{x}^{(t)},\ r)$ **then**
    $r^* \leftarrow r$; $BU^* \leftarrow BU(\mathbf{x}^{(t)},\ r)$; $\mathbf{x}^* \leftarrow \mathbf{x}^{(t)}$
  end if
end for
Output: r^*, $\mathbf{x}^*$, BU^*

2) Borrower Vehicle's Strategy in Stage I: Similar to the independent pricing scheme, in the uniform pricing scheme, the borrower vehicle maximize its profit based on the Nash equilibrium of the lender vehicles' investing strategies in the Stage II. The optimal pricing strategy of the borrower vehicle in the uniform pricing scheme can also be formulated as an optimization problem as follows:

$$\begin{aligned} \underset{r}{\text{maximize}}\ \ & BU(\mathbf{x},\ r) = \eta \ln\left[\sum_{i\in N} x_i - X + 1\right] \\ & \quad - r\sum_{i\in N} x_i - R \\ \text{subject to}\ \ & r \in \left[\max\left\{r_i^{\min}\right\}_{i\in\mathcal{N}}, r^{\max}\right]. \end{aligned} \tag{31}$$

Under the uniform pricing scheme, the borrower vehicle sets the loan rate for each lender vehicle uniformly instead of independently. Therefore, in the uniform pricing scheme, the conditions (21) and (22) are not satisfied. It is difficult to apply the gradient-based searching algorithm to achieve the borrower vehicle's maximize profit as Algorithm 1. However, we notice that the strategy space of borrower vehicle in the uniform pricing scheme, i.e., $r \in [\mathbf{max}\{r_i^{\min}\}_{i\in\mathcal{N}}, r^{\max}]$, is a subset of the strategy space in independent pricing scheme, which is $r_i \in [r_i^{\min},\ r^{\max}], \forall i \in \mathcal{N}$. Thus, in the uniform pricing scheme, the convergence of borrower vehicle's profit is also guaranteed by the conditions in Theorem 2. We can adopt Algorithm 2, which applies a distributed pricing way for the borrower vehicle, to approach the borrower vehicle's optimal uniform pricing strategy r^*.

V. Performance Evaluation

In this section, we first provide the security analysis of the blockchain-based data-trading and debt-credit system. Then, we conduct extensive simulations to evaluate the performance of the proposed pricing schemes, including both the independent pricing scheme the and the uniform pricing scheme.

A. Security Analysis

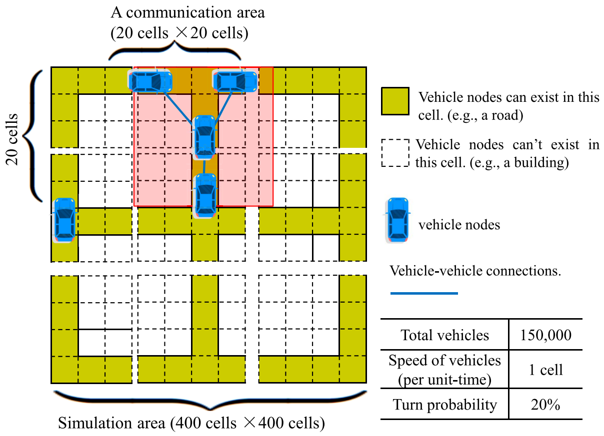
Our proposed blockchain-based data-trading and debt-credit system can provide feasible solution for trusty enhancement, cost reduction and failure avoidance for data interactions. Specially, the proposed system satisfies the following security requirements.

1) Decentralization and Privacy Protection: The blockchain-based trading system enables vehicles to conduct data-trading in a pure P2P manner without relying on a globally trusted intermediary, thus the privacy protection is guaranteed.

2) Account Security: The proposed system also guarantees the account security of vehicles by encrypted signature. Adversaries cannot open vehicles' wallets without the corresponding keys and certificates.

3) Publicly Audit: Transactional data are publicly audited and authenticated by all authorized aggregators such that compromising all entities is impossible because of the overwhelming cost.

4) Encrypted Signature: The encrypted signature ensure that no adversary can pose as a user or corrupt the network, because the adversary cannot forge a signature of a vehicle or gain control over the majority of system resources [8].



Total vehicles	150,000
Speed of vehicles (per unit-time)	1 cell
Turn probability	20%

Fig. 5. Simulation in the virtual map.

B. Simulation of IoV Scenario

We perform the simulation of IoV with a virtual map as shown in Fig. 5. This virtual map consists of 200 cells ×200 cells. A cell is a grid in the map which represents a 50 m × 50 m area in the actual map. The cells can be divided into two groups: 1) road cells in which vehicle nodes can exist and 2) building cells in which vehicle nodes cannot exist. The road cells are located per 10 cells in row and in column in the virtual map, representing roads in the actual map. Vehicle nodes are distributed in the road cells. All vehicle nodes move to their neighboring road cells per unit-time, and change direction only at the crossing. We consider the unit-time in our IoV scenario is 5 s, thus the speed of each vehicle node is 36 km/h averagely. The probability of a vehicle node changing its direction at the crossing is set to 20%. We define that a communication area of a vehicle node as the area 10 cells ×10 cells from it.

In our scenario, a vehicle only executes debt-credit business with vehicles in its communication areas. We call the set of vehicles that can lend for a vehicle is the lender set of it. Because of the mobility, a lender vehicle that enters the communication area of the borrower vehicle will become a new member of its lender set. The borrower vehicle will repricing if there are new lender vehicles joining its communication areas.

We study the performance of proposed debt-credit pricing schemes by simulations. To illustrate the impacts of different parameters on the performance, we consider a group of N vehicles providing loan services when the borrower vehicle asks for loans. The default parameter values of the numerical experiments are set as follows: $\eta = 120$, $r^{\max} = 30\%$, $R = 20$, $w = 6$, $X = 200$, $N = 10$. We assume that $\{x_i^{\max}\}_{i\in\mathcal{N}}$ and $\{r_i^{\min}\}_{i\in\mathcal{N}}$ follow continuous uniform distributions with parameters [40, 60] and [0.8%, 1%], respectively. Besides, we evaluate the performance of the independent pricing scheme and the uniform pricing scheme in the following.

C. Impact of Mobility and Competition

The mobility of vehicles frequently cause that the lender set of a borrower vehicle changes, and further influences both the pricing and lending processes. Since, we adopt low-complex Algorithm 2 under uniform pricing scheme, here we only investigate the impact of mobility under independent pricing scheme. Fig. 6 shows the dynamics of average lending rate and loan amount over time. In the scenario of Fig. 6, new lender vehicles join in the lender set of the borrower vehicle one by one with an unit-time as time interval, the amount of lender vehicles, i.e., N, increases from 8 to 12.

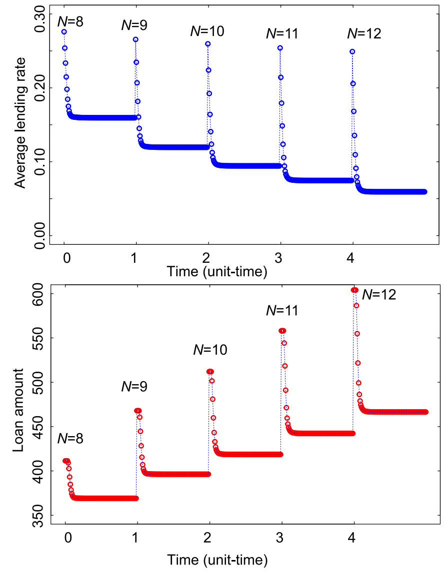


Fig. 6. Impact brought by mobility of vehicles on loan amount and average lending rate.

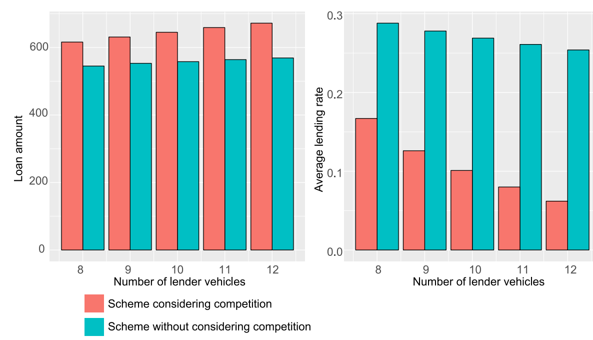


Fig. 7. Comparison of independent pricing scheme with the scheme without considering competition among lender vehicles.

We observe from Fig. 6 that the average lending rate and loan amount quickly becomes constant because the borrower vehicle gets its optimal pricing strategies in which the Nash equilibrium is reached. The participating of new lender vehicle will not decrease the pricing efficiency. Both average lending rate and loan amount will convergence within 20 iterations. Therefore, the proposed independent pricing scheme is efficient and has good convergence even the lender set is changed.

In Fig. 7, we compare the independent pricing scheme with another Stackelberg game-based credit mechanism which was used in [28]. In the compared algorithm, the competition among lender vehicles is not considered. The unstable reward is divided and equally distributed to each lender vehicle.

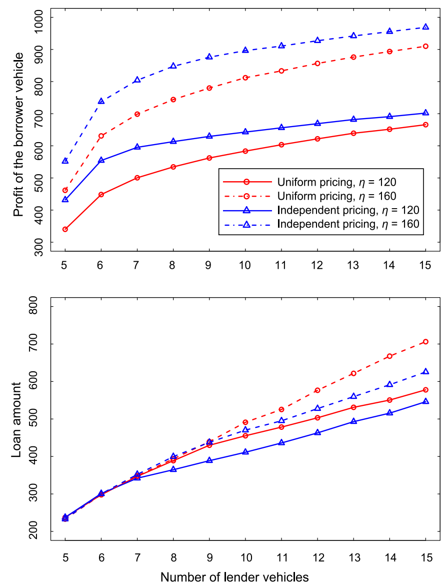


Fig. 8. Profit and loan amount of borrower vehicle versus the number of lender vehicles.

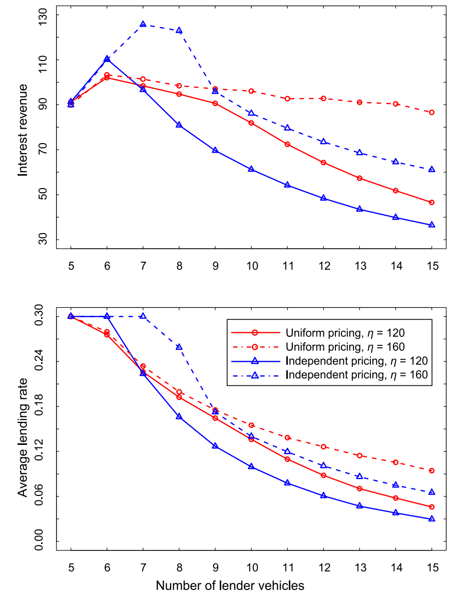


Fig. 9. Interest revenue of borrower vehicle and average lending rate of lender vehicles versus the number of lender vehicles.

Fig. 7 shows that our proposed pricing scheme outperforms the compared schemes both in loan amount and average lending rate. We also observe that the borrower vehicle can obtain more loans with lower rate under independent pricing scheme with the increase of N. With the compared scheme, the borrower vehicle's profit and loan amount are not influenced by N.

Furthermore, we observe that the average lending rate is decreased, and loan amount is increased, when new lender vehicles join the loan business. This is because that more lender vehicles can intensify competition among lender vehicles. The number of lender vehicles represents the competition level among lender vehicles. We then investigate the impacts brought by the number of lender vehicles, i.e., N, on the profit and expenditure of the borrower vehicle. We also investigate the impacts of greedy factor η, and address the comparison of the independent pricing scheme and the uniform pricing scheme.

Fig. 8 shows the impact of N on the profit and loan amount of the borrower vehicle. We observe that the profit of the borrower vehicle and its total loan amount increase with the increase of N. This is due to that more lender vehicles will provide more funds for the borrower vehicle. Therefore, the borrower vehicle can collect more loan when there are more lender vehicles. We also find that both the profit and loan amount of the borrower vehicle under independent pricing scheme are larger than that under the uniform pricing scheme. This is because under independent pricing scheme, the strategy space of the borrower vehicle is much lager than that of the uniform pricing scheme. The borrower vehicle sets pricing strategies for each lender vehicle independently thus can achieve better pricing strategies. Further, we notice that both the profit and loan amount of the borrower vehicle increase when the greedy factor η increases. This is because when η increases, the borrower vehicle is inclined to obtain more loans instead of to reduce the costs.

Fig. 9 shows the impact of N on the interest revenue and lending rate of the lender vehicles. The lender vehicles' interest revenue is also the expenditure of the borrower vehicle for its loan. From Fig. 9, we observe that the average lending rate of lender vehicles decreases with the increase of N. The interest revenue of lender vehicles is also decreased with the increase of N, except for the initial part. This is because that with the increase of N, the competition among lender vehicles also increases. As a result, the borrower vehicle can obtain more funds without paying more interest to the investors. Therefore, we can get the conclusion that the competition intensifying among lender vehicles will increase the borrower vehicle's profit and decrease its expenditure.

We also notice that the interest expenditure of the borrower vehicle increases with N when N is no large than 7 from Fig. 9. This is due to the borrower vehicle set the maximum loan rate, i.e., 30%, as its pricing in this situation. Therefore, its interest expenditure increases with N until there are enough lender vehicles in the loan market. We also find that when there are enough lender vehicles in the loan market, the borrower vehicle will set lower loan rate under the independent pricing scheme than under the uniform pricing scheme. Thus, we can conclude that under the independent pricing scheme the borrower vehicle can obtain more loans from the lender vehicles by paying less interest than under the uniform pricing scheme.

We next investigate the impacts of minimum lending rate of lender vehicles, i.e., the set of $\{r_i^{\min}\}_{i\in\mathcal{N}}$, on the interest revenue and average lending rate of lender vehicles. Fig. 10 shows the results. In Fig. 10, $r^{\min} = 0.01$ means the set of $\{r_i^{\min}\}_{i\in\mathcal{N}}$ follows an uniform distribution among [0.8%, 1%], $r^{\min} = 0.02$ means the set of $\{r_i^{\min}\}_{i\in\mathcal{N}}$ follows an uniform distribution among [1.8%, 2%]. From Fig. 10, we can find that when lender vehicles increase their setting of $\{r_i^{\min}\}_{i\in\mathcal{N}}$,

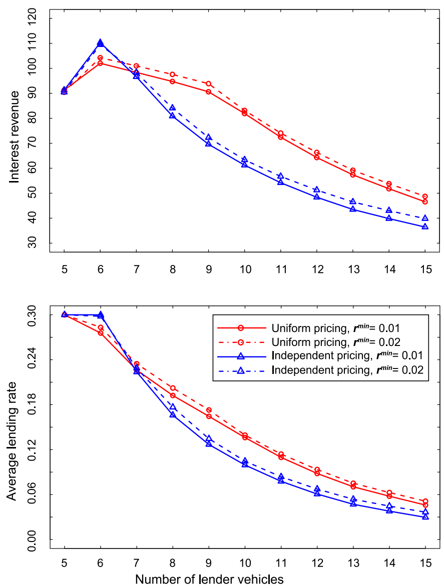


Fig. 10. Impact of lender vehicles' minimum lending rate on the interest revenue of borrower vehicle and average lending rate of lender vehicles.

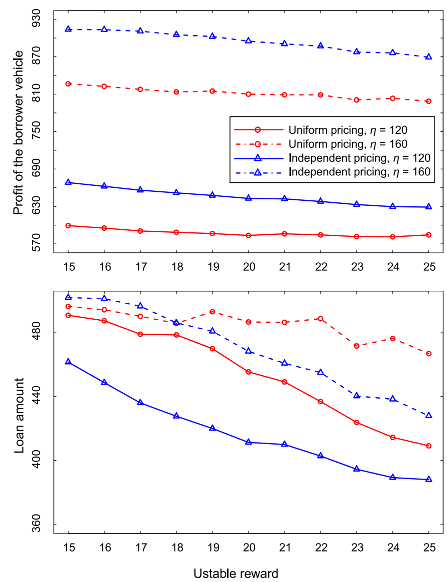


Fig. 11. Interest revenue of borrower vehicle and average lending rate of lender vehicles versus the unstable reward.

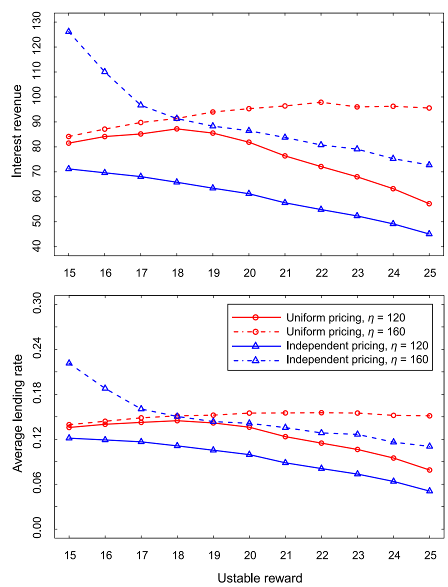


Fig. 12. Interest revenue of borrower vehicle and average lending rate of lender vehicles versus the unstable reward.

the interest revenue and average lending rate of lender vehicles are also increased. This is due to the setting of $\{r_i^{\min}\}_{i\in\mathcal{N}}$ can influence the lender vehicles' utility. The borrower vehicle must increase its pricing strategies to satisfy the increased interest demand of lender vehicles.

D. Investigation on the Impacts of the Unstable Reward

Then, we investigate the impacts of unstable reward R on the profit and expenditure of the borrower vehicle. The results are shown in Figs. 11 and 12.

Fig. 11 shows the impact of R on the profit and loan amount of the borrower vehicle. From Fig. 11, we find that with the increase of R, the profit of the borrower vehicle and its total loan amount decrease. This is contrary to our intuition, because when the borrower vehicle increases the reward the investors reduce their investments. This can be explained as that each lender decides its investing strategy not only based on the reward R, but also for its interest revenue. The increasing of R intensify the competition of lender vehicles. This enables the borrower vehicle to increase its profit by reducing its loan rate for each lender, which reduces the investment willingness of lender vehicles conversely.

Fig. 12 shows the impact of R on the interest revenue and lending rate of the lender vehicles. We observe that under the independent pricing scheme, both interest revenue and average lending rate of lender vehicles decrease with the increase of R. This is because that intensified competition makes the borrower vehicle reduce its pricing strategies. We find that although the borrower vehicle increase the reward cost, its total expenditure is decreased due to the reduced interest rate. We can conclude that under the independent pricing scheme, the increasing of R will reduce the borrower vehicle's expenditure. We also find that under the uniform pricing scheme, the borrower vehicle's expenditure dose not decrease significantly. This also shows that the borrower vehicle can save more costs under the independent pricing scheme.

E. Investigation on the Normalized Loan Rate of the Borrower Vehicle

At last, we examine the impact of N and R on the normalized loan rate of the borrower vehicle. The borrower vehicle's normalized loan rate is calculated by dividing the total cost, including the interest cost and the unstable reward, by the total loan amount. The results are shown in Figs. 13 and 14. Fig. 13 demonstrates the borrower vehicle's normalized loan rate versus N. We observe that the borrower vehicle's normalized loan rate decrease with the increase of N. This shows

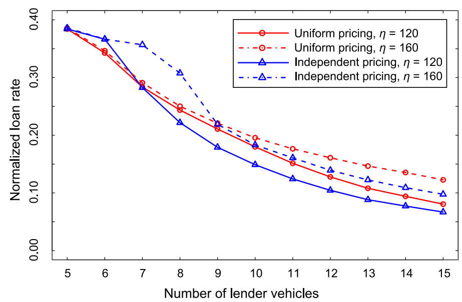


Fig. 13. Nomalized loan rate of borrower vehicle versus the number of lender vehicles.

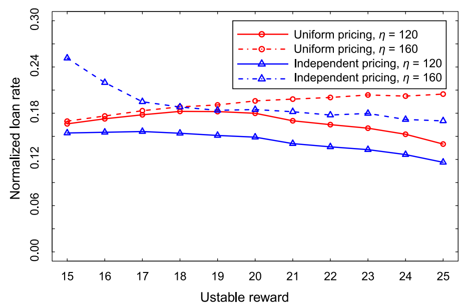


Fig. 14. Normalized loan rate of borrower vehicle versus the unstable reward.

that the borrower vehicle will gain funds with more affordable pricing strategies when there are more competition among investors. We also observe that the borrower vehicle's normalized loan rate is lower under the independent pricing scheme than that under the uniform pricing scheme when there are enough investors in the market. However, when there are not enough investors, the borrower vehicle can gain lower normalized loan rate under the uniform pricing scheme. This is because when there are limited investors in the market, the borrower vehicle is inclined to raise the interest rates for gaining more loans. On the contrary, when there are enough investors, the borrower vehicle is inclined to reduce the interest rates for saving the costs. Therefore, we obtain the conclusion that under the independent pricing scheme the borrower vehicle can set better pricing strategies to maximum its profit. Fig. 14 demonstrates the borrower vehicle's normalized loan rate versus R. We find that under independent pricing scheme, the normalized loan rate of the borrower vehicle decrease with the increase of R. However, under the uniform pricing scheme, the increasing of R is not conducive to gain more profit for the borrower vehicle. Therefore, we can conclude that there is no significant advantage when the reward R is introduced under the uniform pricing scheme. The introduction of R is of benefit to the borrower vehicle only under the independent pricing scheme.

VI. Conclusion

In this paper, we have proposed a secure, decentralized data-trading and debt-credit system for IoV based on blockchain technology. To address the efficiency challenges caused by transaction confirmation delays and cold-start problem of new users, we designed an debt-credit mechanism to encourage borrowing and lending among vehicles by a motivation-based debt-credit mechanism. In this mechanism, the lender vehicles act as the investors. we have adopt a two-stage Stackelberg game to jointly maximize the profits of the borrower vehicle and the lender vehicles. We adopt independent pricing scheme and uniform pricing scheme in the debt-credit mechanism. We have conducted numerical simulations to evaluate the performance of both independent and uniform pricing schemes. The numerical results show the effectiveness and efficiency of the proposed debt-credit mechanism. Specially, with the independent pricing schemes, the borrower vehicle can gain more loans with less interest cost. In future work, we will further investigate other important problems in the blockchain-based data-trading and debt-credit system, such as the valuation of data, and the problem of cooperative purchasing of data.

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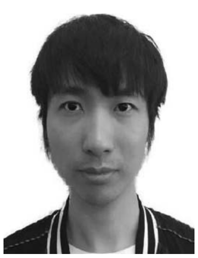

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