Perishable Digital Goods Trading Mechanism for Blockchain-based Vehicular Network

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***Abstract*—Recently, Internet of Vehicles (IoV) equipped with autopilot technology show much concern in their quality of service (QoS), especially in how to ensure the quality of crowdsourcing data for QoS. It is an open issue to encourage high-quality data to be sold as digital goods. Although existing works manage to design incentive mechanisms in data trading for IoV, they fail to address the trust problem. The blockchain technology has been widely studied to establish trust among participants, however, little is currently known about the perishability in the data market, which leads to the failure in explaining the price difference of digital goods. In this paper, we propose a perishability-oriented pricing mechanism to support perishable digital goods trading among IoVs. We also introduce consortium blockchain that provides distributed hyper ledger to address the trust issue in the market. By employing Stackelberg game theory, we obtain the optimal response of selfish users and providers. And finally, we propose a distributed algorithm to simulate our mechanism. Our experiment results demonstrate the efficiency of our distributed algorithm and prove the correctness and consistency of our mechanism.**

***Index Terms*—perishability, digital goods, internet of vehicles, consortium blockchain, Stackelberg game**

I. Introduction

Data-trading market, which strongly enlarges the quantity and enhances the quality of data, has been developing rapidly in recent years. High-quality data from remote IoVs will be of benefit to the quality of service (QoS) of local ones. Such kinds of digital products collected and sold by their holders are called digital goods. However, in practice, digital goods holder might refuse to provide their goods because of the enormous costs and potential risks. Moreover, as price discrimination fails in IoV's digital goods trading market, high-quality digital goods might not be appropriately priced. Therefore, it remains a challenge on how to design an incentive to motivate digital goods trading and how to adapt a price discrimination strategy to pricing digital goods.

Some works have been conducted to study incentive mechanisms in digital goods tradings and pricing strategies in recent years. For example, Gao *et al*. [1] proposed an incentive mechanisms in a vehicle-based system. And Al *et al*. [2] analyzed coordinating unidirectional vehicle-to-grid (V2G) services with energy trading. Unfortunately, two critical drawbacks remain unsolved.

First, the perishability of digital goods is omitted. Perishability is a metric to evaluate the data quality with time expired. Some data are perishable, which means they will gradually lose their value with time being. For instance, the road condition data recorded in the past five minutes is far more valuable than that recorded hours ago, just like newly-arrived fruits and overnight ones. Previous works [1], [2] ignored perishability of digital goods, and thus led to failure in explaining some phenomena in the data market.

Second, trust issues remain unsolved. Previous works [3], [4] failed to ensure the security in data trading because malicious nodes might perform a Man-in-the-middle attack (MITM) to steal data from providers. Also, both users and providers do not trust each other because of the conflict of interest. For instance, fraud might occur if providers offer expired digital goods instead of valuable ones. Meanwhile, users might refuse to pay after receiving digital goods. To sum up, both perishability and trust issues in trading lead to an urgent need to design an effective digital goods trading mechanism, which takes perishability into account, in a trustless scenario.

Motivated by the issues mentioned above, in this paper, we model a realistic digital goods trading market and design a PERIshable Digital gOods Trading (PERIDOT) mechanism to support decentralized transactions. To address the trust challenge, we introduce a consortium blockchain-based trading system with a series of roles and processes. To model the

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market, we employ Stackelberg game where digital goods providers play as leaders, and users play as followers. Then, we design a utility function for users and a revenue function for providers, then obtain their optimal response to maximize their interest. Our design is later proved to obtain a unique Stackelberg Equilibrium. Next, we build a decentralized algorithm to simulate the whole process. Finally, some numerical results show the effectiveness of our design. Our main contributions are as follows.

1) Consortium blockchain-based trading system: We introduce a consortium blockchain-based system into digital goods trading and innovatively design processes to provide secure and auditable perishable digital goods transactions. Through our PERIDOT mechanism, we address security and privacy vulnerability in this market successfully.
2) Perishability-oriented pricing mechanism: We study digital goods' perishability, and to the best of our knowledge, this is the first attempt to apply the Perishability-oriented pricing mechanism into a vehicular network. Via our mechanism, the price of digital goods shows their perishability properly.
3) Users and providers Stackelberg game: To model the digital goods trading market and to find the optimal responses of both users and providers, we employ Stackelberg game theory. Our novel formulation simulates the selfishness nature of goods market perfectly.

The rest of the paper is organized as follows. In Section 2, we briefly introduce previous works related to ours. Then, we illustrate the framework of our blockchain-based trading system in Section 3. In Section 4, we model the market, calculate the best response of users and providers and reach Stackelberg Equilibrium. We propose a distributed algorithm of PERIDOT mechanism to solve the problem of perishable digital goods trading in Section 5. Numerical results are shown in Section 6, and the whole paper is concluded in Section 7.

II. Related Work

Up to now, several studies have investigated the data trading market, including the value of data, data pricing and economic theory applications. Luong *et al*. [3] surveyed state-of-the-art data pricing models of wireless sensor networks (WSNs), which is the main components of Internet of Things (IoT). Jiao *et al*. [5] studied the perishability of data that affects the service quality and provide a quality decay function. Wang *et al*. [6] used noncooperative game theory to formulate the energy exchange market between plug-in hybrid electric vehicles (PHEV), which maximizes the utility considering both revenue and cost. Cao *et al*. [7] formulated a trading system of multiple data owners, collectors, and users, and introduced an iterative auction mechanism to coordinate the transactions among selfish players. Liu *et al*. [8] introduced two-stage Stackelberg game to solve the pricing and purchasing problem of consumers and the agents. The main difference between our work and Liu's is that there is no an authorized agency to determine the pricing strategy, which significantly preserves the privacy of sellers. However, previous works fail to combine the perishability of data with its trading mechanism. What is more, the trust issues in distributed parties like IoVs are still unsolved.

Many pieces of research employed consortium blockchain to build trust in a trustless scenario. Shuaib *et al*. [9] proposed a decentralized energy exchange system which allows for energy exchanging between producers and consumers using a form of electronic blockchain-based smart contracts. Kang *et al*. [10] designed a localized P2P energy-trading system for electric vehicles called PETCON by exploiting a consortium blockchain, and solved the pricing and charging problem by an iterative double auction mechanism. Li *et al*. [11] designed a payment scheme based by credit to increase the efficiency in blockchain-based IIoT energy-trading system. Blockchain is also applied to computing resource and data trading to reach a truthful bid [12], [13]. Singh *et al*. [14] introduced a blockchain-based crypto Trust point (cTp) mechanism to regulate the illegitimate vehicles behavior, and reward the share of data. Liu *et al*. [15] proposed a debt-credit mechanism to accelerate the data trading among IoVs in a blockchain-based market. However, data value investigation, especially in perishability, has not yet been studied.

In summary, digital goods share some natures with physical goods, like perishability, but, to our best knowledge, no relevant research analyzed perishable digital goods trading among IoVs. This motivates us to further consider perishable digital goods trading among IoVs in the blockchain-based system, and thus we propose PERIDOT mechanism to solve digital goods trading problem effectively.

III. Framework

In this section, we introduce the blockchain-based market framework of our PERIDOT mechanism.

A. Components of PERIDOT mechanism

The components in the system mainly consist of three parts, *i.e.*, IoVs, sensors, and edge servers.

IoVs: IoVs are the main component in the road, which are supposed to find the optimal path to their destinations according to the current traffic condition. Due to the lack of information, their path planning might not be precise and thus need extra information from the other IoVs or sensors to increase the confidence. Also, IoVs that already have data of road condition tend to sell them for profit. They are connected to the closest edge server and participate in consortium blockchain via the edge server.

Sensors: Sensors are kinds of fixed-position equipments, which collect information about the road condition around them. Enabled by 5G technology, they can transfer digital goods to the nearby IoVs and make profit from them. Similar to IoVs, sensors indirectly join consortium blockchain with the help of the closest edge server.

Edge Servers: Edge servers are the servers with relatively better computing resources established near the road, which can communicate with both IoVs and sensors in a low latency.

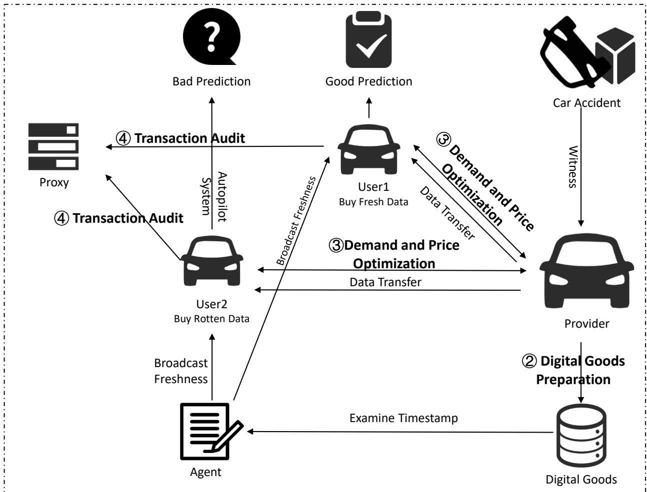

Fig. 1. Illustration of PERIDOT mechanism processes

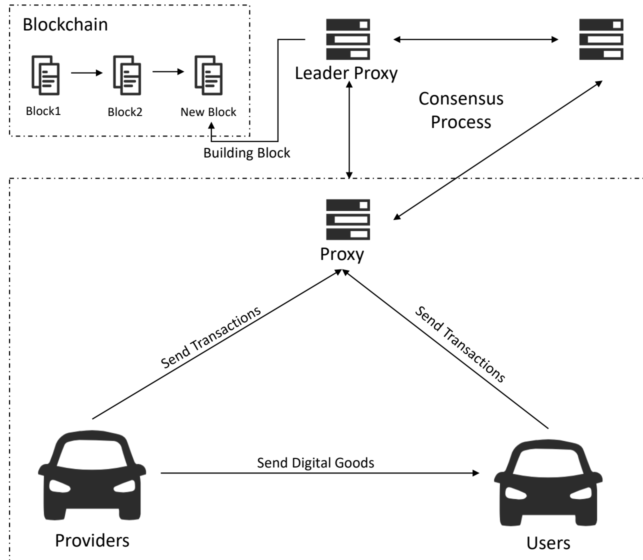

Fig. 2. IoV-Proxy-Blockchain hierarchical structure of transaction audit in PERIDOT mechanism

A edge server is connected to many devices, *i.e.*, sensors and IoVs, at the mean time receives and audits the transactions made by them. All the edge servers together build the consortium blockchain in PERIDOT mechanism. With the help of the consortium blockchain, all the transactions are audited transparently in the whole market, enabling IoVs to track possible frauds, which addresses the security problem in traditional centralized market. Moreover, since there is no centralized servers to inspect all the transfer, the privacy of users can be protected.

The roles in our system contain three parts, *i.e.*, perishable digital goods users, providers, and the agent. Users of perishable digital goods are mainly those IoVs who need data for path planning or autopilot. And Providers of perishable digital goods consist of IoVs that have data of road condition and sensors. An agent can tell the perishability of digital goods according to their timestamps, which is enabled by smart contract in the blockchain.

B. Processes of PERIDOT mechanism

The processes in our blockchain-based trading mechanism consist of four key operations, *i.e.*, system initialization, digital goods preparation, demand and price optimization, and transaction audit. Fig. 1 illustrates the whole process, as well as two possible choices and their outcome respectively of different users. Firstly, a car accident is witnessed and collected by provider. Second, two users who need the information to plan a better path come. User 1 buys the digital goods when they are still fresh, say, only five minutes after the accident. As a result, it obtains a good prediction, which helps it avoid the traffic jam. On the contrary, user 2 buys the rotten goods, say, five hours after the accident, to save money. There is a probability that the accident is already handled now, so it would not affect the current path. Consequently, user 2 fails to get a rather precise prediction about whether it should find an alternative path or not.

System Initialization: In this process, all participants in the system shall identify themselves by their public keys. Participants can also select their roles according to their own demands.

Digital Goods Preparation: Providers start collecting data in this process. Once they enquire a collection of data, the dataset is ready to be packed to digital goods. The freshness of digital goods is examined by the agent before being released to the market. After examination, perishable digital goods with their freshness will be on sale.

Demand and Price Optimization: When users witness the digital goods along with their unit price and freshness, they will give their optimal demand matrix as a response. Providers will then update their unit price vectors to maximize their profits. This process loops until the unit price vector converges to a stable point, which means the users and providers reach an agreement.

Transaction Audit: Fig. 2 illustrates this process. Once users and providers reach an agreement, the transaction is made. All transactions is also recorded to consortium blockchain for edge servers to audit. Edges servers collect transactions for a period and structure them to their blocks and consensus process is conducted. Finally, the leader edges server in this consensus process broadcasts its block to all the edge servers, and they add it to the blockchain. The transactions are now audited and unchangeable.

IV. Digital Goods Trading Scheme

A. Provider-User Stackelberg Game

Users and providers compete at the market level. Different from a perfect-competition market, digital goods trades remain an imperfect competition. The providers always attempt to profit from this seller market, which means that they grasp the initiative in the unit price setting. Dynamic noncooperative game theory provides a natural paradigm to model the players' behaviors in such a case. Thus, We can employ a Stackelberg game into this market.

B. User Optimal Response Scheme

Let $x_{n,k}$ be the demand of user n from provider k. We define the utility of user n, $U_{user,n}$ as

$$U_{user,n} = \alpha_n \sum_{k\in\mathcal{K}} ln(\beta_n + \omega_k x_{n,k}), \forall k \in \mathcal{K}, \tag{1}$$

where α_n and β_n are constants and ω_k is the freshness of goods. The natural logarithm function $ln(x)$ is widely used in commodity markets because it shows the reducing marginal benefit with the increasing amount of digital goods [16], [17] . α_n is to modify users' willingness to buy digital goods. β_n is to avoid negative value in logarithm function [18]. Meanwhile, β_n can also adjust the initial utility of users. ω_k is given by $\omega_k = -\exp(-t_k)$, where t_k is the duration of digital goods being sold. The exponential function indicates that the value of goods declines with time being from full value (where ω_k is 1) to nearly no value. Its decreasing tendency reflects the nature of perishable goods.

Let y_k be the unit price of digital goods, $C_n(C_n \geq 0)$ be the budget of user n. Given a unit price vector $\boldsymbol{y} = \{y_k, k \in \mathcal{K}\}$, user n will solve an optimal problem OP_{user}:

$$\max_{\boldsymbol{x_n}=\{x_{n,k}\forall k\in\mathcal{K}\}} U_{user,n} \tag{2}$$

$$s.t. \sum_{k\in\mathcal{K}} y_k x_{n,k} \leq C_n \tag{3}$$

$$x_{n,k} \geq 0; \forall k \in \mathcal{K}. \tag{4}$$

To show that the optimization problem is convex, we calculate the Hessian matrix of objective function

$$f(\boldsymbol{x_n}) = -\alpha_n \sum_{k\in\mathcal{K}} ln(\beta_n + \omega_k x_{n,k}), \forall k \in \mathcal{K}, \tag{5}$$

which is

$$H(f) = \begin{bmatrix} \frac{\alpha_n \omega_1^2}{(\beta_n+\omega_1 x_{n,1})^2} & 0 & \cdots & 0 \\ 0 & \frac{\alpha_n \omega_2^2}{(\beta_n+\omega_2 x_{n,2})^2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\alpha_n \omega_K^2}{(\beta_n+\omega_K x_{n,K})^2} \end{bmatrix} \tag{6}$$

We can observe that all elements in the Hessian matrix are non-negative, which means the Hessian matrix is half positive define. This result shows that OP_{user} is a convex optimization problem. Hence, its stationary solution is unique and optimal.

By introducing the augmented Lagrangian multiplier $\boldsymbol{\lambda_n} = \{\lambda_{n,k}, \forall k \in \mathcal{K}\}$, (2) to (4) become:

$$L_{user,n} = \alpha_n \sum_{k\in\mathcal{K}} ln(\beta_n + \omega_k x_{n,k}) \tag{7}$$
$$-\lambda_{n,1}\left(\sum_{k\in\mathcal{K}} y_k x_{n,k} - C_n\right) + \sum_{k\in\mathcal{K}} \lambda_{n,k+1} x_{n,k}.$$

The first order optimal solution is $\frac{\partial L_{user,n}}{\partial x_{n,k}} = 0$, and $L_{user} = \{L_{user,n}, \forall n \in \mathcal{N}\}$, thus we have slackness condition:

$$\lambda_{n,1}\left(\sum_{k\in\mathcal{K}} y_k x_{n,k} - C_n\right) = 0 \tag{8}$$

$$\lambda_{n,k+1} x_{n,k} = 0, \forall k \in \mathcal{K} \tag{9}$$

$$\lambda_{n,1} > 0 \tag{10}$$

$$\lambda_{n,k+1} \geq 0, \forall k \in \mathcal{K} \tag{11}$$

$$x_{n,k} \geq 0, \forall k \in \mathcal{K}, \tag{12}$$

and $\frac{\partial L_{user,n}}{\partial x_{n,k}} = 0$, which is equal to

$$\frac{\alpha_n \omega_k}{\beta_n + \omega_k x_{n,k}} + \lambda_{n,1} y_k + \lambda_{n,k+1} = 0, \forall k \in \mathcal{K}. \tag{13}$$

To satisfy (8) to (13), we have to discuss these cases:

Case 1: $x_{n,k} > 0, \forall k \in \mathcal{K}$. In this case, $\lambda_{n,k+1} = 0, \forall k \in \mathcal{K}$ according to (12). And thus, (13) becomes

$$\frac{\alpha_n \omega_k}{\beta_n + \omega_k x_{n,k}} + \lambda_{n,1} y_k = 0, \forall k \in \mathcal{K}. \tag{14}$$

From (14), we have

$$x_{n,k} = \frac{\alpha_n}{\lambda_{n,1} y_k} - \frac{\beta_n}{\omega_k}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}. \tag{15}$$

Use (15) substitute $x_{n,k}$ in (12), we get

$$\lambda_{n,1}\left(\sum_{k\in\mathcal{K}} y_k \left(\frac{\alpha_n}{\lambda_{n,1} y_k} - \frac{\beta_n}{\omega_k}\right) - C_n\right) = 0 \tag{16}$$

$$\frac{1}{\lambda_{n,1}} = \frac{C_n \omega_k + \beta_n \sum_{k\in\mathcal{K}} y_k}{K \omega_k \alpha_n}. \tag{17}$$

From (17) we obtain

$$x_{n,k} = \frac{\omega_k C_n + \beta_n \sum_{k\in\mathcal{K}} y_k}{K \omega_k y_k} - \frac{\beta_n}{\omega_k}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}.$$

Case 2: There is an $\exists i \in \mathcal{K}$ divide $\mathcal{K}$ into $\mathcal{K}_1$ and $\mathcal{K}_2$, and $x_{n,k} = 0, \forall k \in \mathcal{K}_1$ and $x_{n,k} > 0, \forall k \in \mathcal{K}_2$. That is to say, the buyer chooses to buy digital goods from partial sellers (in $\mathcal{K}_1$), instead of those who in $\mathcal{K}_2$. In this case, $\lambda_{n,k+1} > 0, \forall k \in \mathcal{K}_1$ and $\lambda_{n,k+1} = 0, \forall k \in \mathcal{K}_2$ according to (12). And thus, (13) become

$$\frac{\alpha_n}{\beta_n} + \lambda_{n,1} y_k + \lambda_{n,k+1} = 0, \forall k \in \mathcal{K}_1 \tag{18}$$

$$\frac{\alpha_n \omega_k}{\beta_n + \omega_k x_{n,k+1}} + \lambda_{n,1} y_{k+1} = 0, \forall k \in \mathcal{K}_2. \tag{19}$$

The same as what we have discussed in Case 1, we have:

$$x_{n,k} = \begin{cases} 0 & \text{if } k \in \mathcal{K}_1 \\ \frac{\omega_k C_n + \beta_n \sum_{k=1}^{K} y_k}{K \omega_k y_k} - \frac{\beta_n}{\omega_k} & \text{if } k \in \mathcal{K}_2 \end{cases}$$

Case 3: $x_{n,k} = 0, \forall k \in \mathcal{K}$. In this case, since $\lambda_{n,1} > 0$, only $C_n = 0$ can satisfy (12). In other word, user n have no budget.

Finally, we draw a conclusion that the solution of OP_{user}, which is the optimal demand of user n, is

$$x_{n,k} = \frac{\omega_k C_n + \beta_n \sum_{k=1}^{K} y_k}{K \omega_k y_k} - \frac{\beta_n}{\omega_k}, \forall n \in \mathcal{N}, \forall k \in \mathcal{K}. \tag{20}$$

C. Provider Optimal Response Scheme

Let y_k denote the digital good's unit price of provider k. Let $\boldsymbol{y_{-k}}$ denote the price vector of providers except k. Provider k will be a monopoly and set an extremely high price or unlimited amount of copy if there are no limitations. To avoid this case, we employ two methods: transfer limitation and market competition. Let T_k denote the max transfer of provider k, provider k can only transfer T_k units of digital goods. We define the revenue of provider k

$$R_{provider,k}(y_k, \boldsymbol{y_{-k}}) = y_k \sum_{n\in\mathcal{N}} x_{n,k}. \tag{21}$$

According to (20), user demand $x_{n,k}$ is influenced by the price of y_k and $\boldsymbol{y_{-k}}$. All the providers play a noncooperative game in price setting. Providers aim to maximize their revenues $R_{provider,k}(y_k, \boldsymbol{y_{-k}})$, so we get the optimization problem of provider, which is formulated as:

$$\max_{\boldsymbol{y}=\{y_k,\forall k\in\mathcal{K}\}} R_{provider,k}(y_k, \boldsymbol{y_{-k}}) = y_k \sum_{n\in\mathcal{N}} x_{n,k} \tag{22}$$

$$s.t. \sum_{n\in\mathcal{N}} x_{n,k} \leq \eta_k T_k \tag{23}$$

$$y_k > 0, \forall k \in \mathcal{K}, \tag{24}$$

where η_k indicates the transfer bonus coefficient from other IoVs who have the same digital goods already, which is defined as $\eta_k = \frac{2}{1+\omega_k}$. Since the revenue of provider increase with a fixed y_k and an increasing $\sum_{n\in\mathcal{N}} x_{n,k}$, any rational decision maker will try to reach its upper bound. As a result, we can take (23) as an equality constraint.

$$\sum_{n\in\mathcal{N}} x_{n,k} = \frac{2}{1+\omega_k} T_k. \tag{25}$$

Then, we can prove that the optimal solution of (22) also satisfy (25).

Let's define $L_{provider,k}$:

$$L_{provider,k} = y_k \sum_{n\in\mathcal{N}} x_{n,k} - \mu_k \left(\sum_{n\in\mathcal{N}} x_{n,k} - \frac{2}{1+\omega_k} T_k \right). \tag{26}$$

, where μ_k is the Lagrangian multiplier.

Using $x_{n,k}$ in (20), we obtain

$$L_{provider,k} = \left(\frac{\omega_k C + B\sum_{k\in\mathcal{K}} y_k}{K\omega_k} - \frac{y_k B}{\omega_k} \right) - \mu_k \left(\frac{\omega_k C + B\sum_{k\in\mathcal{K}} y_k}{K\omega_k y_k} - \frac{B}{\omega_k} - \frac{2}{1+\omega_k} T_k \right), \tag{27}$$

where $B = \sum_{n\in\mathcal{N}} \beta_n$ and $C = \sum_{n\in\mathcal{N}} C_n$. From $\frac{\partial L_{provider,k}}{\partial y_k} = 0$ we obtain

$$(K-1)By_k^2 - \mu_k \left(B \sum_{g\in\mathcal{K},g\neq k} y_g + \omega_k C \right) = 0. \tag{28}$$

Using (20) and (25), we get y_k:

$$\sum_{n\in\mathcal{N}} \left(\frac{\omega_k C_n + \beta_n \sum_{k\in\mathcal{K}} y_k}{K\omega_k y_k} - \beta_n \right) = \frac{2}{1+\omega_k} T_k, \tag{29}$$

$$y_k = \frac{(1+\omega_k)\left(B\sum_{g\in\mathcal{K},g\neq k} y_g + C\omega_k \right)}{(1+\omega_k)(k-1)B + 2K\omega_k T_k}. \tag{30}$$

Since all β_n, C_n, T_k and K are greater than 0, we can obtain that $y_k > 0, \forall k \in \mathcal{K}$, which meets our previous hypothesis.

From (28) and (30), we obtain

$$\mu_k = (K-1)B \left(\frac{C + \frac{B}{\omega_k}\sum_{g\in\mathcal{K},g\neq k} y_g}{(\frac{2}{\omega_k+1}KT_k + (K-1)\frac{B}{\omega_k})^2} \right) = \frac{(\omega_k+1)(K-1)B}{2\omega_k KT_k + (\omega_k+1)(K-1)B} y_k, \tag{31}$$

which means whatever y_k is set, there is an optimal μ_k and optimal solution y_k^*. We observe that when $K = 1, \mu_k = 0$. Therefore, if there is only one provider, there is no game. We only focus on where $K \geq 2$.

For further discussion of the response of leader, we transform (30) into matrix form:

$$\boldsymbol{Ay} = \boldsymbol{F} \tag{32}$$

where,

$$\boldsymbol{A} = \begin{bmatrix} \frac{2\omega_1}{1+\omega_1}T_1 + D & -E & \dots & -E \\ -E & \frac{2\omega_2}{1+\omega_2}T_2 + D & \dots & -E \\ \vdots & \vdots & \ddots & \vdots \\ -E & -E & \dots & \frac{2\omega_k}{1+\omega_k}T_k + D \end{bmatrix}, \tag{33}$$

$\boldsymbol{y} = \{y_1, y_2, \dots, y_k\}$, $D = \frac{K-1}{K}B$, $E = \frac{B}{K}$, $F = \frac{\omega_k C}{K}$. If $\boldsymbol{A}$ is invertible the solution of (32) is

$$\boldsymbol{y} = \boldsymbol{A}^{-1}\boldsymbol{F}. \tag{34}$$

Definition 4.1: A real matrix $A = \{a_{i,j}, i, j = 1, 2, \dots, K\} \in R^{K\times K}$ is said to be strictly diagonally dominant if satisfies the following condition:

$$|a_{i,i}| > \sum_{j\neq i} |a_{i,j}|. \tag{35}$$

Theorem 1: The unique solution of (32) is (34).

Proof: For each $a_{i,i}, \forall i \in \mathcal{N}$ in A, since

$$a_{i,i} - \sum_{j\neq i} |a_{i,j}| = \frac{2\omega_k}{1+\omega_k}T_k + D - (K-1)E = \frac{2\omega_k}{1+\omega_k}T_k > 0. \tag{36}$$

According to Definition 1, A is a strictly diagonally dominant matrix. And thus, A is non-singular and invertible.We now can yield a unique solution of (32) is (34). ∎

D. Stackelberg Equilibrium

The providers play the static noncooperative game with each other to set the unit price $\boldsymbol{y}^*$, which is at Nash Equilibrium point and announce to users. The user n adjust its optimal response $\boldsymbol{x_n^*}$ to maximize its profit. $(\boldsymbol{y}^*, \boldsymbol{x}^*)$ make up of the Stackelberg Equilibrium of the whole system [19].

Let $\Gamma_{provider,k}$ and $\Gamma_{user,n}$ denote the strategy set of provider k and user n respectively. The whole strategy set of provider can be described as cartesian product of all single provider $\Gamma_{provider} = \Gamma_{provider,1} \times \Gamma_{provider,2} \times \ldots \times \Gamma_{provider,K}$. Similarly, The whole strategy set of user is $\Gamma_{user} = \Gamma_{user,1} \times \Gamma_{user,2} \times \ldots \times \Gamma_{user,N}$. The Stackelberg Equilibrium of provider is

$$R_{provider,k}(\boldsymbol{y}^*, \boldsymbol{x}(\boldsymbol{y}^*)) \geq R_{provider,k}(\boldsymbol{y_k}, \boldsymbol{y^*_{-k}}, \boldsymbol{x}(\boldsymbol{y_k}; \boldsymbol{y^*_{-k}})), \tag{37}$$

where $\boldsymbol{y}$ and $\boldsymbol{x}(\boldsymbol{y})$ denote the unit price of all providers and users response to unit price respectively. And $\boldsymbol{y}^*$ and $\boldsymbol{x}(\boldsymbol{y}^*)$ denote their optimal response.

Since we have proved that there is a unique optimal solution to OP_{user} for a given $\boldsymbol{y}$, we can reach a unique Stackelberg Equilibrium if a unique Nash Equilibrium of providers exists.

Theorem 2: A unique Nash Equilibrium exists in providers and thereby a unique Stackelberg Equilibrium exists in PERIDOT mechanism.

Proof: A Nash Equilibrium exists for providers if $\boldsymbol{y}$ is a non-empty, convex and subset of R^k. $R_{provider,k}(\boldsymbol{y})$ is continues in $\boldsymbol{y}$ and concave in $y_k \forall k \in \mathcal{K}$, because the second order derivative of $R_{provider,k}(\boldsymbol{y})$ w.r.t. $y_k = 0$. Therefore, a unique Nash Equilibrium exists in providers game and thereby a unique Stackelberg Equilibrium exists in providers-users game. ■

V. Distributed Algorithm

In this section, we propose a distributed algorithm using a messaging mechanism [20]. The message types used in communications between entities of PERIDOT mechanism can be classified as follows:

1) Information Message (IM): Participants need to share their identities before entering the market in PERIDOT mechanism. Shared information includes the budget and demand willingness of users, the total number of providers and the briefing of the digital goods.
2) Freshness Message (FM): After collecting and packing data into digital goods, providers need to validate their freshness with the help of the agent. Freshness information includes the timestamp and the freshness of digital goods.
3) Demand Message (DM): Each user sends its optimal demand to all the providers, and this message is called the demand message. Providers collect demand message and calculate their revenues.
4) Price Message (PM): Each provider sends its optimal unit price to all the players in PERIDOT mechanism. Other providers will update their unit price, and all users will update their demands according to the price message.
5) End Message (EM): When a provider reaches its stable optimal revenue, it will broadcast EM to inform users that transactions have been made.

Algorithm 1 Distributed Algorithm of PERIDOT mechanism

PHASE 1: New player join and data freshness validation
for all newly arrived players **do**
  Broadcast its briefing as IM
  if the player is a provider **then**
    Send timestamp of digital goods to agent and agent broadcasts FM
  end if
end for
PHASE 2: User response
Collect PM and DM from all participant providers
for all user **do**
  if receive EM from all providers **then**
    return $x_{n,t}$
  else
    Update $x_{n,t}$ to $x_{n,t+1}$ according to PM in PHASE 3, using (20)
    Update utility according to PM and broadcast DM
  end if
end for
PHASE 3: Provider response
Collect DM from all participant users and PM from other participant providers
for all providers **do**
  if $|y_{k,t} - y_{k,t+1}| > \epsilon$ **then**
    Update unit price $y_{k,t}$ to $y_{k,t+1}$ according to last PM, using (30)
    Update revenue according to last DM and broadcast PM
  else
    Broadcast EM
    return $y_{k,t}$
  end if
end for

Given these five types of messages, our algorithm can be shown as Algorithm 1. We predefine a period Δt which equals the time used to transmit a message between the players in PERIDOT mechanism. The algorithm runs in each time slot until the game terminates and comprises the key actions of three phases as follows.

In Phase 1, our PERIDOT mechanism accepts newly arrived players. Then, to validate the freshness of digital goods, all providers should prove their freshness via a trusted third-party agent. In Phase 2, users collect sufficient messages to calculate their optimal responses. After that, users can continue their decision-making process until providers put an end. In Phase 3, providers wait for DM from users and PM from other providers to calculate their revenues and the next unit price vector. If a provider meets its convergence requirement ϵ, it stops iteration and makes a transaction. Otherwise, it updates the unit price vector and revenue again.

Based on the description of distributed algorithm of PERIDOT mechanism above, we can map from the time slot to the real scenario. In Phase 1, all IM broadcast and freshness validation are parallel, costing $\Delta t + 2\Delta t$ time. Before users can make decisions in Phase 2, waiting costs Δt, and response can be done immediately. We can apply the same theory to Phase 3. In conclusion, the maximum time in the real scenario in our distributed algorithm is $5\Delta t$.

VI. Experiment

In this section, we examine the convergence and efficiency of our distributed algorithm. Then, we show how players optimize their best responses based on different budget and transfer constraints. Finally, we try to analyze how the perishability of digital goods influences other indexes.

By default, we consider six providers and two users with parameters $\alpha_n = \beta_n = 1, \forall n \in \mathcal{N}$. The budgets of users are $C_1 = 100, C_2 = 200$, and the transfers of all providers are 50. The timestamps of perishable digital goods from providers are $t_1 = 0.2, t_2 = 0.4, t_3 = 0.6, t_4 = 0.8, t_5 = 1.0, t_6 = 1.2$ respectively. The convergence requirement ϵ is 10^{-5}. Any modifications in parameters will be mentioned otherwise.

A. Algorithm convergence

Fig. 3 shows the performance of the algorithm. As we can see, all indexes of users and providers reach equilibrium after five iterations, and all metrics keep stable in the remaining iterations. In Fig. 3 (a), providers selling different goods start iterating from $y_k = 1$, and converge at a threshold from 0.65 to 0.95 respectively. We can also see that user utility in Fig. 3 (b) and provider revenue in Fig. 3 (c) increase to their highest point and eventually stabilize at iteration 5. From Fig. 3, we claim that our distributed algorithm converges to its optimal values in a few iterations, which shows the brilliant performance of our algorithm.

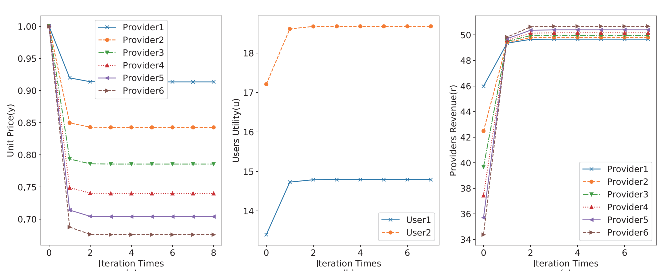

Fig. 3. The changes in the (a): unit price, (b): users utility and (c): providers revenue with algorithm iteration.

B. Best Response in Different Constraints

Fig. 4 shows the reaction of entities in the system when one user's budget changes. In this case, for not losing the universality, we add another two new users. Their budgets are

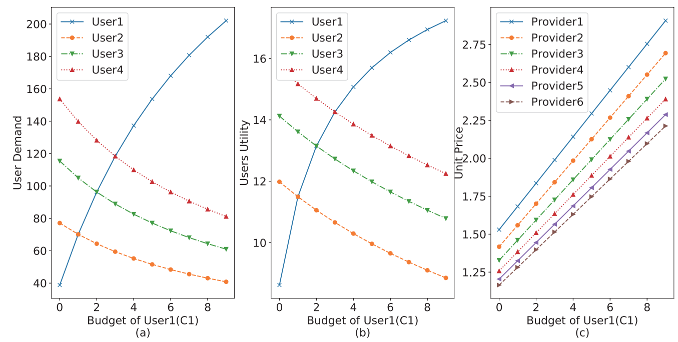

Fig. 4. (a): User demand changes when user 1's budget increases. (b): Users utility changes when user 1's budget increases. (c): Unit prices change when user 1's budget increases.

$C_1 = 50, C_2 = 100, C_3 = 150, C_4 = 200$. As we can see from Fig. 4(a) and (b), when the budget of one user increases, both its demand and utility increase accordingly, while the others' decrease. It indicates that increasing fund to one user will strengthen its competitiveness in the user side, leading to others' losses. According to Fig. 4(c), when the budget of user 1 increases, all providers tend to appreciate their goods to collect more revenue from user 1. The provider selling the freshest goods increases its unit price faster than others. From Fig. 4, we can draw a conclusion that adding the budget of one user will significantly alter the action of other players–other users will reduce their demand and thus lead to utility decrease, while all providers will increase their unit prices for more revenues.

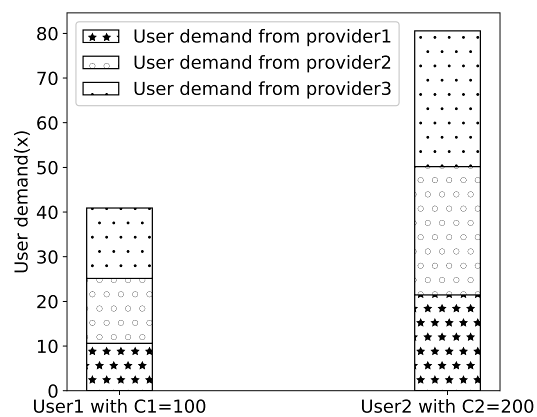

Fig. 5. Demands of users with different budget vary according to providers.

Fig. 5 shows the users' demands from different providers selling data with various freshness. The user demand consists of three parts from different providers. These providers have the same transfer, *i.e.*, $T_1 = T_2 = T_3 = 50$, but their goods are packed at different moments, which are $t_1 = 0.2, t_2 = 1.2, t_3 = 2.2$. Other parameters of users are unchanged. As we mentioned in Section 4.B, if other IoVs have the same digital goods as the seller does, they can help distribute the goods by using their own transfer. These IoVs form Content Distribution Network (CDN), increasing the transfer of the seller. As can be seen from Fig. 5, provider 3 contributes more goods than provider 1 does. That is because of provider 3's digital goods are not as fresh as provider 1's, and thus provider 3 can enjoy more transfer enable by CDN, and sell more than provider 1. This phenomenon occurs to both user 1 and user 2. Fig. 5 shows that although rotten digital goods might not be appealing to users, it costs less and sells more, and finally reaches better sales. In the following part, we can see how CDN influences the revenues of providers.

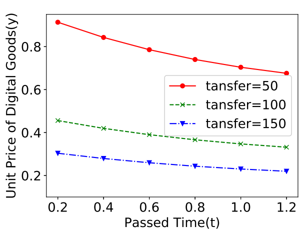

Fig. 6. Unit prices with time being when the transfer vary.

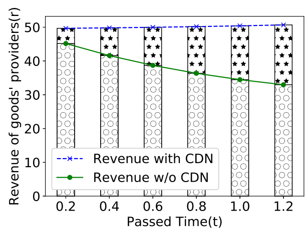

Fig. 7. Providers' revenues with time being when the CDN vary.

Fig. 6 and 7 show how unit price and revenue change when digital goods start rotting. In Fig. 6, we repeat experiment three times and the transfers of providers are $T_{0,k} = 50, T_{1,k} = 100, T_{2,k} = 150$ respectively. Other parameters are unchanged. Users prefer fresher goods which can benefit them better and are willing to pay more for them. Our result in Fig. 6 can support this hypothesis: unit prices do decrease with time expired regardless of the value of T_k. And so does the revenue without CDN, as we can see in Fig. 7. However, the gross revenues of providers in Fig.7 increase alternatively. Contributed to CDN, providers can have more transfer when the number of data copies increases. And thus they sell more and earn more even if their unit prices are lower than those of fresher goods. From Fig. 6 and 7, we can say that our mathematical model correctly shows the market that appeals to fresher goods. And we surprisingly observe that, with the help of CDN, perishable goods can still earn money in some circumstances.

VII. Conclusion

In this paper, we propose a blockchain-based trading mechanism, PERIDOT mechanism, to solve the problem of perishable digital goods trading. First, to model the market, we propose a utility function of users and a revenue function of providers, as well as define the action of the agent. Then, we prove the existence and uniqueness of Stackelberg Equilibrium. We also propose a decentralized algorithm to simulate the market. Finally, we carry out experiments to show the numerical results of our algorithm. The results show that our algorithm not only has numerical stability but also simulates the reactions of players as it does in a real digital goods market. Besides, our experiments show that rotten digital goods, despite contributing less utility, outsell fresh digital goods, which contribute more utility, because rotten ones are cheaper.

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