Blockchain-Based Digital Goods Trading Mechanism in Internet of Vehicles: A Stackelberg Game Approach

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***Abstract*—Recently, digital goods trading in Internet of Vehicles (IoV) is attracting increasing attention because of the high value they generate. Although previous studies focused on how to motivate consumers and providers to trade, relay nodes have not been sufficiently rewarded for supporting digital goods transmission. Besides, trust and security problems exist widely in the centralized system, which severely impairs the effectiveness and robustness of the system. To solve these challenges, in this paper, we utilize the consortium blockchain technique to establish trust between nodes and guarantee the digital goods trading security. We formulate the problem as a two-layer Stackelberg game and prove the existence and uniqueness of Stackelberg equilibrium. Our optimization algorithm motivates every role to get involved in trading by allowing each party to make an optimal strategy. Extensive numerical experiments show that our algorithm can achieve the maximum total utility and outperforms other methods in various situations. To our best knowledge, this is the first attempt to apply the two-layer Stackelberg game approach to digital goods trading in hybrid IoV system.**

***Keywords*-Internet of Vehicles; consortium blockchain; digital goods trading;**

I. INTRODUCTION

With the advent of the era of big data, IoV data market is developing rapidly. It is predicted that two-fifths of the new cars will have connectivity and the global vehicular traffic is expected to reach 30 thousand exabytes by the year of 2020 [1], [2]. Larger quantities of vehicles mean more sensors and higher data production. It is estimated that more than 22 billion sensors will generate around 4000 GB data with the value of 570-2027 million dollars every day [3], [4], [5] in 2025. In IoV, the data is majorly utilized through digital goods trading. Various types of communication in hybrid VANETs construct stable and multi-hop connections to deliver valuable digital goods between providers and consumers. However, most vehicle nodes may not be willing to participate in trading due to the possibility of copyright and privacy leakage. Therefore, the buyer and seller market are asymmetric and idle nodes lack sufficient motivation to help with the digital goods transmission.

Several attempts have been tried for digital goods trading in IoT/IoV system. Sun *et. al.* [6] study the optimal energy transaction in the hybrid market, using a centralized manager. Moreover, some frameworks [7], [8] have been proposed to model the energy trading in a Vehicle-to-Vehicle scenario, where electric vehicles determine the exchanging amount and unit price. However, all these researches do not consider the utility of relay and are based on centralized systems. The main challenges of the digital goods trading in hybrid-connected IoV system are as follows.

First, the nodes lack sufficient motivation to participate in trading as relays. Multi-hop transmission of digital goods in hybrid IoV requires some vehicle nodes to act as relays. Without adequate incentives, the system will not have enough relays to guarantee high-quality transmission. Second, trust and security issues are critical in the centralized system. As each node only consider the benefit of itself, no mutual trust exists between nodes. Additionally, the third party in centralized system suffers from problems such as the single point of failure and privacy leakage. Byzantine failure and two-army problem indicate that it is impossible to achieve consistency through messaging on unreliable channels.

In this study, we introduce a consortium blockchain named Digital Goods Blockchain (**DG-Chain**) to address trust and security challenges, where aggregators act as peers in the blockchain system to manage transactions between vehicle nodes. We present a digital goods trading mechanism using a two-layer Stackelberg game approach, where the relay, provider and consumer act as leader, follower and sub-follower respectively. In this game, an optimization algorithm is proposed to solve the optimal strategies. We prove a unique Stackelberg equilibrium exists in our system where all parties get the maximum utilities.

Our contributions can be briefly summarized as follows.

- We establish a digital goods trading system based on **DG-Chain** to support anonymous and traceable trading in IoV system, where local aggregators act as blockchain peers to manage trading issues and audit transaction records among vehicle nodes.
- We design a pricing mechanism to increase participation of consumers and providers in trading. As the transaction volume is greatly increased, the system throughput of IoV is improved as well.

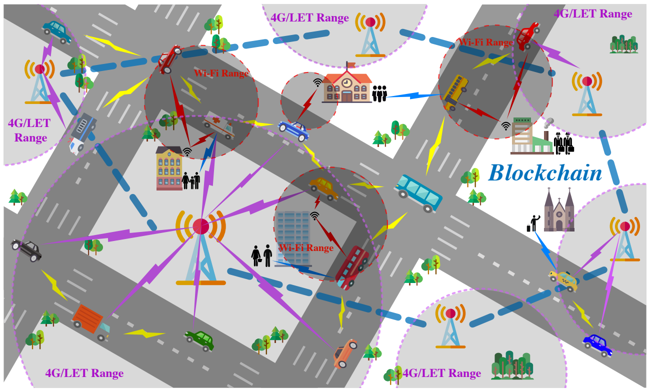

Figure 1. IoV digital goods trading scenario.

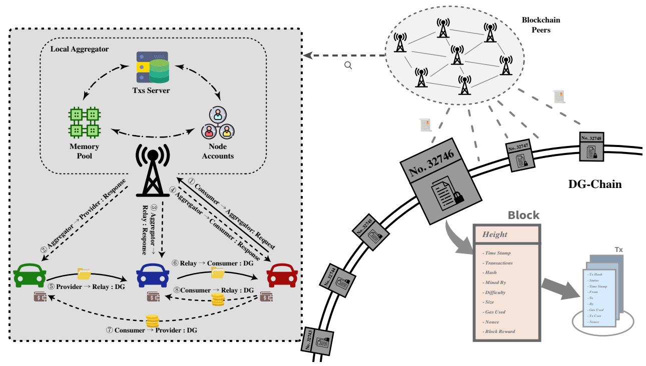

Figure 2. Digital goods trading flow chart.

- We present an incentive mechanism for vehicle nodes to participate in trading as relays. Therefore, more digital goods can be transmitted through multi-hop connection, in case of the poor or intermittent network connectivity. Consequently, high-quality data transmission will be guaranteed.

The rest of this paper is organized as follows. We briefly introduce the general system model in Section II. Section III formulates the problem in our system as a two-layer Stackelberg game model. Section IV puts forward our optimization algorithm based on **DG-Chain**. Afterwards, numerical results of our algorithm are shown in Section V. Some related works are listed in Section VI before the paper is concluded in Section VII.

II. System Model

In this section, we introduce a blockchain-based market framework for digital goods trading in IoV. Fig. 1 depicts the IoV trading scenario where vehicle nodes of different roles share the digital goods with heterogeneous network (e.g. wave, 4G/LET, and Wi-Fi). Roles and major operations in our system are discussed in this section.

A. Entities for Digital Goods Trading System

The entities in our system can be divided into vehicle nodes and aggregators. Local aggregators assemble to form the blockchain system. Blockchain peers are responsible for managing local transactions between vehicle nodes.

Vehicle Nodes: Vehicle nodes play different roles in our digital goods trading system. They can be consumers, providers, relays or idlers according to their digital goods requirements and economic status. Specially, customers with sufficient financial capacity can offer Digital Goods Coins (**DG-coins**) to available providers for raw data or its associated service with the help of relays. The complexity of roles requires us to consider the utilities from the perspectives of different roles.

Aggregators: In our trading scenario, local aggregators act as peers and form the blockchain system, which mainly consists of the following components. Authentication institution authenticates node accounts by their digital signatures. Memory pool records the transaction details in its local ledger for subsequent consensus process. Transaction server works as the broker to manage trading issues including accepting purchasing requests of consumers, looking for available providers and relays, and notifying each party. Communication infrastructures like base stations are usually chosen as the aggregators in IoV system.

B. Consortium Blockchain for Secure Digital Goods Trading

The consensus process is performed by authorized aggregators on **DG-Chain**. The trading flow chart involving vehicle nodes and aggregators is depicted in Fig. 2. Key operations of trading are shown as below.

System Initialization: We utilize Boneh-Boyen short signature scheme for system initialization. After registering on the authentication institution in the local aggregator, a vehicle node obtains its public and private keys, certification, and wallets. After that, this node becomes a legitimate entity. Authentication institution in each aggregator uses a mapping list to keep record of node accounts.

Digital Goods Trading: Trading requests from consumers are sent to the transaction server of a nearby aggregator. After finding the available provider and relay, each party will act a suitable strategy through calculation. The digital goods are then transmitted from the provider to consumer.

DG-coin Payment: Once received desired digital goods, the digital goods consumer transfers **DG-coins** from its wallet to a wallet address given by the digital goods provider. The provider can obtain the latest transaction status from the memory pool to verify this payment activity. After getting the consumer's coins, the provider generates a new transaction record. Afterwards, these transaction record is verified and digitally signed by digital goods consumer and uploaded to the memory pool.

Transaction Blocks: The local aggregator collects information of transactions for a certain period, including transaction hash, trading participants, and transaction status,

Table I
NOTATIONS TABLE

Symbol	Definition
n, k, l	Consumer, provider and relay index
α_n, β_n	Willingness indices of consumer n
λ	Freight sharing ratio of consumer n
x_n	Purchasing amount of consumer n
x_n^*	Optimal purchasing amount for consumer n
$\underline{x_n}, \overline{x_n}$	Lower-Bound and upper-bound of purchasing amount
y_k	Digital goods price of provider k
y_k^*	Optimal digital goods price for provider k
$\underline{y_k}, \overline{y_k}$	Lower-Bound and upper-bound of digital goods price
p_l	Digital goods freight of relay l
p_l^*	Optimal digital goods freight for relay l
$\underline{p_l}, \overline{p_l}$	Lower-Bound and upper-bound of digital goods freight
U_n, U_k, U_l	Utility of n, k and l respectively
t	The t^{th} iteration in the game
ϵ	The convergence indicator

etc. Transactional information is structured into transaction blocks. Besides, each block contains important clues such as time-stamp, miner, rewards, etc. Blocks are linked in chains and are transparent to other peers in the blockchain system.

Consensus Process: At the beginning of the consensus process, the first peer who gives a valid PoW is selected as blockchain leader. The blockchain leader broadcasts its block to the whole system. Other peers then reply with their audit results. If the consensus is reached, the blockchain leader will add this block into the blockchain and get some coins as mining rewards.

III. PROBLEM FORMULATION FOR DIGITAL GOODS TRADING

In the digital goods trading scenario, consumers obtain their required digital goods by paying **DG-coins** to the providers. With the target of improving the system throughput and service quality, we propose a trading scheme to maximize social welfare. In this section, we formulate this problem as a two-layer Stackelberg game by giving the game definition and quantifying our goals. The often-used notations are listed in Table. I.

Generally, the operation process of the system is as the following. A consumer n sends the purchasing request of a certain type of digital goods to the local aggregator. After receiving the purchasing requests, the aggregator evaluates the willingness indices α_n and β_n of consumer n and tries to find the available provider k and relay l. The message is sent to all potential participants repeatedly until transaction parties are confirmed. Then, the freight sharing between n and k is evaluated according to the current market demand and supply. Optimal strategy of each party (*i.e.*, x_n, y_k and p_l) is calculated by iteration. Finally, local aggregator informs all parties of their strategies.

The core of this process is to calculate the optimized strategy of each party. We can formulate this problem as a two-layer Stackelberg game.

Definition 1. *The Stackelberg game in our model can be defined as $\mathcal{G} = \langle P, D, U \rangle$, where $P = (n, k, l)$ denotes the selected provider k and relay l for consumer n; $D = (x_n, y_k, p_l)$ is the decision profile; $U = (U_n, U_k, U_l)$ is the utility tuple.*

Definition 2. *A Stackelberg equilibrium $(x_n^*, {y_k}^*, {p_l}^*)$ of $\mathcal{G}$ is a decision profile with these properties:*

$$\begin{cases} U_n\big({x_n}^*, {y_k}^*, {p_l}^*\big) \ \geq \ U_n\big(x_n, {y_k}^*, {p_l}^*\big)_{\forall n} \\ U_k\big({x_n}^*, {y_k}^*, {p_l}^*\big) \ \geq \ U_k\big({x_n}^*, y_k, {p_l}^*\big)_{\forall k} \\ U_l\big({x_n}^*, {y_k}^*, {p_l}^*\big) \ \geq \ U_l\big({x_n}^*, {y_k}^*, p_l\big)_{\forall l} \end{cases}. \quad (1)$$

To take the interests of each party into account, we formulate our problem from three respects.

Consumer side: Digital goods have attributes such as validity period, service scale and user rights, so their quantity can be measured. Considering that the consumer's satisfaction is positively correlated with their purchasing amount, it's rational to formulate the satisfaction function of consumer n as

$$sat_n = \alpha_n \ln(\beta_n + x_n). \quad (2)$$

To maintain the market balance, the consumer and provider are supposed to share the freight proportionately. The consumer will bear λ of relay freight. Thus, the utility function of n is denoted as

$$\begin{aligned} U_n &= sat_n - \lambda x_n p_l - x_n y_k \\ &= \alpha_n \ln(x_n + \beta_n) - x_n(y_k + \lambda p_l). \end{aligned} \quad (3)$$

Provider side: Given that the quantity of digital goods can be measured, it's reasonable for providers to set a unit price for them. The provider prefers to raise digital goods price for earning more profits. Meanwhile, it also needs to undertake $(1 - \lambda)$ of the freight for transmission. As the costs of production are negligible, we can express the utility function of provider k as

$$U_k = x_n y_k - (1 - \lambda) x_n p_l. \quad (4)$$

Relay side: Similar to providers, we assume that the transmitting freight of digital goods is related to their quantity. Relay nodes will set a unit freight to help with data transmission between consumers and providers. And since the transmitting costs are trivial, we define the utility of relay l as

$$U_l = x_n p_l. \quad (5)$$

Therefore, our goals are formulated as convex optimization problems, and our objective functions for a transaction are denoted as

$$\begin{cases} \arg\max\limits_{x_n} U_n, \ \text{ s.t. } 0 \ \leq \ x_n \ \leq \ \overline{x_n} \\ \arg\max\limits_{y_k} U_k, \ \text{ s.t. } \underline{y_k} \ \leq \ y_k \ \leq \ \overline{y_k} \\ \arg\max\limits_{p_l} U_l, \ \text{ s.t. } \underline{p_l} \ \leq \ p_l \ \leq \ \overline{p_l} \end{cases}. \quad (6)$$

IV. Algorithm Design

In the two-layer Stackelberg game, we put forward an optimization algorithm on **DG-Chain** to achieve the goal above (Eq. 6). The first iteration is initialized with $(0, \overline{y_k}, \overline{p_l})$ (*i.e.*, zero purchasing amount, the maximum price and freight). We use the backward deduction method in the iterative process. Specially, in the t^{th} iteration, the optimal purchasing amount $x_n^{*(t)}$ and provider price $y_k^{*(t)}$ are first calculated as the strategy of sub-follower and follower, then the optimal relay freight $p_l^{*(t)}$ is determined as leader's strategy. This dynamic process finally converges to an equilibrium, where each party's utility reaches the local optimization.

Sub-follower side: As proved later in Thm. 1, consumer's utility function (Eq. 3) is a concave function. Thus, we can get the optimized purchasing amount x_n^* by calculating the point when $\frac{\partial U_n}{\partial x_n^*} = 0$ (Eq. 7). Since the utility function of consumer n reaches the peak at this point, n updates the optimized strategy according to Eq. 8 and 9.

$$\frac{\partial U_n}{\partial x_n} = \frac{\alpha_n}{\beta_n + x_n} - (y_k + \lambda p_l). \tag{7}$$

$$x_n^* = \frac{\alpha_n}{y_k + \lambda p_l} - \beta_n. \tag{8}$$

$$x_n := x_n^*, \quad s.t. \quad 0 \le x_n \le \overline{x_n}. \tag{9}$$

Follower side: By substituting Eq. 8 into Eq. 4, we can get the provider's utility function when the consumer has already made a fixed strategy (*i.e.* x_n^*). As proved later in Thm. 1, the provider's utility function (Eq. 10) is concave. Thus, we can get the optimized provider price y_k^* by setting Eq. 11 to zero. Since the utility function of provider k reaches the peak at this point, k generates the optimized strategy according to Eq. 12 and 13.

$$U_k = \Big(\frac{\alpha_n}{y_k + \lambda p_l} - \beta_n\Big)\big(y_k - (1-\lambda)p_l\big). \tag{10}$$

$$\frac{\partial U_k}{\partial y_k} = \frac{\alpha_n p_l}{(y_k + \lambda p_l)^2} - \beta_n. \tag{11}$$

$$y_k^* = \sqrt{\frac{\alpha_n p_l}{\beta_n}} - \lambda p_l. \tag{12}$$

$$y_k := y_k^*, \quad s.t. \quad \underline{y_k} \le y_k \le \overline{y_k}. \tag{13}$$

Leader side: By substituting Eq. 8 and 12 into Eq. 5, we can get relay's utility function when the consumer and provider have already made fixed strategies (*i.e.* x_n^* and y_k^*). As proved later in Thm. 1, the relay's utility function (Eq. 14) is a concave function. Thus, we can get the optimized relay freight p_l^* according to $\frac{\partial U_l}{\partial p_l^*} = 0$ (Eq. 15). Since the utility function of relay l reaches the peak at this point, l generates the optimized strategy according to Eq. 16 and 17.

$$U_l = \Big(\sqrt{\frac{\alpha_n \beta_n}{p_l}} - \beta_n\Big)p_l. \tag{14}$$

$$\frac{\partial U_l}{\partial p_l} = \frac{1}{2}\sqrt{\frac{\alpha_n \beta_n}{p_l}} - \beta_n. \tag{15}$$

$$p_l^* = \frac{\alpha_n}{4\beta_n}. \tag{16}$$

$$p_l := p_l^*, \quad s.t. \quad \underline{p_l} \le p_l \le \overline{p_l}. \tag{17}$$

Algorithm 1 OPTIMIZATION ALGORITHM on DG-Chain

Input: α_n, β_n, λ, ${x_n}^{(0)} := 0$, ${y_k}^{(0)} := \overline{y_k}$, ${p_l}^{(0)} := \overline{p_l}$, ϵ.
for the t^{th} iteration **do**
  for consumer n **do**
    Calculate optimal purchasing amount according to $x_n^{*(t)} = \frac{\alpha_n}{{y_k}^{(t-1)} + \lambda {p_l}^{(t-1)}} - \beta_n$.
    n updates its purchasing amount to ${x_n}^{(t)} := x_n^{*(t)}, \quad s.t. \quad 0 \le {x_n}^{(t)} \le \overline{x_n}$.
  end for
  for all provider k **do**
    Calculate optimal provider price according to $y_k^{*(t)} = \sqrt{\frac{\alpha_n {p_l}^{(t-1)}}{\beta_n}} - \lambda {p_l}^{(t-1)}$.
    k updates its prices to ${y_k}^{(t)} := y_k^{*(t)}, \quad s.t. \quad \underline{y_k} \le {y_k}^{(t)} \le \overline{y_k}$.
  end for
  for all relay l **do**
    Calculate optimal relay freight according to $p_l^{*(t)} = \frac{\alpha_n}{4\beta_n}$.
    l updates its freight to ${p_l}^{(t)} := p_l^{*(t)}, \quad s.t. \quad \underline{p_l} \le {p_l}^{(t)} \le \overline{p_l}$.
  end for
  if $\big({x_n}^{(t)} - {x_n}^{(t-1)} \le \epsilon\big) \bigwedge \big({y_k}^{(t)} - {y_k}^{(t-1)} \le \epsilon\big) \bigwedge \big({p_l}^{(t)} - {p_l}^{(t-1)} \le \epsilon\big)$ **then**
    Stop iteration.
  end if
end for
Output: x_n^*, y_k^* and p_l^*.

Theorem 1. *A unique Stackelberg equilibrium* (x_n^*, y_k^*, p_l^*) *exists in* $\mathcal{G}$.

Proof 1. *To prove the existence and uniqueness of Stackelberg equilibrium, we need to prove a unique optimization exist in all three parties.*

- For sub-follower*: When provider and relay already have fixed strategies,* (i.e., y_k, p_l)*, the second derivative of purchasing amount is*

$$\frac{\partial^2 U_n}{x_n^2} = -\frac{\alpha_n}{(x_n + \beta_n)^2} < 0. \tag{18}$$

Thus, the consumer utility function (Eq. 3) is a concave *function. The concavity indicates that the consumer has optimal purchasing amount x_n^*.*

- For follower*: When consumer and relay already have fixed strategies, (i.e., $x_n = \frac{\alpha_n}{y_k+\lambda p_l} - \beta_n$, p_l), the second derivative of provider price is*

$$\frac{\partial^2 U_k}{y_k^2} = -\frac{1}{2}\frac{\alpha_n p_l}{(y_k+\lambda p_l)^3} < 0. \tag{19}$$

Thus, the provider utility function (Eq. 10) is a concave function. The concavity indicates that the provider has optimal provider price y_k^*.

- For leader*: When consumer and provider already have fixed strategies, (i.e., $x_n = \frac{\alpha_n}{y_k+\lambda p_l} - \beta_n$, $y_k = \sqrt{\frac{\alpha_n p_l}{\beta_n} - \lambda p_l}$), the second derivative of relay freight is*

$$\frac{\partial^2 U_l}{p_l^2} = -\frac{1}{4}\sqrt{\frac{\alpha_n \beta_n}{(p_l)^3}} < 0. \tag{20}$$

Thus, the relay utility function (Eq. 14) is a concave function. The concavity indicates that the relay has optimal relay freight p_l^*.

Hence, each of the three parties above has only one optimal strategy. According to Def. 2, a unique Stackelberg equilibrium exists in game $\mathcal{G}$.

V. Numerical Results

Based on the formulation of the Stackelberg game in Section III, we show the numerical results of the market equilibrium and the impacts of influential factors. First, we obtain the Stackelberg equilibrium of $\mathcal{G}$ in the process of iteration. We then explain the meaning of best responses and Stackelberg equilibrium. Next, some influential factors are discussed to analyze how they influence the digital goods market. In the end, we compare our method with the greedy and random algorithm and show the effectiveness of our algorithm.

A. Converge Analysis

To analyze the process of iteration, we set the willingness indices as constant numbers, *i.e.*, $\alpha_n = 100$ and $\beta_n = 1$. According to Eq. 8, 12 and 16, we get the strategy and utility of each party in 30 epochs.

Fig. 3 shows the converging process of utilities achieved by our algorithm. Note that the strategies and utilities rapidly converge after 12 iterations (*i.e.*, the dotted lines). Fig. 3(a), (b) and (c) indicate that strategy changes are mainly reflected in the price and freight reduction to stimulate more purchases. As shown in Fig. 3(d), (e) and (f), the utilities gradually increase with the iteration and eventually converge to stability (*i.e.*, Stackelberg equilibrium).

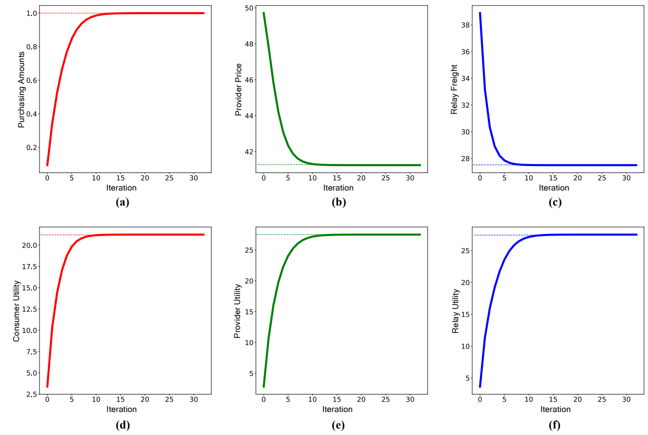

Figure 3. Iteration of (a) purchasing amount; (b) provider price; (c) relay freight; (d) consumer utility; (e) provider utility; (f) relay utility.

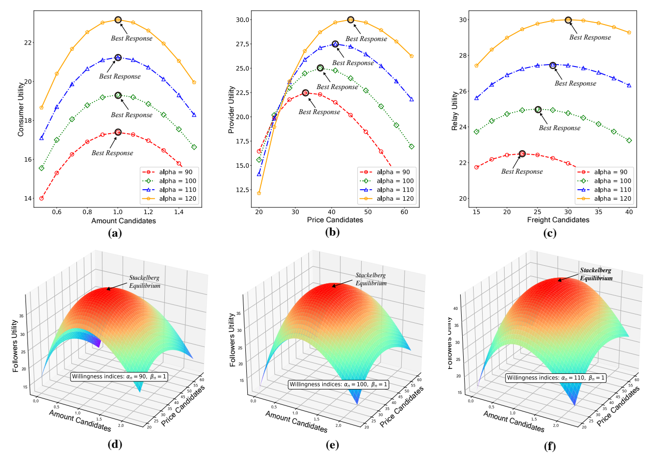

Figure 4. Best Responses of the (a) consumer; (b) provider; (c) relay. Stackelberg equilibrium meaning when (d) $\alpha_n = 90$; (e) $\alpha_n = 100$; (f) $\alpha_n = 110$, $\beta_n = 1$.

B. Performance Analysis

In this part, we make insights on what are the best responses in each iteration and the meaning of Stackelberg equilibrium. We use algorithm 1 to generate optimal strategies for all parties.

In Fig. 4(a), we longitudinally compare our optimized purchasing amount for consumers with ten candidates from 0.5 to 1.5 in the last iteration. Likewise, in Fig. 4(b), we compare our optimized prices for providers with ten candidates from 20 to 62. In Fig. 4(c), ten candidates from 15 to 40 are compared with our optimized relay freights. Results show that the obtained strategies get the maximum utilities for all parties, indicating that they are the best responses at that time. Moreover, a higher purchasing willingness will lead to a higher price and freight, but it does no affect the purchasing amount, as shown in Fig. 4(a), (b) and (c) above.

Later, we treat the consumer and provider as followers

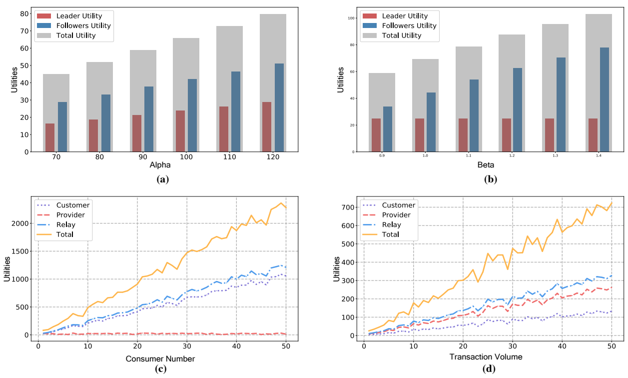

Figure 5. The impacts of (a) α_n, (b) β_n, (c) the consumer number of a transaction, and (d) the transaction volume on utilities.

and consider their utilities as a whole. Fig. 4(d), (e) and (f) demonstrate the Stackelberg equilibrium obtained when $\beta_n = 1$ and $\alpha_n = 90, 100, 110$ respectively. Results show that when the leader has a fixed strategy, the followers' utility cannot increase with the changes of purchasing amount and provider prices. Thus, according to Def. 2, our algorithm converge to the Stackelberg equilibrium.

C. *Impacts of Parameters*

In this part, we discuss some market influential factors and show their impacts on each party's utility. Fig. 5(a) and (b) demonstrate the influence of the willingness indices α_n and β_n respectively. When increasing α_n from 90 to 120, the leader's and followers' utility both increase. When increasing β_n from 0.5 to 1.4, the followers' utility increases, while the leader's utility remains the same. These indicate that the higher willingness of purchasing will increase the total utilities of our system.

We also conduct our experiment in the multi-consumer instance where the provider sells digital goods to many consumers. We assume the willingness of consumers follows the normal distribution and preset $\alpha_n \sim \mathcal{N}(100, 20)$, $\beta_n \sim \mathcal{N}(1, 10^{-2})$. Since we cannot directly get the solutions to higher order equations in this case, here we utilize Newton method to get the numerical results. Fig. 5(c) shows the growth trend of utilities when 50 consumers gradually participate in this game. The total utility of consumer and relay grow approximately linearly as the number of consumers increases. The provider utility, however, remains nearly the same. As Fig. 5(c) shows, the higher participation of consumers helps to increase the total utility in a transaction.

We also explore the impact of transaction volume on our system. Similarly, the willingness of consumers follows the normal distribution and we preset it as $\alpha_n \sim \mathcal{N}(100, 10)$, $\beta_n \sim \mathcal{N}(1, 10^{-3})$. Fig. 5(d) shows the growth trend of utilities from 1 to 50 transactions. In the multi-transaction case, the utilities of all parties increase as the transaction volume expands. This experiment demonstrates that more transactions will increase the utilities of our system.

D. *Performance Comparison*

Finally, we evaluate our algorithm in comparison with benchmark algorithms (*i.e.*, the greedy and random algorithm). In the greedy algorithm, the leaders always chose highest freights as strategies (*i.e.*, $p_l = \overline{p_l}$) to maximize their profits. In the random algorithm, the leaders chose freights randomly as strategies (*i.e.*, $\exists l, p_l = \xi_l$, where $\xi_l \in (0, \overline{p_l})$). We use utility of each party and total utility as indicators to evaluate different methods in different situations (*i.e.*, the regular case, strong-desired case and multi-consumer case).

Table. II shows the comparison of algorithms in three situations. In the regular case, one consumer is involved in each stoke of transaction and the willingness indices are set to be $\alpha_n = 100$ and $\beta_n = 1$ as baseline. In the strong-desired case, where the consumer is more willing to purchase certain digital goods, the satisfaction return for per unit of purchasing is correspondingly higher than the regular case. Thus, we adjust the willingness indices to $\alpha_n = 110$ and $\beta_n = 1$. In the multi-consumer situation, ten consumers purchase digital goods from the same provider. Considering the homogeneity of the consumers in the local area, their willingness indices follow the normal distribution, where $\alpha_n \sim \mathcal{N}(100, 20)$ and $\beta_n \sim \mathcal{N}(1, 10^{-2})$. Results show that our algorithm generates the highest utilities among the three. On the contrary, the greedy algorithm shows the poorest performance. And the comparison between situations shows that higher willingness and more consumers contribute to the high total utility of our system. In a nutshell, our algorithm is effective and applicable under various circumstances.

VI. Related Works

Many studies employed the demand response mechanism in the IoT/IoV system. For example, in [9], the energy consumption scheduling problem was formulated as a non-cooperative game. In [10], the authors proposed a distributed framework for demand response problem in the smart grids. In [11], Caron *et. al.* proposed a dynamic pricing scheme incentivizing consumers to achieve an aggregate load profile. However, all of these studies were based on centralized management systems and relied on a trusted third party. As a result, they could suffer problems such as single point of failure and privacy leakage, which lead to the vulnerability of these systems.

To solve the defects of the centralization, some studies applied blockchain technology in the IoT/IoV trading scenario. For instance, energy trading schemes in decentralized energy exchange system were proposed in [12], [13], [14], [15]. The authors in [16], [17] utilized the double-sided auction scheme to optimize computing resource trading in decentralized IoT system. Besides, in [18], [19], the consortium blockchain is exploited in the IoV data-trading

Table II
METHODS COMPARISON RESULTS

Utility	Regular Case			Strong-desired Case			Multi-consumer Case		
	Ours	Greedy	Random	Ours	Greedy	Random	Ours	Greedy	Random
Consumer	19.31	9.03	18.77	21.25	11.97	27.16	215.94	90.21	140.24
Provider	25.00	13.49	20.45	27.50	17.33	21.69	26.23	13.50	19.64
Relay	25.00	23.16	24.84	27.50	26.33	15.73	259.75	230.47	240.68
Total	69.31	45.86	64.06	76.25	55.64	64.58	501.92	334.18	400.56

market. While, these blockchain-based works overlook the utility of relay in multi-hop scenarios. Without sufficient incentives, vehicle nodes would not be willing to participate as relays, which can lead to some performance problems like low throughput and high response delay.

In this paper, we model a two-layer Stackelberg game and execute the optimization algorithm on a secure and dependable blockchain to incentivize all vehicle nodes to get involved in the transactions.

VII. CONCLUSION

In this paper, we propose a digital goods trading mechanism in hybrid-connected IoV scenario. We introduce a consortium blockchain to address the distrust and security challenges of the centralization. Moreover, to encourage nodes to participate in the transactions, we put forward an optimization algorithm using the two-layer Stackelberg game approach. Extensive experiments are conducted to evaluate the performance of our optimization algorithm. After getting the iterative convergences, we deep into each iteration to find the best response and analyze the meaning of the Stackelberg equilibrium. Extensive experiments demonstrate the impacts of several market influential factors and the effectiveness of our method is shown by comparison with benchmark algorithms. Specially, each party can maximize its economic utility with our algorithm, and the nodes will be most motivated in various situations.

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