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An Incentive Mechanism for Mobile Crowd Sensing in Vehicular Ad Hoc Networks

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Abstract

In the mobile crowdsensing of vehicular ad hoc networks (VANETs), in order to improve the amount of data collection, an effective method to attract a large number of vehicles is needed. Therefore, the incentive mechanism plays a dominant role in the mobile crowdsensing of vehicular ad hoc networks. In addition, the behavior of providing malicious data by vehicles as data collectors will have a huge negative impact on the whole collection process. Therefore, participants need to be encouraged to provide data honestly to obtain more available data. In order to increase data collection and improve the availability of collected data, this paper proposes an incentive mechanism for mobile crowdsensing in vehicular ad hoc networks named V-IMCS. Specifically, the Stackelberg game model, Lloyd's clustering algorithm and reputation management mechanism are used to balance the competitive relationship between participants and process the data according to the priority order, so as to improve the amount of data collection and encourage participants to honestly provide data to obtain more available data. In addition, the effectiveness of the proposed mechanism is verified by a series of simulations. The simulation results show that the amount of available data is significantly higher than the existing incentive mechanism while improving the amount of data collection.

Keywords

VANETs, Mobile Crowd Sensing, Data Collection, Incentive Mechanism, Clustering Algorithm

1. Introduction

With the development of sensor technology and embedded computing devices, mobile crowdsensing (MCS) has become a popular technology [1] [2]. In addition, with the increasing demand for a social event and phenomenon analysis, MCS is gradually applied to the Internet of vehicles [3]. MCS of vehicles refers to that mobile vehicles use advanced sensor technology to collect and transmit perception data in real time [4]. For example, the vehicle can regularly report the current vehicle status, traffic status and weather conditions by using the on-board unit and sensor device [5]. MCS of the Internet of vehicles can be applied to various life situations. However, due to the demand of MCS for massive data, more vehicles need to participate in MCS [6] [7]. In addition, false data will affect the data results, and service consumers hope that the data provided by participating vehicles are true and effective [8]. How to ensure the amount of available data while meeting the needs of massive data is one of the challenges faced by the current MCS of the Internet of vehicles [9]. An incentive mechanism is needed to increase the amount of data available while increasing the amount of data collected.

In recent years, scholars at home and abroad have done a lot of research on the perceived incentive mechanism of group intelligence [10] [11] [12] [13] [14]. Among them, Yang *et al.* [11] designed two auction based incentive mechanisms, focusing on the platform or users, to encourage users to participate in perception and complete perception tasks. J. S. Lee *et al.* [12] proposed a reverse auction mechanism, which allows users to send the valuation of their data to the service provider (SP), and SP decides whether to purchase their data. T. Luo *et al.* [13] proposed an incentive mechanism for users to participate in the game, which sets a full reward for SP according to users' contributions to the auction. The above studies only consider the interaction between SP and data collectors (DC), while ignoring the payment and consumption behavior of service consumers (SC). In order to solve this problem, Kaoru *et al.* [14] proposed an incentive mechanism (quality and usability of information, QUOIN), which considers the price competition relationship between SP and DC, SP and SC, but ignores the availability of collected data.

In order to solve the above problems, this paper proposes an incentive mechanism in MCS of the Internet of vehicles. Firstly, the reputation mechanism is used to update the reputation of participants in real time, so as to encourage participants to provide data honestly, so as to improve the proportion of effective data; Secondly, the incentive mechanism scheme of Kaoru *et al.* is optimized, and the Stackelberg game model [15] is used to achieve the Nash equilibrium [16]. On the basis of the maximum data output, more participants are further encouraged to participate in data collection through the integral reward mechanism; Finally, Lloyd's clustering algorithm is used to sort the collected data, so as to improve the amount of available data.

An incentive mechanism for mobile crowd sensing in vehicular ad hoc network (V-IMCS) proposed in this paper can balance the competitive relationship between SP, SC and DC, and improve the amount of data collection and available data. The main contributions of this paper are: using Stackelberg game model to find the Nash equilibrium point and obtain the data volume of profit maximization, so as to balance the competitive relationship among SP, SC and DC, and improve the data collection volume; in the incentive mechanism, Lloyd's clustering algorithm is used to improve the amount of available data; introduce reputation management mechanism and point reward mechanism to further encourage more participants to honestly provide data and improve the amount of data collected and available; compared with the existing incentive mechanism, the mechanism proposed in this paper improves the amount of data collection and available data.

The remaining sections are as follows. Section II covers the essential technologies relevant to the mechanism. Section III discusses the mechanism content, including five stages; Initialization; service request between the service consumer and the SP; data collection between SP and DC; SP processes the collected data; Reputation feedback and strategy update. Overall results and future work can be found across Sections IV.

2. Related Works

2.1. Stackelberg Model

When leading manufacturers decide their own output, they will expect the impact of their own output on follower manufacturers [17] [18]. Therefore, the output determined by leading manufacturers is a profit maximization output constrained by following the manufacturer's response function. With the continuous growth of the price of leading manufacturers, the price of follow-up manufacturers will also increase, and maintain a relative maximum price to achieve Nash equilibrium [19] [20].

2.2. Lloyd's Clustering Algorithm

Lloyd's clustering algorithm is a classical clustering algorithm that can maintain scalability and efficiency when processing large data sets [21] [22]. Its execution process is as follows [23]:

1) Input points are divided into k groups, the center point of each group is calculated, and K initial points are randomly selected in the input point data set;

2) Calculate Voronoi diagram of K central points;

3) Integrate Voronoi diagram and calculate centroid;

4) Then move each center point to the centroid of the Voronoi diagram.

Repeat the above process until the center point does not change.

2.3. Network Model of Mobile Crowd Sensing of Vehicular Ad Hoc Networks

MCS of vehicular ad hoc networks means that in the Internet of vehicles, mobile vehicles use advanced sensor technology to collect and transmit perception data in real time. The MCS of the Internet of vehicles is often composed of the following parts [24] [25].

1) Trusted authority (TA)

In order to ensure the normal operation of the organizational structure of the Internet of vehicles, it is usually necessary to introduce a trusted certification authority named TA to store the identity information of all users in the corresponding area.

2) Service provider (SP)

SP pays a certain reward to the data collector, obtains data from the data collector, processes the data and sends it to the service consumer. The reward meets the following principles [14]: if the data validity is high, the payment reward is high; If the data schedule is high, the payment reward is high; The more similar data are provided, the lower the reward will be paid; If the collected data is more important for data coverage, the payment reward will be higher.

3) Data collector (DC)

DC is responsible for selecting an appropriate data collection strategy, collecting perceptual data, and providing the collected data to the SP. Vehicles in the Internet of vehicles have certain computing and storage capabilities [24], and can act as DC in the MCS of the Internet of vehicles.

4) Service consumer (SC)

Refers to some management departments (e.g. traffic management department, meteorological bureau) that generate demand for some data and want to extract valuable information (e.g. traffic conditions, accident conditions, weather conditions) from the existing perceived data. SC consider the optimal consumption strategy according to their own needs and choose the corresponding SP to provide services for themselves.

3. Incentive Mechanism Named V-IMCS

The incentive mechanism V-IMCS proposed in this paper mainly includes five stages: the first stage is initialization; the second stage is the service request between SC and SP; the third stage is data collection between SP and DC; in the fourth stage, SP processes the collected data; the fifth stage is reputation feedback and strategy update. The overall flow chart of incentive mechanism is shown in **Figure 1**.

3.1. Initialization

In order to avoid malicious data transmission by vehicles and ensure the availability of vehicle information data, the trusted organization generates time interval $T_\alpha \in \{T_1, T_2, \cdots\}$, sets unique identification and initial reputation score for each vehicle, stores the information in the database, updates the vehicle reputation immediately according to the time interval, and sets the initial reputation score through Equation (1).

$$RM_{V_i}^0 = \begin{cases} 0.9 & V_i \in LE \\ 0.5 & V_i \in PS \\ 0.1 & V_i \in OT \end{cases} \tag{1}$$

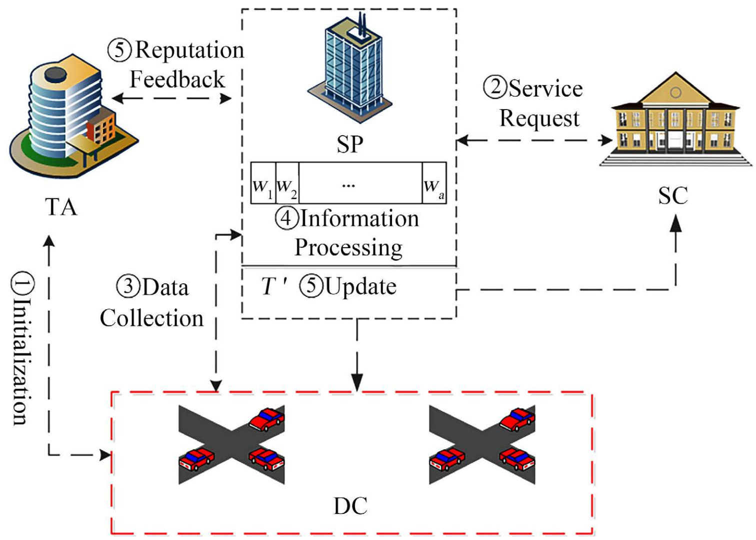


Figure 1. System architecture.

where *LE* is law enforcement vehicles, *PS* is public service vehicles and *OT* is other vehicles [26].

3.2. Service Request

When SC requests information, it determines the task number *TID*, task content *CM* and the number of requested information N_0 according to the specific requirements of the perceived task, and then sends a request message Qt_{C_i} to SP through Equation (2).

$$Qt_{C_i} = \left(TID, CM, N_0\right) \tag{2}$$

After receiving Qt_{C_i}, SP publishes the service information Pm_{S_i} to SC through Equation (3).

$$Pm_{S_i} = \left(TID, CM, AW_{S_i}\right) \tag{3}$$

where, AW_{S_i} is service pricing.

Then, SC selects the desired SP to send the demand message according to the service information Qm_{C_i}, as shown in Equation (4).

$$Qm_{C_i} = \left(TID, CM, N_0, Pc_{C_i}, T_0\right) \tag{4}$$

where, Pc_{C_i} is Compensation amount, T_0 is deadline.

3.3. Data Collection

After receiving the demand information, SP generates a request task Qt_{s_i}, such as Equation (5) to the vehicle V_i.

$$Qt_{s_i} = \left(TID, CM, TM, RM_2^0, RM_1^0\right) \tag{5}$$

where *TM* is expiration time, RM_1^0 and RM_2^0 ($1 \ge RM_1^0 \ge RM_2^0 > 0$) are the minimum reputation requirements of the two collection schemes described below, which are uniformly set by SP.

This paper provides two collection schemes: direct payment and cumulative compensation:

1) Direct payment: If V_i selects this scheme and the collected data passes the verification, a reward AW_{V_i} will be issued. Otherwise, the vehicle reputation feedback will be updated and the reward will be cancelled. For ease of illustration, the collection scheme is recorded as M_1^0.

2) Cumulative compensation: If V_i selects this scheme and the collected data passes the verification, it will submit the vehicle reputation feedback and accumulate points for the vehicle. Otherwise, it will update the vehicle reputation feedback and cancel the reward. Calculate the cumulative integral by Equation (6).

$$SW_{V_i}' = SW_{V_i}^n + AW_{V_i} \tag{6}$$

where $SW_{V_i}^n$ is total points before vehicle accumulation, n means that the vehicle has participated in n times of integral accumulation.

In addition, when the vehicle's points accumulate to a certain amount, you can get additional rewards. Specifically, calculate the total points SW_{V_i}'' after additional rewards through Equation (7).

$$SW_{V_i}'' = \begin{cases} (1+\sigma) SW_{V_i}' & \text{if } SW_{V_i}' \geq SW_0 \\ SW_{V_i}' & \text{otherwise} \end{cases} \tag{7}$$

where, $\sigma(0 < \sigma < 1)$ is Incentive factor and SW_0 is extra bonus line by SP.

If $n > n^0$, the vehicle can choose to extract points and convert the points owned into reward according to Equation (8). The collection scheme is recorded as M_2^0.

$$AW_{V_i} = \delta \cdot SW_{V_i}\left(n - n^0\right) \tag{8}$$

where n^0 is extractable times threshold and δ is conversion scale factor by SP.

According to the above collection scheme, the follow-up operations are as follows:

After receiving the request task from SP, if V_i decides to participate in the collection task, select the corresponding collection scheme, generate the final feedback information Rm_{V_i}, such as Equation (9), and feed back the results to SP.

$$Rm_{V_i} = \left(Ps_{V_i}, M_{1,2}^0, AW_{V_i}, T_{V_i}\right) \tag{9}$$

where Ps_{V_i} is vehicle unique identification, $M_{1,2}^0 \in \left\{M_1^0, M_2^0\right\}$ is collection method selected for the vehicle, AW_{V_i} is price, and T_{V_i} is current time.

3.4. Information Processing

Service provider collects the feedback information sent by the vehicle, and then sends a reputation query request, such as Equation (10), to TA.

$$Qs_{S_i} = \left(TID, Ps_{V_i}\right) \tag{10}$$

Then, TA retrieves the reputation value according to the unique identification of the vehicle, generates a feedback message and sends it to SP as shown in Equation (11).

$$As_{S_i} = \left(TID, RM_{V_i}\right) \tag{11}$$

After that, the collected information and data are processed. The main process is shown in Figure 2. The specific process is as follows:

Service provider judges whether the vehicle meets $RM_{V_i} \geq RM_{1,2}^0$ ($RM_{1,2}^0 \in \left\{RM_1^0, RM_2^0\right\}$) according to the retrieved reputation value. If not, generate feedback on the current vehicle dishonesty. Otherwise, SP uses the following Lloyd's clustering algorithm to cluster the information data.

Lloyd's clustering algorithm are as follows:

Firstly, the vehicle is divided into several priorities according to the value ratio of $\partial = \dfrac{RM_{V_i}}{AW_{V_i}}$, and they are pressed into the corresponding priority queue. The steps are as follows: first, SP input the number of priorities *a* to be divided, and randomly generate *a* random center point, expressed as $\left\{w_1, w_2, \cdots, w_a\right\}$. Secondly, SP assign each vehicle value ratio $\partial_i \in \left\{\partial_1, \partial_2, \cdots, \partial_n\right\}$ to the closest area according to the value of the center point. Integrate the Voronoi diagram of the center point in each region to calculate its centroid. Finally, SP move the center point to the centroid position and update the center point.

Repeat the above steps until the center point of the area does not change. Finally, output the values of a center points, and sort the values of the center points from large to small to obtain the final collection $\left\{w_1', w_2', \cdots, w_a'\right\}$.

Service provider can divide the received vehicle information data into *a* groups according to the ratio for priority judgment, and the groups with large values are given priority. Compared with random authentication, authentication according to clustering priority order can improve the total availability of data.

SP determines whether the data provided by each vehicle is null or inconsistent with the data required by the task and other invalid data according to the clustering priority order obtained from the above operations. If the above situation exists, reputation feedback $Rf_{V_j} = 0$ is generated; Otherwise, reputation feedback $Rf_{V_j} = 1$ is generated.

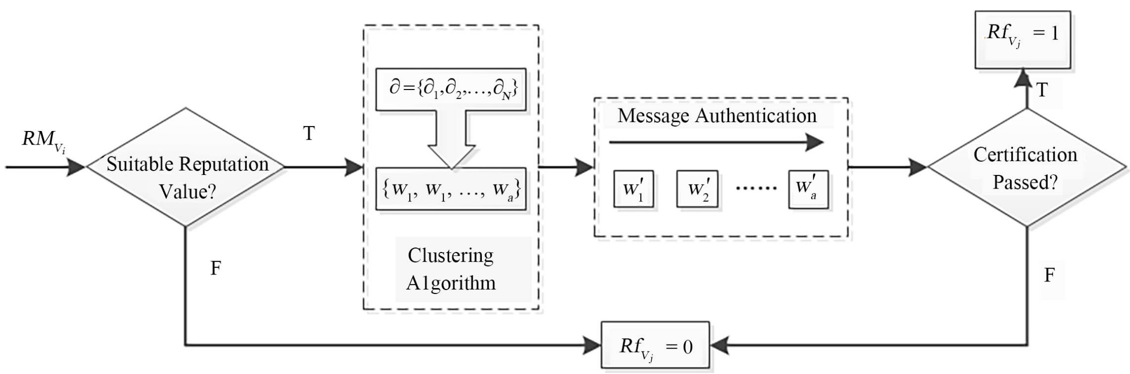


Figure 2. Information processing flow chart.

Then, service provider sends the feedback information, such as Equation (12), to the trusted institution for updating the vehicle reputation value.

$$Af_{V_i} = \left(TID, Ps_{V_i}, Rf_{V_i}\right) \tag{12}$$

Then, service provider sends the reliable data set after verification processing to SC and pays DC with reliable data.

3.5. Information Update

At intervals T_α, the trusted institution updates the reputation value of each vehicle according to the received vehicle reputation feedback. The set of n reputation feedback received by the vehicle in the current time period is $Fs_{V_i} = \left\{Rf_{V_i}^1, Rf_{V_i}^2, \cdots, Rf_{V_i}^n\right\}$, and the new reputation value Equation (13) is:

$$RM'_{V_i} = \begin{cases} \dfrac{\sum Fs_{V_i}}{n} RM_{V_i} & \text{if } Fs_{V_i} = \phi \\ \gamma \cdot RM_{V_i} & \text{otherwise} \end{cases} \tag{13}$$

In addition, at regular intervals T_α, SC and DC will change their strategies under the influence of SP, and finally minimize costs and maximize profits [14]. Detailed proofs are proved in Varian's Microeconomics [20].

4. Results and Discussion

This chapter evaluates the effectiveness of the mechanism through simulation and compares it with the existing schemes to prove the performance advantages of the scheme proposed in this paper.

4.1. Simulation Sample

In this section, corresponding experiments are designed to test the performance of the mechanism. All experiments run on the host configured with 1.8 GHz Intel processor, 8 GB memory and windows 10 operating system. This mechanism simulates and collects the data according to the pricing demand relationship and the Stackelberg optimization model [20], in which the pricing meets the normal distribution [27], the time period division is referred to [14], and the parameter values are shown in **Table 1**.

For 230 data of Nash equilibrium point, the reputation and pricing are sampled according to the normal distribution [26] [27] [28]. In this simulation experiment, the real numbers within the range of [0, 1] are randomly sampled for 7 times, and 230 data are randomly generated according to the normal distribution $N\left(\mu, \sigma^2\right)$. Since 99.7% of the value of normal distribution is within the range of three standard deviations around the average, let $\mu = 0.5, \sigma = \mu/3$, so as to meet that most of the obtained data are within the range of [0, 1].

According to Lloyd's clustering algorithm, the seven times of data can be divided into six clustering center points. After 2000 iterations, the center point image shown in **Figure 3** can be obtained.

Table 1. Simulation sample.

parameter	definition	value
μ, σ	Pricing expectation, pricing variance	3.5, 1.5
d	Data collection conversion constant	250
a, b	Demand function constant	30, 5
c	Cost constant	1.2
AW	price	65 - 85
ϑ	Pricing constant A/B/C	13/20/11
N	Total data	230
d	Data demand conversion constant	10
RL_0	Reputation threshold	0.5
T	time interval	2 s

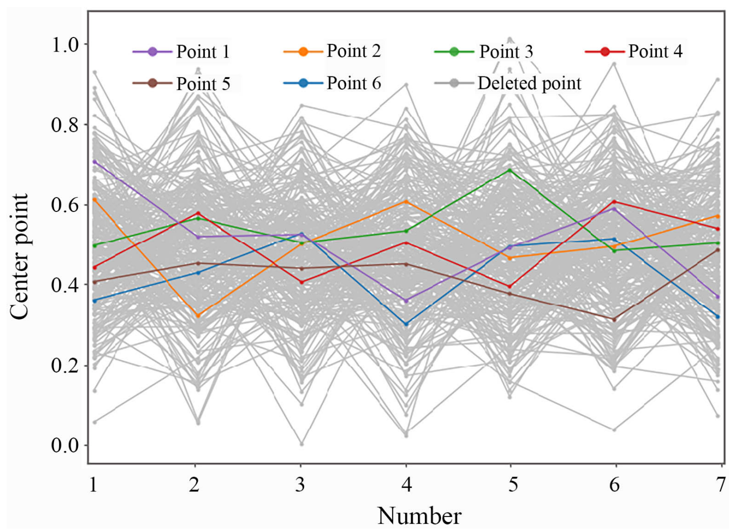


Figure 3. Six kinds of center point images divided by Lloyd's clustering algorithm.

Among them, the higher the center point value, the higher the category priority. SP selects DC according to the priority.

4.2. Result Analysis

Firstly, this paper analyzes the improvement of data collection by the mechanism, and compares it with the non incentive mechanism.

As shown in **Figure 4**, the initial data collection volume of this mechanism will be affected by comprehensive factors such as SP, SC and pricing, with certain randomness [14], while the data collection volume without incentive mechanism is only affected by stable factors such as pricing [20]. Through six experiments and the conclusion put forward by Kaoru *et al.* [14], the initial situation of incentive mechanism can be roughly divided into two types, which are recorded as situation a and situation B. In case a, the vehicle increases the collection

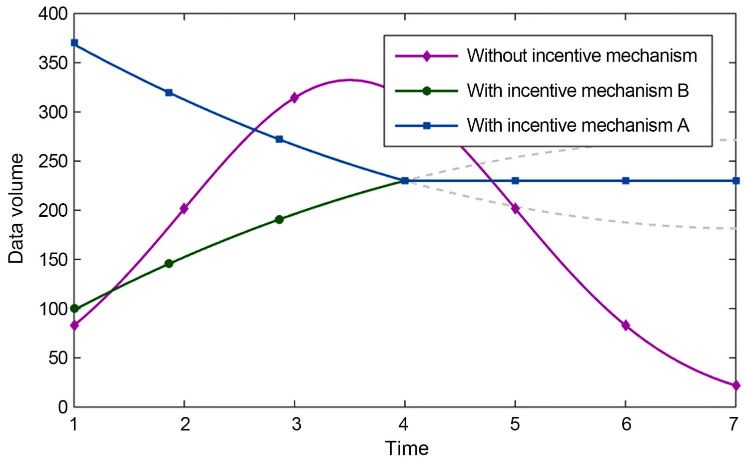


Figure 4. Changes in the amount of data collected by each mechanism in different time periods.

price to obtain a high initial data collection volume, but its profit is also relatively low; the vehicle in case B reduces the collection price, resulting in a low amount of initial data collection, but its profit is correspondingly high.

With the passage of time, the collection price of vehicles in case a will be reduced accordingly in order to improve the profit, so the number of vehicles collected will also be reduced accordingly; similarly, in case B, in order to increase the collection quantity, the collection price will be increased accordingly, so as to increase the collection quantity. Since the operation satisfies the Nash equilibrium, it will reach a corresponding equilibrium point after a period of time [20]. According to a certain proportion, the non incentive mechanism meets the normal distribution with the price fluctuation [25]. It can be seen from **Figure 4** that the non incentive mechanism fluctuates greatly. According to the statistics in **Table 2**, compared with the non incentive mechanism of $t \in \{1,3,5,7\}$ in different time periods, the average data collection of V-IMCS mechanism is significantly higher, and the collection in most time periods is higher than that of non incentive mechanism. Refer to [14] for time period division.

In conclusion, compared with no incentive mechanism, the mechanism proposed in this paper improves the amount of data collection.

Secondly, this paper analyzes the improvement of the amount of available data, and compares it with various incentive mechanisms.

According to [28], the pricing range and pricing constant benchmark can be defined, and the pricing constant can be adjusted according to demand. In this paper, 60% and 70% of the benchmark are taken as supplementary experimental data. According to the relevant parameter settings, **Figure 5** is calculated. The demand curve of SC will intersect with the data supply curve under different pricing parameters, so as to obtain the data demand under different pricing parameters.

According to **Figure 5**, the demand is taken as 150, 130 and 120. Seven simulation experiments are carried out on each mechanism respectively to compare

Table 2. Statistics of data collection in each time period.

	A	B	C
Time = 1	377↑	83	90↑
Time = 3	285↓	394	219↓
Time = 5	230↑	174	230↑
Time = 7	230↑	32	230↑
average	263↑	188	198↑

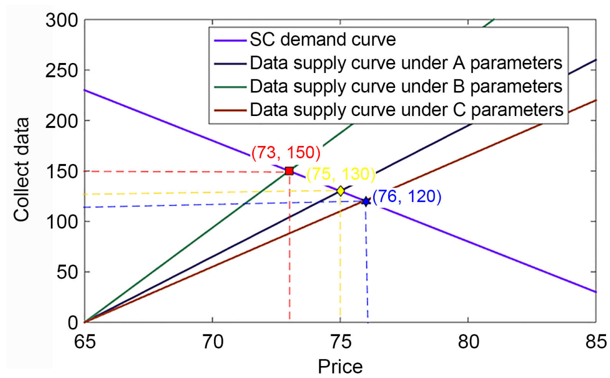


Figure 5. Data demand under each pricing parameter.

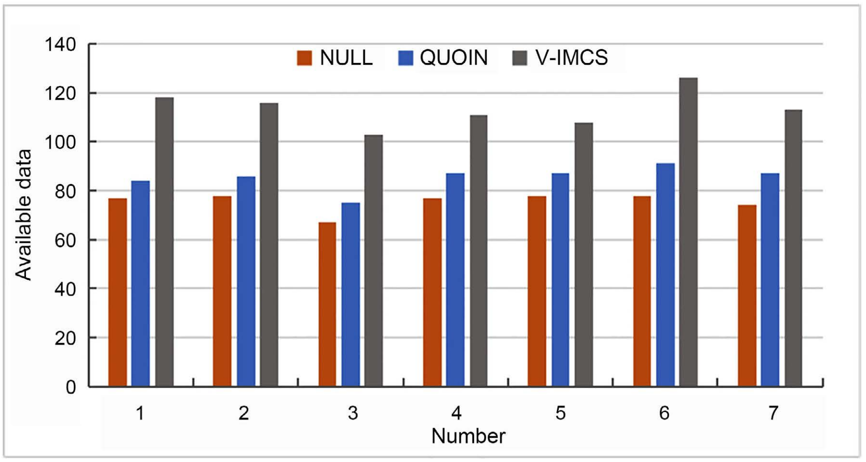
the without incentive mechanism, QUOIN incentive mechanism and V-IMCS mechanism. For the data screening mechanism, refer to the reputation screening principle in [26].

When the amount of data is 150, the comparison of the amount of available data under different mechanisms is shown in **Figure 6(a)**. Due to the use of clustering algorithm, the available data can be selected preferentially. Compared with no incentive mechanism and QUOIN incentive mechanism, the average amount of available data of V-IMCS incentive mechanism is more under 7 simulation experiments.

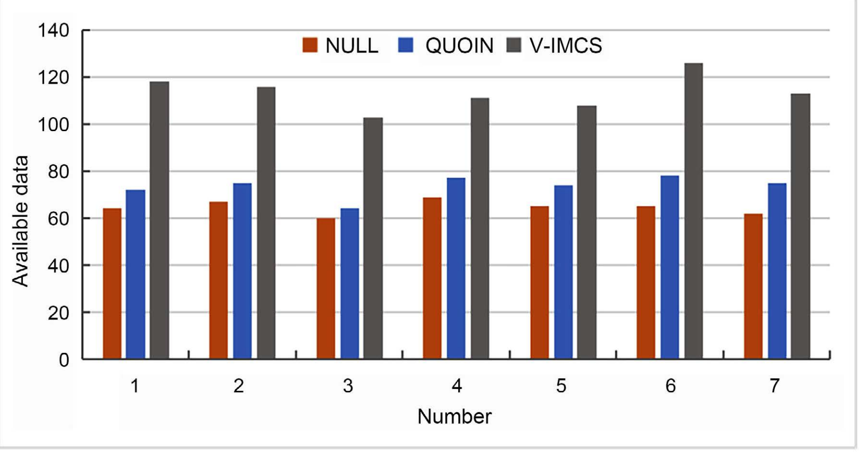
When the data volume is 130 and 120, the comparison of the available data volume under different mechanisms is shown in **Figures 6(b)-(c)**. Compared with 150, the available data volume without incentive mechanism and QUOIN incentive mechanism is reduced, and the V-IMCS incentive mechanism is not greatly affected. Therefore, compared with no incentive mechanism and QUOIN incentive mechanism, the amount of available data obtained by V-IMCS incentive mechanism is not easily affected by the amount of data demand.

In addition, if the provided data is not used by the SP, the vehicle will not be paid accordingly. In order to obtain the reward, the vehicle needs to get a higher priority, which further encourages the vehicle to provide data honestly.

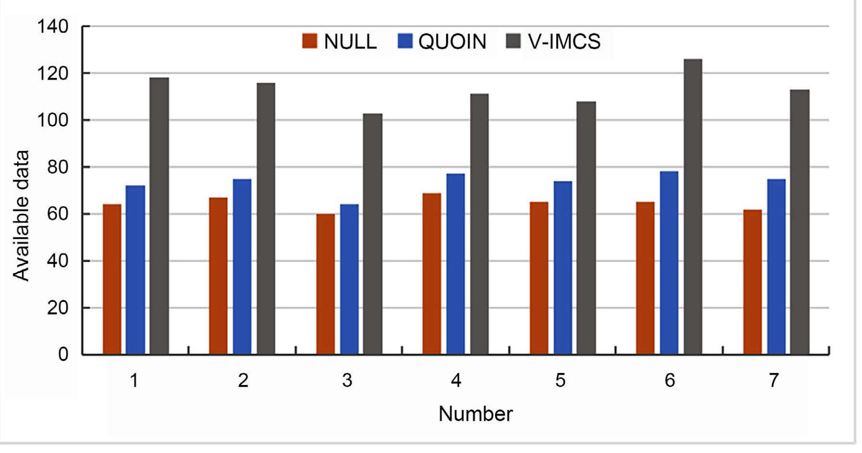
To sum up, in the MCS of the Internet of vehicles, while encouraging vehicles to honestly provide data, the amount of available data received is significantly higher than the existing QUOIN mechanism and without incentive mechanism, and is not easily affected by the amount of data demand.



(a) M = 150



(b) M = 130



(c) M = 120

Figure 6. Comparison of available data of each mechanism under different data requirements.

5. Conclusions

Based on Stackelberg game model and Lloyd's clustering algorithm, this paper proposes a new incentive mechanism V-IMCS for the MCS of the Internet of vehicles. The V-IMCS incentive mechanism proposed in this paper not only balances the competitive relationship between SP, SC and DC, but also improves the amount of data collection and available data.

In addition, this paper analyzes the effectiveness of the proposed mechanism to collect data, then reveals it through a series of simulations. While improving the amount of data collection, the amount of available data is significantly higher than that of QUOIN mechanism and without incentive mechanism. It is also less affected by the amount of data demand.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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