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Data Collection and Trading Strategy Analysis of Stackelberg-Based Vehicle Crowd-Sensing Platform

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Abstract. A data collection and trading strategy based on a three-layer Stackelberg is proposed to address the defects of the data collection and trading strategy of the existing Telematics group wise sensing platform. First, the data trading strategy is designed for the Telematics group intelligence sensing platform, and the platform determines the optimal trading price according to the data volume and time limit demand of each data user; then the data collection strategy is designed for the platform, and the platform incentivizes the sensing vehicles to collect the required data volume within the limit time according to the movement trajectory, sensing and transmission cost of each sensing vehicle, and the strategy minimizes the data collection energy consumption and cost of the system. The strategy minimizes the data collection energy consumption of the system and designs the optimal data trading strategy based on game theory to maximize the economic benefits of the system. The experimental results demonstrate that the proposed strategy makes the telematics group wise sensing platform obtain the best economic utility in data collection and trading and satisfies the data demand of data users and the reward demand of sensing vehicles at the same time.

Keywords: vehicular crowd sensing, data collection, data mining, Stackelberg game

1 Introduction

With the improvement of software and hardware capabilities of intelligent mobile devices, mobile crowed sensing has become a reliable urban data acquisition method [1]. Nowadays, smart mobile devices such as mobile phones, laptops and on-board devices are equipped with a variety of sensors, which have strong communication, computing and storage capabilities. Mobile group intelligence perception can encourage mobile users to operate their own intelligent mobile devices, collect and upload the urban data of the surrounding environment to the central platform. Compared with fixed sensor networks, mobile swarm intelligence perception saves the cost of large-scale sensor layout and achieves effective urban data acquisition [2, 3].

Vehicular crow sensing is a typical scenario of mobile crow sensing [4, 5]. With the development and popularization of vehicle networking and on-board intelligent services, there are a large number of sensors, processing devices and communication equipment on the vehicle. This makes the vehicle have strong data acquisition and processing capabilities and can communicate stably with other vehicles and roadside equipment. The group intelligence perception of the Internet of vehicles encourages car owners to complete the task of urban data collection and upload of the surrounding environment during driving [6, 7]. Due to the wider range, faster speed and more lasting energy supply of vehicle movement, the Internet of vehicles group intelligence perception has wider coverage and finer perception granularity than the ordinary mobile group intelligence perception [8, 9]. The functions of the Internet of vehicles group intelligence perception platform are divided into two parts: data acquisition and data transaction [10]. On the one hand, in data acquisition, the platform gives incentives to make the perceived vehicle complete the data acquisition task. On the other hand, in data transaction, the platform sells the collected data to data users in exchange for return.

However, at present, there are still bottlenecks in the research on the strategy of data acquisition and data

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transaction. On the one hand, the moving paths of perceived vehicles are different [11], and the energy cost [12] and time spent to complete the task are also different. Therefore, it is necessary to comprehensively consider the actual situation of each perceived vehicle to formulate a reasonable data acquisition reward scheme. The current research on reward strategy mainly focuses on the impact of vehicle moving path and acquisition cost, ignores the data transmission cost and the time spent to complete the task, and lacks comprehensive consideration of perceived vehicle situation [13-15]. On the other hand, data users have different requirements for data conversion value ability and time limit for obtaining data, so it is necessary to have a reasonable data transaction scheme and negotiate with data users to determine the optimal transaction price and data volume [4]. The value of data decreases over time, especially in Internet of vehicles services, such as transportation departments, which need the latest road condition information to dredge traffic [12]. However, the current data transaction strategy does not consider the needs of data users for time constraints.

Based on the above problems, this paper proposes a data collection and trading strategy based on the three-layer Stackelberg game with the vehicle networking group wise sensing platform as the carrier, which constructs the utility model of maximizing the platform based on the game theory, and elevates the platform data users and sensing vehicles to the optimal utility, so as to make up for the problem of optimal data collection and data trading in the vehicle networking group wise sensing platform. Therefore, based on game theory, the platform of the strategy proposed in this paper is the master participant, and the data users and sensing vehicles are the subordinate participants, respectively. In data collection, the platform integrates the movement path, required cost and time spent by each sensing vehicle to decide the reward for the sensing vehicle to complete the task. In data trading, the platform integrates each data user's transformation value and time-constrained demand for data to determine the trading price. Specifically, the strategy proposed in this paper has the following innovations.

(1) A data collection and trading strategy based on a three-layer Stackelberg game is proposed, which enables the data center to obtain the maximum economic benefit in data trading while satisfying the needs of data users, effectively solving the urgent problem of optimal data collection and data trading in the Telematics group wise sensing platform.

(2) A vehicle networking group wise sensing system model is designed. The system model effectively combines users, platform and vehicles, integrates the advantages of all three, maximizes the data utilization and conversion rate, increases the economic value, and optimizes the task assignment to minimize the energy cost of data collection.

(3) The strategy and model proposed in this paper are compared in simulation experiments, and the experimental results verify that, using the proposed strategy, the platform can obtain the optimal economic utility in data collection and transaction, and the effectiveness of the system model.

2 System Model

In this paper, we propose a typical model of telematics group wise sensing system, which consists of three parts: data users, telematics group wise sensing platform, and sensing vehicles. The main role of the proposed model is to synthesize the advantages of multiple parties, maximize economic efficiency, and reduce the energy cost of data collection. Data users: acquire urban data of the specified area within the required time through data trading, and analyze urban data to make better decisions and improve the quality of urban services, thus transforming urban data into economic value. Telematics group intelligence sensing platform: issues urban data collection tasks to sensing vehicles passing through the specified area; integrates, cleans and processes urban data collected and uploaded by sensing vehicles; sends processed data to data users through data trading in exchange for economic benefits. Sensing vehicles: complete the data collection task issued by the platform within the required time, use the intelligent equipment in the vehicle to sense the city data in the designated area and upload it to the data center. The vehicle network group intelligence sensing system model, using a cyclical operation mechanism. In each cycle, there are different data users who wish to collect the data they want through the system. Through negotiation, the data center and the data user determine mutually satisfactory incentives and data requirements. The data center then generates the appropriate data collection tasks based on the data requirements. The data collection task contains the desired target area, collection time, data type and data volume. Specifically, first, the user submits the demand in the form of data to the telematics Group Smart Sense platform, and the sensing vehicle submits the information to the platform by submitting the information to satisfy the demand. Second, the platform assigns the data collection task to the sensing vehicles in the sensing vehicle network through the data center, and uses the sensing vehicles to collect the required urban data. Finally, the data center sends the collected urban data to the data users who need the data after processing it through data trading, thus exchanging it for economic benefits. Thus, the telematics group wise sensing system model, which is in a pivotal position in the whole exchange process, improves economic benefits on one hand and rewards energy costs on the other. Fig. 1 shows a typical telematics group wise sensing system model.

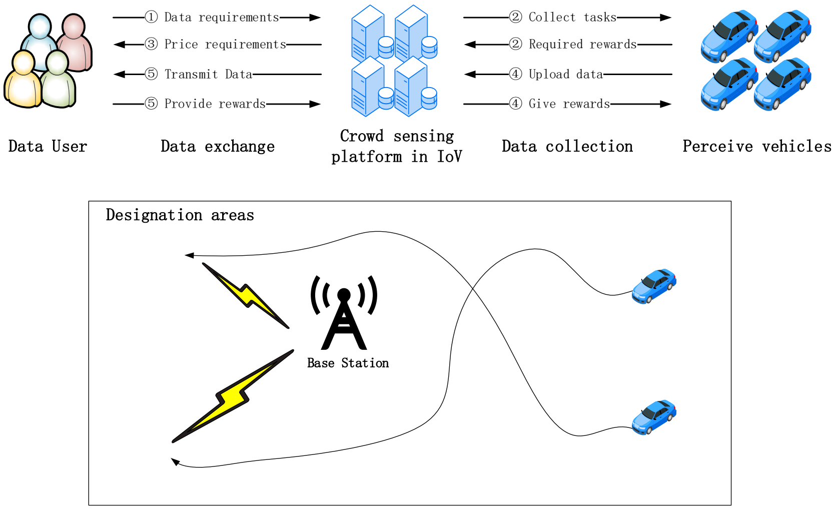

Fig. 1. Group intelligence perception system model of typical Internet of vehicles

2.1 Data User

There are N data users who need to purchase urban data of specified areas in a cycle, such as air quality data, urban noise data, water health index etc. In order to simplify the problem, this paper only considers the collection and transaction of one kind of city data. The amount of data required by the nth data user is y_n, and the unit price is p_n. The accuracy of data analysis increases with the increase of data volume, but the marginal gain decreases [13, 15-19]. The higher the accuracy of data analysis, the greater the economic value to data users [3]. Therefore, the economic value obtained by data users from data transactions is $\theta_n \log(y_n+1)$, where θ_n is the ability of data users to convert data analysis into economic benefits. The transaction cost of data users is $p_n y_n$. Therefore, the utility function of data users is:

$$U_n^u = \theta_n \log(y_n+1) - p_n y_n \tag{1}$$

At the same time, the value of data decreases with the passage of time [10]. For example, in the traffic guidance service, the latest traffic data is more valuable than the past traffic data. Data users need to obtain the required data in time T_n in data transaction.

2.2 Perception Vehicle

M perceptual vehicles pass through the designated urban area in a cycle. The driving track of the m-th vehicle is $L_m = \{(x_m, y_m)\}$, where (x_m, y_m) is the BDS position of the vehicle. Assuming that the vehicle travels at a constant speed v_m, the time of the vehicle travels in the specified area is $t_m^1 = |L_m| / v_m$, Where $|L_m|$ is the total length of the travel track. When the sensing vehicle is driving in the specified area, the sensing frequency f_m of the sensor can be selected for data sensing. During the driving time, the total amount of data collected by the perceived vehicle is $f_m t_m^1$, the energy consumption cost is $c_s f_m t_m^1$, and c_s is the energy consumption cost of the collected unit data. After the sensing vehicle completes the sensing data, it needs to upload the data to the base station through wireless transmission. Assuming that the distance between the sensing vehicle and the base station when the sensing data is completed is d_m, the upload rate of the sensing vehicle is:

$$r_m = B\log_2\left(1+\frac{P_0 h_m (d_m)^{-r}}{w_0}\right) \tag{2}$$

Where B is the leased communication bandwidth between the vehicle and the base station, and P_0 is the transmission power. it is assumed that the leased bandwidth and transmission power of all vehicles are the same, h_m is the channel gain, and w_0 is the power of white noise. The duration of perceived vehicle rental bandwidth is the time spent transmitting perceived data, it is $t_m^2 = \left(f_m t_m^1\right)/r_m$. The communication cost is $c_t t_m^2$, and c_t is the price of renting spectrum bandwidth.

Assuming that the reward given by the platform to all vehicles for completing the acquisition task is R, the reward obtained by each perceived vehicle is directly proportional to the amount of data collected by itself. For similar reward allocation methods have been seen in literature [14, 15]. The utility function of the perceived vehicle is the reward obtained minus the cost of collection and upload, i.e

$$U_m^v = \frac{f_m t_m^1}{\sum_{m\in M} f_m t_m^1} R - c_s f_m t_m^1 - \frac{c_t f_m t_m^1}{r_m} \tag{3}$$

The total time for the vehicle to complete the acquisition task cannot exceed the time delay limited by the data user, i.e. $t_m^1 + t_m^2 \le \min\{T_1, T_2, \cdots, T_N\}$, so there is:

$$f_m \le f_m^{\max} = r_m\left(\frac{\min\{T_n\}}{t_m^1} - 1\right) \tag{4}$$

2.3 Internet of Vehicles Group Intelligence Perception Platform

The group intelligence perception platform of the Internet of vehicles has three functions: giving rewards to the perceived vehicles to complete the data acquisition task, and the reward cost R is required; To process the data uploaded by the perception vehicle cost $c\sum_{m\in M} f_m t_m^1$, and c is the energy consumption cost per unit of data processed by the platform; Deal the processed data to data users to obtain economic benefits $p_n y_n$. Therefore, the utility function of the Internet of vehicles group intelligence perception platform is:

$$U_0 = \sum_{n\in N} p_n y_n - R - c\sum_{m\in M} f_m t_m^1 \tag{5}$$

3 Data Acquisition and Transaction

In the intelligent perception platform of the Internet of vehicles, data acquisition and data transaction are the most important parts. How to determine the optimal transaction price and the optimal task reward is a problem to be solved.

3.1 Three-layer Stackelberg Game

In the problems of data acquisition and data transaction, the group intelligence perception platform of the Internet of vehicles needs to determine the optimal transaction price and task reward respectively. On the one hand, the platform minimizes the reward cost to the perceived vehicle, and the perceived vehicle needs to compete for the reward by collecting the amount of data when completing the acquisition task. On the other hand, the platform maximizes the economic benefits in data transactions, but the platform needs to consider the reward cost and processing cost, so it is impossible to collect the data required by all data users without an upper limit.

This paper uses three-tier Stackelberg game to solve the problems of data collection and data transaction. Stackelberg game is a typical non cooperative game model [15], with master and slave participants. There is a competitive relationship between the slave participants, and the master participants and the slave participants are also antagonistic. It is assumed that both the master participant and the slave participant are selfish and rational, and pursue their own utility maximization. The master participants make decisions first, and all slave participants will choose their own decisions according to the decisions of the master participants and other slave participants to maximize their utility. When all slave participants choose the best response, the slave participants reach Nash equilibrium (NE). When the main participants choose the optimal decision to maximize their utility, the game reaches Stackelberg Equilibrium (SE) [17-20]. At this time, no one is willing to change the decision, and all participants achieve the best utility.

3.2 Game Model

The purpose of this paper is to maximize the utility of the platform, and at the same time, the data users and perceived vehicles also achieve the optimal utility respectively. This is consistent with the Stackelberg game model [21-25]. Therefore, this paper uses Stackelberg game as a platform to design data trading and collection strategies. Among them, the platform is the main participant, and the data user group and the perception vehicle group are two subordinate participant groups. Platform strategy is the unit price provided to each data user and the overall reward of the perceived vehicle group; each data user strategy is the demand of data volume; each perceived vehicle strategy is the amount of data collected. The problem comes down to finding Stackelberg equilibrium to complete data transaction and collection, and the objective function is:

$$
\begin{aligned}
& \max_{p_n, R} U_0 \\
\text{s.t. } & \max_{y_n} U_n \\
& \max_{f_m} U_m \\
& p_n \geq 0, R \geq 0 \\
& y_n \geq 0 \\
& 0 \leq f_m \leq f_m^{\max} = r_m \left(\frac{\min\{T_n\}}{t_m^1} - 1 \right) \\
& \sum_{m \in M} f_m t_m^1 \leq \sum_{n \in N} y_n
\end{aligned}
\tag{6}
$$

The objective function is to maximize the utility of the platform. Conditions 1 and 2 guarantee the optimal utility of each data user and perception vehicle respectively. Condition 3 ensures that the price and reward provided by the platform are not negative. Condition 4 ensures that the amount of data required by the data user is not negative. Condition 5 restricts the perception vehicle to complete data collection within the time delay required by the data user. Condition 6 requires the total amount of data collected by all perception vehicles The amount of data must exceed the total amount of data required by all data users.

4 Game Analysis

4.1 Data Collection Game Equilibrium

The utility function of the perceived vehicle is derived by f_m :

$$\frac{\partial U_m^v}{\partial f_m} = \frac{R t_m^1 \sum_{j \in M \setminus \{m\}} f_j t_j^1}{\left(\sum_{m \in M} f_m t_m^1 \right)^2} - c_s t_m^1 - \frac{c_t t_m^1}{r_m} \tag{7}$$

$$\frac{\partial^2 U_m^v}{\partial {f_m}^2} = \frac{-2R\left(t_m^1\right)^2 \sum_{j \in M \setminus \{m\}} f_j t_j^1}{\left(\sum_{m \in M} f_m t_m^1 \right)^3} < 0 \tag{8}$$

Because the second derivative is negative, the utility function of the perceived vehicle is a convex function about f_m, that is, there is an optimal perceived frequency to maximize the utility of the perceived vehicle.

Theorem 1 the optimal decision of perceptual vehicle is

$$f_m^* = \begin{cases} 0, R < c_m J_m \\ \dfrac{a}{t_m^1}(1 - c_m a), c_m J_m < R \le \dfrac{c_m\left(f_m^{\max} + J_m\right)^2}{J_m} \\ f_m^{\max}, R \ge c_m \dfrac{\left(f_m^{\max} + J_m\right)^2}{J_m} \end{cases} \tag{9}$$
$$a = R\left(|M| - 1\right) / \sum_{m \in M} c_m$$
$$J_m = \sum_{j \in M \setminus \{m\}} f_j t_j^1$$
$$c_m = c_s + c_t / r_m$$

Where $|M|$ is the number of perceived vehicles.
Proof: Let the first derivative of the perceived vehicle is 0,

$$f_m^* = \sqrt{\frac{R J_m}{\left(t_m^1\right)^2 c_m}} - \frac{J_m}{t_m^1} \tag{10}$$

When $f_m^* < 0$, that is $R < C_m J_m$, Optimal strategy of vehicle perception is $f_m^* = 0$. When $f_m^* \ge f_m^{max}$, that is $R \ge c_m(f_m^{max} + J_m)^2/J_m$ Optimal strategy of vehicle perception is $f_m^* = f_m^{max}$. When $0 \le f_m^* = f_m^{max}$, obtained from equation (10):

$$J_m = \sum_{j \in M \setminus \{m\}} f_j t_j^1 = \frac{c_m}{R}\left(\sum_{m \in M} f_m t_m^1 \right)^2 \tag{11}$$

$$\left(|M|-1\right)\sum_{m\in M} f_m t_m^1 = \sum_{m\in M}\frac{c_m}{R}\left(\sum_{m\in M} f_m t_m^1\right)^2$$
$$\sum_{m\in M} f_m t_m^1 = \frac{R\left(|M|-1\right)}{\sum_{m\in M} c_m} \tag{12}$$

Substituting formula (12) into obtained from equation (11):

$$f_m^{\ *} = \frac{R\left(|M|-1\right)}{t_m^1\sum_{m\in M} c_m}\left(1-c_m\frac{R\left(|M|-1\right)}{\sum_{m\in M} c_m}\right) \tag{13}$$

Obviously, the optimal decision of perceived vehicles is related to the reward given by the platform and the driving path and cost of all perceived vehicles participating in the task. According to reference [26-28], when all perceptual vehicles choose the optimal decision, Nash equilibrium is reached between perceptual vehicles to obtain their optimal utility. No matter how much reward R the platform gives, the perceived vehicle can achieve balance and collect the corresponding amount of data. Due to the perception of the amount of data collected by the vehicle, as long as it meets the data needs of data users, giving more rewards will only increase the cost of the platform. Therefore, the optimal incentive cost of the platform is

$$\sum_{m\in M} f_m t_m^1 = \frac{R\left(|M|-1\right)}{\sum_{m\in M} c_m} = \sum_{n\in N} y_n$$
$$R^* = \frac{\sum_{m\in M} c_m \sum_{n\in N} y_n}{|M|-1} \tag{14}$$

Substituting the utility function of the platform yields equation (15):

$$U_0 = \sum_{n\in N} p_n y_n - \frac{\sum_{m\in M} c_m}{|M|-1}\sum_{n\in N} y_n - c\sum_{n\in N} y_n \tag{15}$$

4.2 Data Transaction Game Equilibrium

The utility function of the data user is derived by y_n :

$$\frac{\partial U_n^u}{\partial y_n} = \frac{\theta_n}{y_n+1} - P_n \tag{16}$$

$$\frac{\partial^2 U_n^u}{\partial y_n^{\ 2}} = \frac{-\theta_n}{(\mathrm{y}_n+1)^2} < 0 \tag{17}$$

Because the second derivative is negative, the utility function of data users is a convex function about y_n , so there is an optimal data demand to maximize the utility of data users. When the first derivative is zero, the optimal data demand is $y_n^* = \theta_n / P_{n-1}$, which is substituted into the platform utility function formula (15). When the platform adopts the uniform price strategy, all data users are uniformly priced P, the result of Equation (18) is obtained:

$$U_0 = \sum_{n \in N}(\theta_n - p) - \frac{\sum_{m \in M} c_m}{|M|-1} \sum_{n \in N}\left(\frac{\theta_n}{p} - 1\right) - c\sum_{n \in N}\left(\frac{\theta_n}{p} - 1\right) \quad \textbf{(18)}$$

Derive the equation (19):

$$\frac{\partial U_0}{\partial P} = -|N| + \left(\frac{\sum_{m \in M} c_m}{|M|-1} + c\right)\frac{\sum_{n \in N}\theta_n}{P^2} \quad \textbf{(19)}$$

$$\frac{\partial^2 U_k}{\partial P^2} = \left(\frac{\sum_{m \in M} c_m}{|M|-1} + c\right)\frac{-2\sum_{n \in N}\theta_n}{P^3} < 0 \quad \textbf{(20)}$$

Because the second derivative is negative and the platform utility is a convex function, there is an optimal uniform price. If the first derivative is zero, the optimal uniform price is:

$$p^* = \sqrt{\left(\frac{\sum_{m \in M} c_m}{|M|-1} + c\right)\frac{\sum_{n \in N}\theta_n}{|N|}} \quad \textbf{(21)}$$

When the platform adopts differential pricing strategy and formulates the corresponding unit price P_n for different data users, the utility function can be obtained as Equation (22):

$$U_0 = \sum_{n \in N}(\theta_n - p_n) - \frac{\sum_{m \in M} c_m}{|M|-1} \sum_{n \in N}\left(\frac{\theta_n}{p_n} - 1\right) - c\sum_{n \in N}\left(\frac{\theta_n}{p_n} - 1\right) \quad \textbf{(22)}$$

Derivative can be obtained:

$$\frac{\partial U_0}{\partial P_n} = -1 + \left(\frac{\sum_{m \in M} c_m}{|M|-1} + c\right)\frac{\theta_n}{P_n^2} \quad \textbf{(23)}$$

$$\frac{\partial^2 U_k}{\partial P_n^2} = \left(\frac{\sum_{m \in M} c_m}{|M|-1} + c\right)\frac{-2\theta_n}{P_n^3} < 0 \quad \textbf{(24)}$$

The second derivative is negative, and there is an optimal price. If the first derivative is zero, the optimal price is:

$$p_n^* = \sqrt{\left(\frac{\sum_{m \in M} c_m}{|M|-1} + c\right)\theta_n} \quad \textbf{(25)}$$

Theorem 1 there exists a unique Stackelberg equilibrium in a three-level Stackelberg game.

It is proved from formula (9) that no matter what reward is given by the platform, the perceived vehicles can always achieve equilibrium for data collection. It can be seen from formula (14) that for the demand of data users, the platform has the optimal reward R^* to enable the perceived vehicle to complete data collection. As can be seen from formula (17), the utility function of the data user is a convex function about the data demand. As long as the price required by the platform is less than θ_n , data users have the optimal data demand y_n^* to maximize the utility. That is, as long as there is the optimal price of the platform, there is Stackelberg equilibrium in the three-tier game. From formula (21) and formula (25), for both uniform pricing and differential pricing, the platform has a unique optimal price to maximize the utility. Therefore, there is a unique Stackelberg equilibrium in the three-tier Stackelberg game.

5 Experiment and Simulation

In order to verify the effectiveness of the data collection and transaction strategy of the proposed vehicle network group wise sensing platform in this paper, the simulation environment of this experiment is built based on Python 3.7. The range of the road network in VMEC is 2KM, RSUs are deployed at the edge of the road, and the distribution of vehicle users in the road network conforms to Poisson distribution. In this paper, we test the proposed data collection strategy and data transaction strategy by simulating a real dataset [29-32]. The dataset records the real-time GPS of San Francisco cabs, and through these real trajectory data, the real-life movement of cabs is restored in the simulation, so that the number of selectable cabs, cab trajectories and cab speeds in each cycle of the experiment are directly determined by the dataset data. In this paper, we conduct the simulation experiments on the group wise perception of connected cars in a randomly selected area in the map of the dataset. Based on this dataset, we can set the number of cabs in the target area, their locations and their movement rates in each cycle of the simulation experiment. The parameters set for the simulation experiment, $v'=1unit/s$, $R = 500$, $m = 0.01$, $c = 0.01$ [33-34].

5.1 Effect of Data Acquisition Strategy

In order to further validate the effect of the data collection strategy, firstly, the economic utility of the platform in terms of reward cost is verified. Assuming that the data provider perceives and collects data using selected vehicles in selected target areas in each cycle, setting the total demand data to 60, 80, and 100, respectively, the proposed data collection strategy is compared and analyzed, and the test results are shown in Fig. 2. Fig. 2 shows the effect of the platform's reward strategy on the platform utility for different data demand amounts of data users. The economic utility of the platform reaches the highest when the total data demand is 60 and 80, and reaches 1600 when the total data demand is 100. Therefore, the experimental results show that when the reward is less than the optimal reward R^*, the platform utility is zero because the amount of data collected by the sensing vehicle cannot meet the amount of data demand of the data user, resulting in the data transaction cannot be completed. The optimal utility is obtained when the platform takes the optimal decision R^*. When the reward is greater than R^*, the platform utility decreases as the reward given increases. This is due to the fact that too high a reward increases the cost of the platform. The higher the data demand of the data users, the higher the optimal cost the platform needs based on the perceived vehicles.

Second, the data collection strategy is analyzed in terms of its impact on the economic utility of the platform. It is assumed that in each cycle, data providers sense and collect data using selected buses in selected 20 target areas. Three collection strategies are selected to compare the effects, respectively, the optimal collection strategy is the strategy proposed in this paper, which is to develop the optimal reward amount for data collection. The reward amount proposed by the linear acquisition strategy is proportional to the number of perceived vehicles. The random acquisition strategy i.e., the reward amount is developed randomly under the condition that the data demand is guaranteed to be satisfied. The experimental results are shown in Fig. 3.

As can be seen from Fig. 3, among the three strategies compared, when the number of perceived vehicles is below 8, the platform economic utility value of the three strategies proposed in this paper is higher than the other two, but as the number of perceived vehicles increases, the advantage of the random acquisition strategy gradually decreases, and the platform economic utility gradually tends to be stable, and the platform economic utility value is 1675; the strategy in this paper and the linear acquisition strategy both show an increasing When the number of vehicles is 20, the platform economic utility value of this paper's strategy is 1695, and the platform economic utility value of the linear acquisition strategy is close to 1690, therefore, the platform gets higher economic utility than other strategies by using the strategy proposed in this paper. Meanwhile, the higher the number of perceived vehicles, the higher the economic utility obtained by the platform.

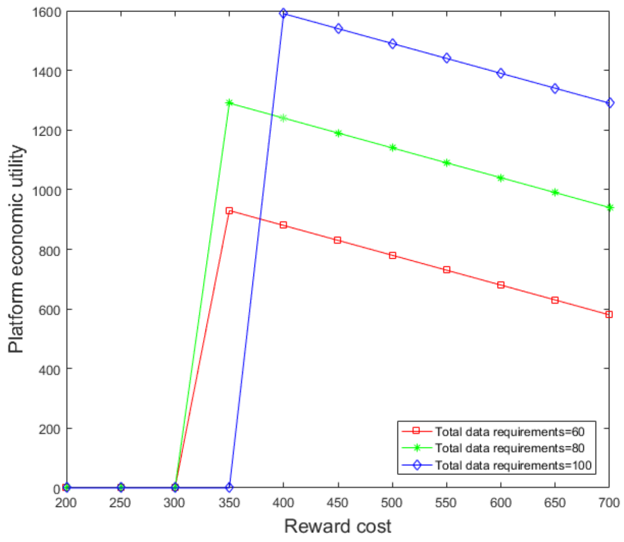

Fig. 2. Impact of incentive cost on economic utility of platform

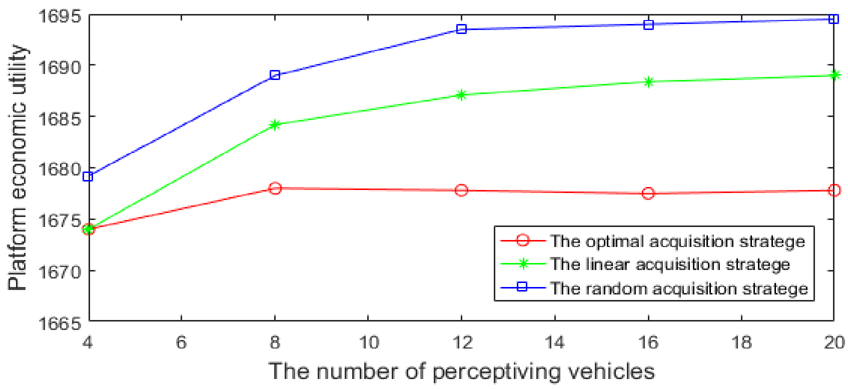

Fig. 3. Comparison of data acquisition strategies

5.2 Effect of Data Transaction Strategy

In order to verify the effectiveness of the effect of data trading strategy, this paper assumes that there are four data users involved in data trading to simulate the experimental simulation. In this paper, three methods are set for comparison, namely, Method 1 is the differential pricing strategy, i.e., the platform decides different unit prices for different data users' data needs. Method 2 is the uniform pricing strategy, i.e., the platform adopts a uniform price per unit for all data users. Method 3 is a random pricing strategy, where the platform decides the unit price randomly for each data user. The experimental results are shown in Fig. 4.

From Fig. 4, it can be seen that the economic utility value of the platform obtained by using method 1 exceeds 420, and the economic utility values of the platform obtained by methods 2 and 3 are less than 420, so the platform can obtain the optimal economic utility by using the differential pricing strategy, and the lowest economic utility is obtained by using the random pricing strategy. The differential pricing strategy is better than the uniform pricing approach due to the fact that the differential pricing strategy fully considers the different data value conversion capabilities of different data users, while the uniform pricing strategy only considers the overall data value conversion capabilities of data users. This shows that both the data collection platform and data users participating in the Stackelberg game reach the so-called Stackelberg equilibrium, thus verifying the effectiveness of the strategy proposed in this paper in data trading.

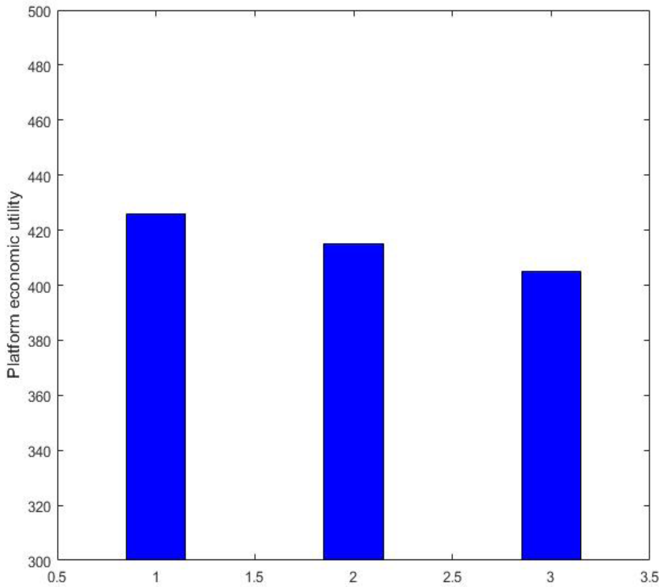

Fig. 4. Data transaction strategy comparison

Fig. 5 shows the impact of the number of data users and the average data value transformation ability on the economic utility of the platform when the differential pricing strategy is adopted. When the number of data users is more, the platform can sell more data, which can obtain higher economic utility in data transaction. The higher the average data value transformation ability of data users, the higher the economic utility of the platform. This is because data users with strong data value transformation ability have greater demand for data.

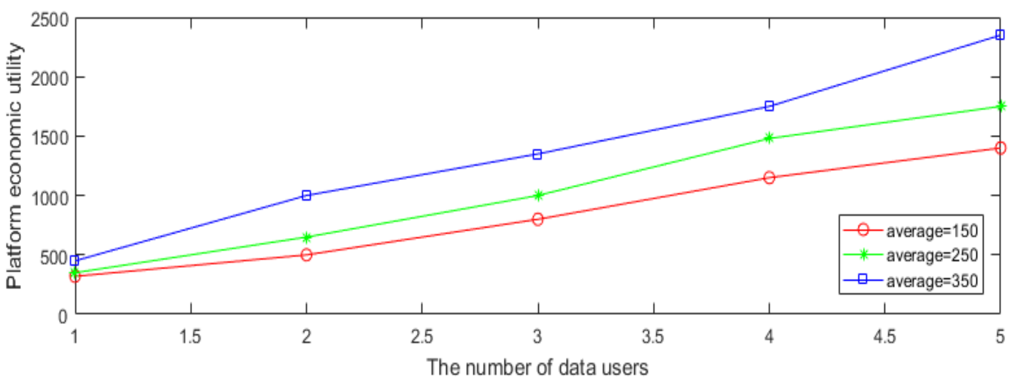

Fig. 5. Impact of the number of data users on the economic utility of the platform

6 Conclusions

This paper conducts an in-depth study on the problem of maximizing the data collection and data transaction in the group wisdom-aware platform of the telematics, and proposes a data collection and transaction strategy based on the three-layer Stackelberg game to achieve the optimal economic utility of data collection and data transaction, as described below.

(1) This paper proposes a data collection and trading strategy based on a three-layer Stackelberg game, which adopts the group wisdom-aware data trading problem between the Stackelberg game theory data platform and data users, minimizes the energy cost of data collection and maximizes the economic utility of both the platform and data users. Finally, the effectiveness and superiority of the proposed data collection and trading strategy are verified through simulation.

(2) The strategy proposed in this paper, fully considering the data trading theory of data user utility first, starts the research based on the data trading in which the data platform is dominant, however, in real life, the data platform and data user may take turns to dominate the market, therefore, the proposed strategy has important theoretical value for the research of data trading model of multi-source fusion.

(3) Although the strategy proposed in this paper maximizes the economic utility, in data collection and data trading, the platform decides the optimal transaction price according to the data user's data value transformation ability, and these require precise and efficient group wise perception task assignment to perception vehicles, and how to further improve the effectiveness of the strategy in the real environment is a problem that we study in order to further research.

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