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Edge-MapReduce-Based Intelligent Information-Centric IoV: Cognitive Route Planning

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ABSTRACT With the rapid development of automatic vehicles (AVs), vehicles have become important intelligent objects in Smart City. Vehicles bring huge amounts of data for Intelligent Transportation System (ITS), and at the same time, they also put forward new application requirements. However, it is difficult to obtain and analyze massive data and provide accurate application services for AVs. In today's society of traffic explosion, how to plan the route of vehicles has become a hot issue. In order to solve this problem, we introduced content-data-friendly information-center networking (ICN) architecture into the Internet of Vehicles (IoV), and achieved efficient route planning for AVs through the Big Data acquisition and analysis architecture in ICN. We use the analytical capabilities of the network to achieve active cognitive access to traffic data. At the same time, we use game theory to achieve the incentive mechanism for task distribution and information sharing. Finally, the simulation results show that the method is effective.

INDEX TERMS IC-IoV, Edge-MapReduce, route planning, evolutionary game.

I. INTRODUCTION

With the rapid growth of large-scale network sensors, computing and communication technologies, and cloud infrastructure, the realization of smart cities is possible in the future [1]. In the smart city scenario [2], the vehicle, a smart object with its own processor, computing and communication capabilities, will become an indispensable smart device for human life in the future due to its rapid growth and high mobility [3]. At the same time, with the rapid development of automation technology and artificial intelligence technology, autonomous vehicles(AVs) have gradually become a major component of the future intelligent transportation system(ITS) [4].

The emergence of AVs has had a huge impact on traditional modes of transportation. With the popularity of autonomous driving technology, people do not need to drive in person. The driving system becomes more precise, and further reduces the time cost of travel [5]. This may make AVs an important part of the public transportation system in the future. However, as the time cost of a single trip decreases and the ease of travel increases, the number of people traveling will increase greatly. How to realize the rational mobility of the AVs, the assignment of public transportation tasks and the route planning in the ITS has become an important issue.

Vehicles, as mobile smart objects in smart cities, have data collection, energy storage, computing and communication functions that provide massive amounts of data for intelligent transportation systems, often referred to as the Big Data [3]. In order to achieve efficient autonomous vehicle routing, this requires efficient collection and analysis of data in the Internet of Vehicles (IoV). However, due to the rapid expansion of the city scale, the number of cars in the city has risen sharply [6]. According to the Shanghai Transportation Industry Development Report, the number of registered motor vehicles in Shanghai was 3.905 million, an increase of 8.5% over the previous year. Faced with such a large amount of data, the Big Data [7] analysis architecture in traditional networks is difficult to meet the data analysis needs in today's IoV.

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As a new network architecture, Information-Centric Networking (ICN) has changed the focus of traditional network, not focusing on the location of data storage, but on specific data content, which is the real concern of today's users and applications [8]. Unlike traditional networks, which can only request data according to known IP addresses, users in ICN directly request data according to data names. This characteristic makes ICN friendly to the network with large-scale data request behavior. Therefore, ICN is an ideal choice for today's content explosion network [9]. So in this paper, we focus on the Big Data analysis in Information-Centric IoV (IC-IoV).

Since the traditional network is concerned with the communication process of the communicating endpoints [10], the big data analysis in the traditional network needs to collect and store the data before further data analysis can be performed [11]. The introduction of a naming mechanism in ICN has changed this approach. The data names in the ICN can reflect content data to a certain extent. That is to say, we can directly manipulate the content data according to the filtering of the data name, which makes the direct big data operation of the routing forwarding layer possible.

Edge computing [12] has emerged as an effective way to mitigate long latency problems and improve current network architectures [13], which has attracted increasing attention [14]. In edge computing, edge servers are deployed at the edge of the network to perform calculations near the data source. This brings two benefits [15]:1) For downstream data, the edge server acts as a cloud service provider, bringing computing resources closer to the end user, making the latency of service requests very low. 2) Regarding upstream data, it helps to improve network transmission on the core network. Using edge computing, we can change the mode of centralized big data computing in traditional networks to achieve the overall big data analysis of intelligent networks [16].

In order to enable AVs to provide efficient transportation services [17], it is also important to analyze user needs and timely assignment of traffic tasks while using intelligent network big data analysis to obtain optimal routes. As the intelligent nodes in the IC-IoV, the AVs can take the initiative to seek the user's traffic tasks. How to motivate vehicles to carry out active task requests and information sharing is very important in the process of traffic task release.

The contributions of this paper are summarized as follows:

- We proposed an edge-based MapReduce big data analysis architecture in IC-IoV to collect vehicle information and traffic conditions of ITS and process the data to obtain the optimal driving path of the vehicle.
- We proposed a task publishing method based on game theory for edge nodes, and proposed an incentive mechanism among vehicle nodes. This approach will motivate the vehicle to make mission requests and encourage vehicles to share data. Finally, we carried out an experimental simulation of this method.

The rest of this paper is organized as follows. Section II discusses the related works. Section III discusses architectural principles of the system. Section IV describes the Cognitive Route Planning System using Edge-MapReduce architecture. Section V and VI introduce the game models of task publishing and information sharing. We evaluate the performance of our proposed strategy in Section VII. Eventually, we draw some conclusions in Section VIII. Besides, we propose the direction of work that can be studied in the future.

II. RELATED WORK

The rapid development of ITS mainly depends on the significant improvement of the Internet of Things(IoT) [18] technology. At present, many studies have introduced ICN network architecture into IoT. In the challenging environment of the IoT [19], ICN opens up new opportunities for new applications in this context with its unique routing and content-based security due to the existence of a large number of heterogeneous and potentially constrained network devices and unique and heavy traffic patterns [20]. The future global scale IoT system will focus on service-oriented data sharing and processing. ICN identifies services as a kind of information, which naturally adapts to the Internet of Things communication. Chen et al.'s work [21] has discussed that ICN architecture can meet the communication requirements of the Internet of Things. Sicari et al.'s research [22] proposed an extensible framework to implement lightweight authentication and hierarchical routing in IoT, thus achieving security protection for the large-scale Internet of Things applications. At the same time, there are also studies to improve the mmWave wireless system to meet the application requirements of IC-IoT [23]. It can be seen that IC-IoT has become one of the important choices for future network development.

IoV can be seen as a convergence of the mobile Internet and the traditional Internet of Things [3]. As a huge interactive network, IoV technology refers to the use of vehicle to vehicle (V2V) [24], vehicle to roadside unit(V2R) [25], vehicle to infrastructure(V2I) [26], vehicle to home (V2H) [27] and vehicle-to-grid(V2G) [28], [29]. Deploying IoV in smart cities can achieve information sharing and large data collection of vehicles, roads, infrastructure, buildings and their surrounding environment [3]. Data Decision Network (NDN), an implementation of ICN, provides great convenience for V2V data exchange in Vehicle Ad Hoc Network (VANET) [30]–[33]. But the ICN based data exchange from vehicle to the core network is less studied.

Route planning has always been an important issue in the field of unmanned driving. The emergence of AVs will revolutionize the transportation industry in the near future. It is a challenge to introduce AV smoothly and safely into the road network, especially for roads sharing vehicles with different levels of autonomy [34]. Zhang et al.'s work [35] has proposed a route planning method based on vehicle and driving environment to save driving time and reduce fuel consumption. Lam et al.'s [36] focused on the parking and charging of electric vehicles, and how to guide the self-driving vehicles to appropriate parking facilities to support V2G services. It can be seen that many current studies focus on route selection for serving driverless vehicles, while few studies focus on route selection based on the characteristics of ICN data exchange.

III. PROPOSAL OF SYSTEM ARCHITECTURE

In this section, we present a cognitive-based route planning system architecture in IC-IoV, as shown in Fig1. First, we introduce the principle of edge-based big data analysis architecture and task allocation system. Based on these principles, we propose this system architecture. After that, we outline the overall system structure. We further introduce the two subsystems: 1) Edge-MapReduce Architecture; 2) Task distribution and information sharing mechanism.

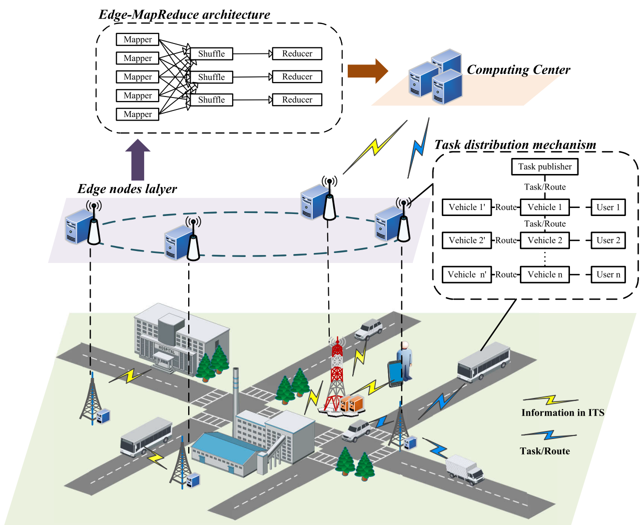

FIGURE 1. Route planning in IC-IoV.

A. ARCHITECTURAL PRINCIPLE

1) BIG DATA PROCESSING IN ICN

Unlike TCP/IP networks, ICN uses a data name-based content request method. Big data analysis in traditional networks requires data to be collected and stored before further data analysis can be performed. The introduction of a naming mechanism in ICN has changed this approach. After obtaining the required data name, we do not need to determine the storage location of the data, and can directly send interest packets to the network for the data request. Introducing the big data analytics architecture to ICN, the entire network logically becomes a distributed database that stores massive amounts of data. The data names in the ICN can reflect the content data to a certain extent, so we can perform preliminary classification and screening of the content data according to the data name. Therefore, direct manipulation of data in the routing process can be achieved. Since the data is directly filtered by the data name, this will greatly reduce the transmission of the data packets in the network, and achieve more efficient transmission efficiency. At the same time, big data analysis has become more timely and convenient.

2) COGNITIVE-BASED DATA ACQUISITION

As a kind of important intelligent mobile nodes in smart cities, vehicles are also an important part of the IoV. The Road Side Units(RSUs) and mobile vehicles in the IoV have provided powerful help for information collection in ITS and even the smart city. Faced with a large vehicle group and a complex road environment, it is necessary to accurately and timely analyze the acquired information, which places great demands on the cloud computing center and network transmission. Therefore, we use the edge computing resources to actively request the required data from the nodes in the IoV based on the historical data analysis results, and provide the obtained traffic information data to the computing center in the recommended form. This will greatly reduce the computational load of the computing center and the transmission tasks of the core network.

3) TRAFFIC TASKS AND ROUTES

In the future traffic system, AVs will become an important part. In order to better realize the dispatch and service of driverless vehicles, we believe that the vehicle routing should be bound to the tasks issued by ITS, rather than to the fixed vehicle individuals and specific driving routes. By analyzing the traffic demand put forward by users, we bind and publish the traffic task and route, and then determine the vehicle to undertake the task.

4) GAME IN TASK/ROUTE PUBLISHING AND INFORMATION SHARING

In order to meet the traffic needs of users, we need to find vehicles in the network that can undertake the task. At the same time, vehicles that are unable to carry out traffic tasks but still want traffic information need to make requests to vehicles that undertake traffic tasks. Vehicles may refuse mission requests or traffic information sharing due to their selfish nature, so there is a game problem in this scenario. Analyzing this problem, our aim is to satisfy the traffic demand of users, encourage information sharing among vehicles, and guarantee the rights and interests of vehicles and users.

B. EDGE-MAPREDUCE ARCHITECTURE

In this section, we propose an edge-MapReduce architecture to implement big data analysis at the network layer.

A traditional big data center is a collection of computing resources in a network, or the computing resources in a network are unified through the center of a logical collection. The routing method of ICN gives the initiative of nodes in the network. The computing node no longer needs to perform calculations through the data distribution of the computing center. It only needs to understand the tasks it undertakes and actively request the calculation data to complete the computing task. Therefore, we introduce the MapReduce architecture into IC-IoV to implement edge-based big data analysis mechanisms.

As shown in the figure, the nodes with computing resources in the ICN are divided into Mapper nodes and Reducer nodes to undertake computing tasks at different stages of big data processing. After the central node assigns the task to the mapper and the reducer, the mapper and the reducer respectively call different algorithms according to different task requirements, and send interest packets to the network to obtain the calculated data. ICN is logically a database for big data centers.

The Edge-MapReduce architecture requires simultaneous analysis of user needs and traffic information:

- Obtain traffic information. According to the historical traffic information, the edge node sends interest packets to the nodes, such as the vehicle and the roadside unit in the IoV, requesting real-time traffic data.
- Analyze traffic information data. The MapReduce architecture analyzes traffic data in real time and updates the corresponding traffic parameters.
- Get user requirements. The edge node obtains the user's needs in the area in real time and determines the corresponding traffic task.
- Analyze user interests. Extract user demand characteristics, classify users, and confirm the traffic resources required by users.
- Comprehensive user interest and traffic conditions form the corresponding driving route. According to user requirements and real-time traffic conditions, the big data center calculates and generates tasks and corresponding driving routes.

C. TASK DISTRIBUTION MECHANISM OF EDGE NODES

In this section, we propose a task distribution mechanism based on game theory.

After analyzing the user's needs and traffic conditions to obtain the traffic tasks and the corresponding driving routes, we need to find the vehicles to undertake these traffic tasks, and there is a game problem between the vehicles.

First of all, when the task is assigned, we encourage the vehicle to request the task by auction. The task is bound to the relevant route, and after the vehicle confirms the task, the vehicle will get the corresponding driving route.

When the vehicle is unable to complete the traffic task but still needs to obtain the driving route and traffic information, we encourage the vehicle to share the traffic information and the driving route through the game information sharing incentive mechanism based on the game theory.

IV. COGNITIVE ROUTE PLANNING SYSTEM

In the future of social life, autonomous driving is already the way we want to travel. Faced with the gradual popularization of unmanned vehicles, public transportation can be completed by multiple unmanned vehicles, gradually replacing the traditional modes of travel such as buses. Therefore, it is very important to analyze the user's needs efficiently and arrange the traffic tasks and driving routes of the self-driving vehicles. In this section, we introduce a cognitive IC planning framework based on intelligent IC-IoV.

According to network big data analysis, we can get traffic information and user needs in real time. Through the network layer big data analysis architecture, real-time data analysis in the network transmission process can be realized. According to the data analysis result and the user demand analysis result, the intelligent ICN network actively analyzes the required data, and actively acquires the required data by sending the interest package. It will also mean that according to the needs of users and the traffic conditions that the network has acquired, and actively seeking additional required data, through the intelligent analysis of the network, the corresponding traffic tasks, and corresponding traffic routes are obtained.

The traffic conditions acquired by the roadside unit, the real-time road information acquired by the smart vehicle, the distribution of the charging piles and the corresponding energy information, and additional information provided by other intelligent terminals. IC-IoV actively recognizes this information, and further analyzes the obtained data through analytical methods such as artificial intelligence and machine learning to obtain corresponding traffic information. This information forms the topological weight map of the traffic network in the big data analysis architecture.

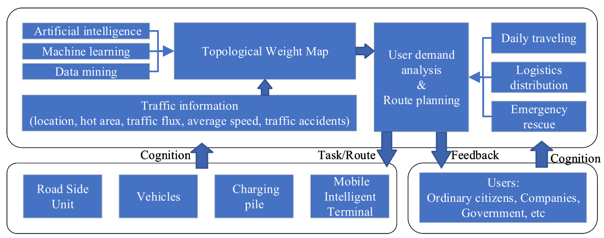

FIGURE 2. Edge-MapReduce based cognitive route planning.

As shown in Fig2, the intelligent IC-IoV based on big data analysis actively seeks real-time data in ITS through historical analysis results. After active knowledge of the data, the big data architecture analyzes the acquired data by calling different analysis algorithms to obtain real-time traffic topology weights. The network simultaneously recognizes the user's needs, and according to the user's needs, the big data architecture requests the traffic weight topology and calculates the corresponding driving route. Finally, the IC-IoV assigns the calculated corresponding tasks and routes to the smart vehicles in the ITS.

At the same time, the user's needs and related information are also obtained by IC-IoV in real time. By analyzing the user information, according to the topology weight map of the transportation network, the big data architecture performs data analysis and calculation, thereby obtaining the traffic task and the corresponding driving route. Finally, these tasks and routes are delivered to the vehicles in the intelligent transportation system.

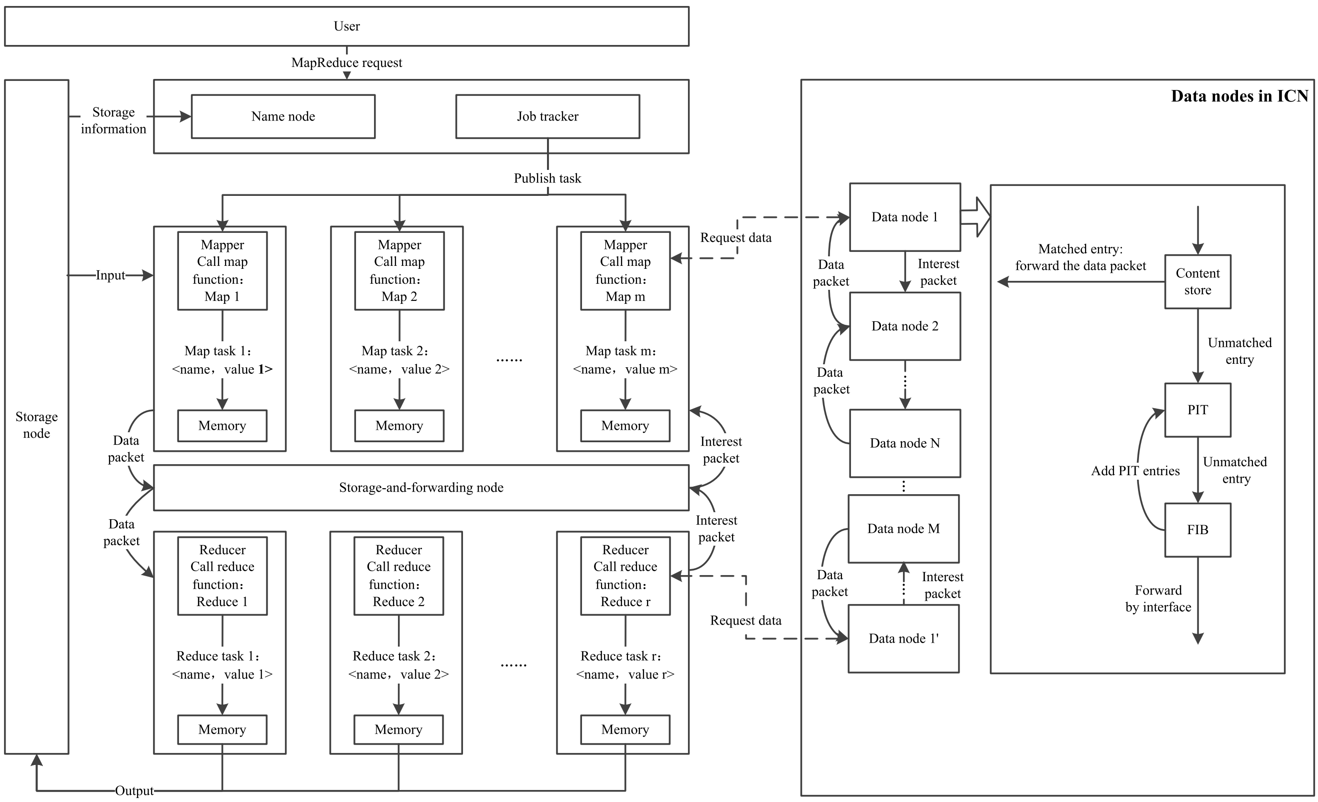

FIGURE 3. MapReduce-ICN architecture specific network [37].

The specific network diagram of the Edge-MapReduce architecture is shown in Fig3. Edge-MapReduce specific steps are as follows [37]:

Step 1. According to the analysis requirement of the whole network, network users send requests to the master and set up tasks in job tracker.

Step 2. Job tracker sends tasks to mappers according to the type of requirement.

Step 3. Mapper sends interest packets to adjacent ICN nodes according to the specific information of tasks. Through the forwarding of interest packets in ICN, mapper obtains the corresponding returned data. Mapper calls different functions and algorithms to analyze and calculate the data.

Step 4. When Mappers complete their tasks, they inform job tracker and storage-and-forwarding node of the completed message. After receiving the message of task completion, job tracker sends the corresponding task to Reducers.

Step 5. Reducer sends interest packet according to the specific information of the task, and the storage-and-forwarding node forwards them to the corresponding mapper to request data. After receiving the corresponding data packet, reducer calls different functions or algorithms to analyze and calculate the data.

Step 6. After Reducers complete the task, they notify the master and job tracker of the completed message and provide the calculated results to users. So far we have completed the entire MapReduce task.

Big data analysis is divided into three processes: content filtering, content acquisition, and route generation.

For content filtering and content acquisition, Mapper sends the interest packet to the edge node for recommendation requesting, then Mapper classifies the traffic data through the recommended information. And the Reducer determines the specific data types needed according to the classification result. After getting the required data, Mapper requests the data and performs data analysis.

The big data analysis mechanism in IC-IoV is done through ICN's interest\data routing, as shown in Fig4. The edge node requests traffic information and user requirements in real time. The Mapper node requests the traffic information at the edge and analyzes it to update the traffic topology weight value in real time. The Reducer node obtains the traffic weight through the mapper, and calculates the traffic task and the driving route according to the user requirements of the edge.

V. MODEL AND PROBLEM FORMULATION OF TASK PUBLISHING

In this game, the task publisher acts as the buyer and the vehicle acts as the seller. The reward of the task publisher to the vehicle that completed the mission (such as the evaluation

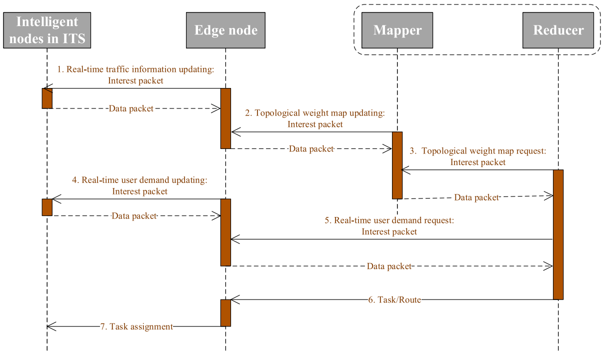

FIGURE 4. Route planning sequence diagram.

of the vehicle) is paid as a result of the completion of the transaction.

A. AUCTION TRADING RULES

In the course of the transaction, the buyer and the seller must abide by the following rules:

a) First the vehicle and the task publisher evaluate the same task. Set the vehicle's estimate to J_v, and the task publisher's estimate to J_{task}.
b) The vehicles participating in the auction give quotes for this task. The quote given by the vehicle is p_v, and the lowest quote is p_s.
c) If $p_s \leq J_{task}$, the vehicle giving the lowest quote is concluded with the mission publisher; otherwise, the transaction is not made.

B. THE VALUATION FUNCTION

When there are more idle vehicles, there will be more vehicles seeking missions, so the valuation is lower. When the task has not found the vehicle to be taken for a long time, it is necessary to raise the price to realize the task assignment as soon as possible. Therefore, we set the task publisher's valuation function to:

$$J_{task} = R_t + \alpha T + \beta(1 - \frac{N_f}{N_s}) \tag{1}$$

$\alpha > 0$ and $\beta > 0$. T is the time the task has waited, N_f is the number of idle vehicles, N_s is the total number of vehicles, R_t is the lowest reward.

Every time the vehicle is auctioned for a mission, it must hope to receive no less than the previous reward. When the vehicle has more energy remaining, the vehicle will be more active in seeking tasks, thereby reducing the quotation. Therefore, we set the valuation function to:

$$J_v = R_v - \mu k_v + \nu(1 - \frac{N_f}{N_s}) \tag{2}$$

$\mu > 0$ and $\nu > 0$. k_v is the percentage of remaining energy of the vehicle.

C. GAME ANALYSIS

According to the trading rules: If the winning vehicle evaluates the mission as J_v, the quote is p_s, and $p_s \leq J_{task}$, the task publisher selects this vehicle to complete the task.We abstract the transaction process of N ($N > 1$) vehicles for the same task as a first-class sealed price auction model, and encourage vehicles to voluntarily participate in task requests to maximize their own interests, thereby improving task publishing efficiency.

The two sides of the task release transaction dynamic game are: the task publisher (buyer) and the vehicle for the tasks application (the$N$ sellers participating in the auction). We give the following assumptions:

a) Information is incomplete. The buyer only knows the its estimate J_{task} of this task, and the seller i only knows the its own estimate $J_{vi}$of the task;
b) J_v of any seller is distributed over the same interval $[\rho_1, \rho_2]$ and is the same distribution. Wherein, the distribution function F and its density function f are common knowledge;
c) The seller node i gives the quotation p_{vi} according to its own estimate J_{vi} and the game strategy. Moreover, the higher the estimate J_v, the higher the quotation p_v. For any two different seller nodes i and j, if $J_{vi} > J_{vj}$, then $p_{vi} > p_{vj}$.

For the buyer, the game strategy is to select the vehicle with the lowest quote and lower than its estimate J_{task}.

For seller i, if it is quoted the lowest in the auction and lower than the buyer's estimate, it is selected as the winning vehicle, and the expected external income obtained is $p_{vi} - J_{vi}$, otherwise the return is 0.

The vehicles participating in the auction use the same game strategy:

$$p_{vi} = Q(J_{vi}) \tag{3}$$

For any two seller nodes i and j participating in the game, the probability that the quotation of node i is lower than the quotation of node j is:

$$P\{Q(J_{vi}) \leq Q(J_{vj})\} = 1 - F(Q^{-1}(p_{vi})) \tag{4}$$

Then the expected value of the additional income of the vehicle i is:

$$\prod_{j \neq i} [1 - F(Q^{-1}(p_{vi}))](p_{vi} - J_{vi}) \tag{5}$$

Maximize revenue and get:

$$\max \prod_{j \neq i} [1 - F(Q^{-1}(p_{vi}))](p_{vi} - J_{vi}) = \max\, [1 - F(Q^{-1}(p_{vi}))]^{N-1}(p_{vi} - J_{vi}) \tag{6}$$

To get the maximum value, make the first derivative equal to 0. Get the equation:

$$p_s = p_{vi} = J_{vi} + \frac{\int_{\rho_1}^{\rho_2} [1 - F(x)]^{N-1} dx}{[1 - F(J_{vi})]^{N-1}} \tag{7}$$

Assume $\rho_1 = 0, \rho_2 = 1$, we can get the equation as follows:

$$p_s = p_{vi} = J_{vi} + \frac{1 - J_{vi}}{N} \tag{8}$$

Users who participate in the auction will be quoted higher than their estimate. And the more nodes involved, the closer the transaction price is to its estimate.

VI. MODEL AND PROBLEM FORMULATION OF INFORMATION SHARING

In IoV, vehicles are connected to each other, so they have the function of a network communication node in addition to their own driving functions. However, the resources contained in the vehicle are limited. Each node will try to save resources and show selfishness. In this chapter, we propose two incentives to encourage route sharing, and node caching in IC-IoV.

A. GAME MODEL

In IC-IoV, when a vehicle requests a traffic task, it transmits a corresponding interest package. The interest package is forwarded between vehicles and eventually reaches the task publisher in the edge node. After receiving the interest packet, the edge node requests the content packet according to the interest packet, and returns the corresponding data packet. These packets are simultaneously returned to the requested vehicle by the vehicle's forwarding. Vehicles that do not apply for a traffic mission need to seek route sharing with other vehicles when they have the same form of route demand.

Caching after receiving data and responding actively when requested by other nodes will greatly improve the transmission efficiency of the network, but at the same time bring certain storage resources and energy loss to the vehicle. Some vehicles themselves may save energy and save storage space, and adopt a negative attitude towards cache content data and response route sharing requirements, thereby affecting the efficiency of task/route publishing in the Internet of Vehicles.

In game theory, participants are allowed to make corresponding countermeasures by considering the countermeasures of other participants under certain constraints to obtain the maximum benefit. There is a conflict of interest between the participants, and the use of game theory to design the incentive mechanism can better solve the conflict of use between participants. Therefore, we propose an evolutionary dynamic game model released by the edge task to suppress the selfish behavior of the vehicle, and encourage the vehicle to share the driving route and cache the data packets passing through the node.

B. INCENTIVE MECHANISM FOR VEHICLE NODE CACHING

In IC-IoV, large-scale distributed caching of data can greatly reduce the request response time of vehicle nodes, but it also occupies the storage space of the vehicle. We use the evolutionary game model to motivate vehicles to actively cache data and improve network forwarding efficiency.

Vehicles with additional storage resources in the IoV constitute the group A. These nodes can choose to cache route data or reject cache route data while forwarding data. The strategy set of the group A is $G_A = \{a_1, a_2\}$. a_1 represents the node caching the data packet and forwarding the data packet at the same time; a_2 indicates that the node does not cache the data packet and directly forwards the data packet.

We set the reward for getting a fast data request to be R_r, the reward for data caching is R_c, the resource for cached data is E, and $R_c > E$.

According to the evolutionary game rules, we can get the participant's payoff matrix as Table 1.

TABLE 1. The payoff matrix of game theory.

strategy	a_1	a_2
a_1	$(R_r + R_c - E, R_r + R_c - E)$	$(R_c - E, R_r)$
a_2	$(R_r, R_c - E)$	$(0, 0)$

$x(t)$ is the probability of selecting a_1, then the probability of selecting a_1 is $1 - x(t)$.

The reward of selecting a_1 is shown as follows:

$$\begin{aligned} U_{a_1}(t) &= x(t) * (R_r + R_c - E) + [1 - x(t)] * (R_c - E) \\ &= x(t)R_r + R_c - E \end{aligned} \tag{9}$$

The reward of selecting a_2 is shown as follows:

$$\begin{aligned} U_{a_2}(t) &= x(t) * R_r + [1 - x(t)] * 0 \\ &= x(t)R_r \end{aligned} \tag{10}$$

So the reward of group A is shown as follows:

$$\begin{aligned} U_A(t) &= x(t)U_{a_1}(t) + [1 - x(t)]U_{a_2}(t) \\ &= x(t)(R_r + R_c - E) \end{aligned} \tag{11}$$

In each evolutionary process, each vehicle node evaluates its own revenue with other vehicle nodes and chooses a higher-yield strategy the next time.

The replication dynamic equation is shown as follows:

$$\begin{aligned} \frac{dx(t)}{dt} &= x(t)[U_{a_1}(t) - U_A(t)] \\ &= x(t) * [1 - x(t)] * (R_c - E) \end{aligned} \tag{12}$$

Theorem 1: In the evolution process, the ESS exists and there is only one evolutionarily stable strategy.

Proof: Let $\frac{dx(t)}{dt} = 0$, we get:

$$\frac{dx(t)}{dt} = x(t) * [1 - x(t)] * (R_c - E) \tag{13}$$

$R_c - e > 0$, so there are two stable points $x_1(t) = 0$ and $x_2(t) = 1$.

Let $F(x) = \frac{dx(t)}{dt}$, x^* is the ESS, so

$$\begin{cases} F(x^*) = 0 \\ F'(x^*) < 0 \end{cases} \tag{14}$$

According to (12),

$$\begin{cases} x^* * (1 - x^*) * (R_c - E) = 0 \\ (1 - 2x^*) * (R_c - E) < 0 \end{cases} \tag{15}$$

So $x^* = x_2(t) = 1$, x^* is the only ESS.

As explained above, after time evolution, all participating vehicles will choose strategy a_1.

C. INCENTIVE MECHANISM FOR ROUTE SHARING

When the vehicle cannot take on the traffic task but still needs to obtain the driving route and traffic information, the vehicle needs to seek route sharing with other vehicles. We use the evolutionary game model to motivate vehicles to share routes and improve the efficiency of request response.

Group B is composed of vehicles that travel routes and traffic information needs. These nodes may choose to accept traffic data sharing or reject traffic data sharing. The strategy set of group B is $G_B = \{b_1, b_2\}$. b_1 indicates that the vehicle accepts traffic sharing data, and b_2 indicates that it refuses to accept traffic sharing data.

Group C is composed of vehicles with driving routes and traffic information. These nodes can choose to share traffic data or refuse to share traffic data. The strategy set of group V is $G_C = \{c_1, c_2\}$. c_1 indicates sharing traffic data and c_2 indicates refusing to share traffic data.

Assume that the node accepts the traffic data as R_b, and the energy consumed is E_b; the revenue of each node sharing traffic data is R_s, and the energy consumed is E_s.

In group B, the probability of selecting b_1 for vehicle nodes is $y(t)$, where $y \in [0, 1]$;In group C, the probability of selecting c_1 for vehicle nodes is $z(t)$, where $z \in [0, 1]$.

According to the evolutionary game rules, we can get the participant's payoff matrix as Table 2.

TABLE 2. The payoff matrix of game theory.

strategy	b_1	b_2
c_1	$(R_s - E_s, R_b - E_b)$	$(0, 0)$
c_2	$(0, -E_b)$	$(0, 0)$

In group B, if the node chooses b_1, the reward is as follows:

$$\begin{aligned} U_{b_1} &= z(t)(R_b - E_b) - [1 - z(t)]E_b \\ &= z(t)R_b - E_b \end{aligned} \tag{16}$$

If the node chooses b_2, the reward is 0. So the reward of group B is shown as follows:

$$U_B = y(t)[z(t)R_b - E_b] \tag{17}$$

In group C, if the node chooses c_1, the reward is as follows:

$$U_{c_1} = y(t)(R_s - E_s) \tag{18}$$

If the node chooses c_2, the reward is 0.So the reward of group C is shown as follows:

$$U_C = y(t)z(t)(R_s - E_s) \tag{19}$$

The replication dynamic equation is shown as follows:

$$\begin{cases} \frac{dy}{dt} = y(t)[1 - y(t)][z(t)R_b - E_b] \\ \frac{dz}{dt} = y(t)z(t)[1 - z(t)](R_s - E_s) \end{cases} \tag{20}$$

After time evolution, all participating vehicles will choose strategy b_1 and c_1.

VII. EXPERIMENTAL

In this section, we simulate and analyze the incentive mechanism of caching and sharing information in IoV based on evolutionary games.

A. CACHING INCENTIVE MECHANISM SIMULATION

In group A, we assume that the probability of initial selection strategy a_1 is 10%, that is, the vehicle has 10% probability of choosing to cache and then forward. The net benefit of the vehicle's cache is $R_c - E = 3$. Over time, the percentage of vehicles that choose to cache data and reject cached data is shown in Fig 5.

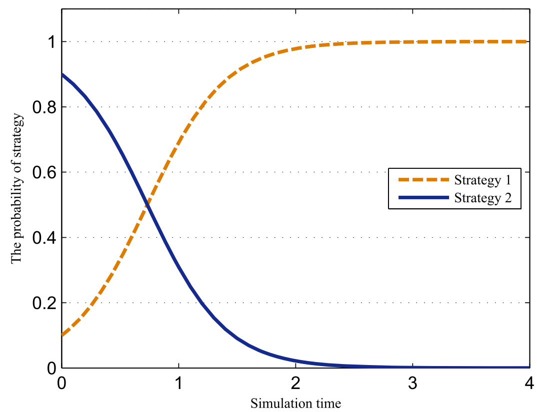

FIGURE 5. Simulation results of the method's effectiveness.

It can be seen that when only 10% of the vehicles initially select data buffering, all vehicles will eventually choose strategy a_1 over time, and the proportion of vehicles selecting strategy a_2 will be reduced from 90% to 0. This shows that the vehicle that initially refused to cache the data will eventually choose to cache the data after a period of the evolutionary game.

When the probability of initial selection strategy a_1 is 10%, 20%, 30%, 40% and 50%, the percentage change of vehicles selecting strategies a_1 and a_2 is as shown in Fig 6.

It can be seen that at different initial probabilities, all vehicles will eventually choose strategy a_1. Moreover, as the initial probability increases, the proportion of vehicles selecting strategy a_1 converges to 1 more quickly. This shows that the higher the initial proportion of the selection strategy a_1, the less time required for all vehicles to select the strategy a_1.

The probability of initial selection strategy a_1 is set to 10%, the energy consumed by the cache is $E = 1$, and R_c is set to 3, 4 and 5. The trend of the vehicle proportion change of the

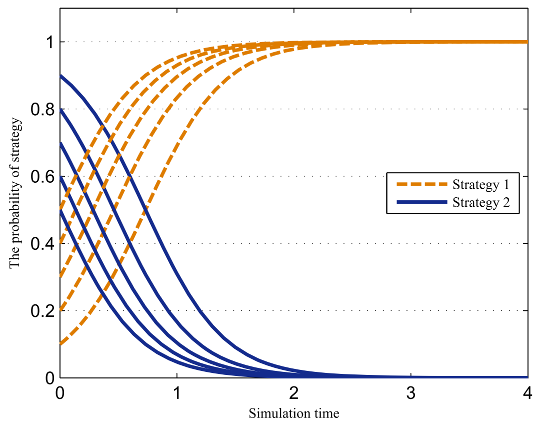

FIGURE 6. Influence of initial strategy selection probability on the evolution process.

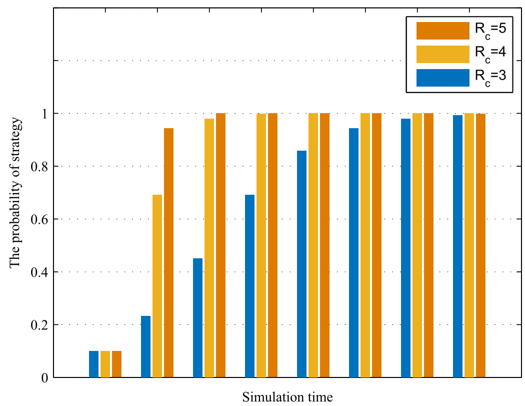

FIGURE 7. Influence of rewards on strategy choices.

selection strategy a_1 is as shown in Fig 7. It can be seen that the more the revenue is selected, the easier it is to stabilize the vehicle to 100.

Through the above simulation, we can know that by setting appropriate parameters, the purpose of stimulating the vehicle for content caching can be achieved.

B. INFORMATION SHARING INCENTIVE MECHANISM SIMULATION

In group B, we assume that the proportion of vehicles that choose strategy b_1 is 10%. At the same time in group C, we assume that the proportion of vehicles that choose strategy c_1 is also 10%. As time passes, the percentage of vehicles that choose strategies b_1 and c_1 is as shown in Fig 8.

It can be seen that, with the remaining variables fixed, that is, the incentive measures are certain, the probability of selecting the strategies b_1 and c_1 among the two groups is increasing with time and is stable at 1.

When the vehicle requests the acquisition of the traffic information R_b is 6, 10 and 14, and the remaining variables are unchanged. As time passes, the percentage of vehicles that choose strategies b_1 and c_1 is as shown in Fig 9 and Fig 10.

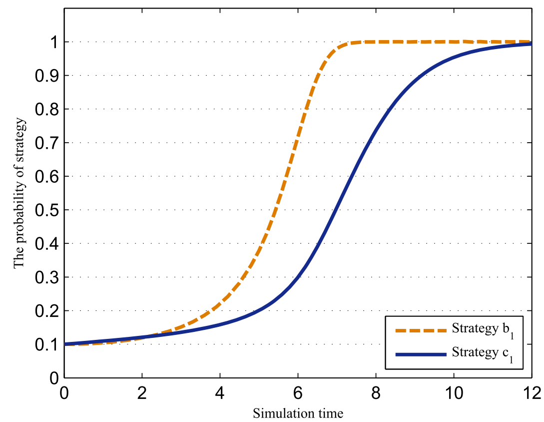

FIGURE 8. Simulation results of the methodâĂŹs effectiveness.

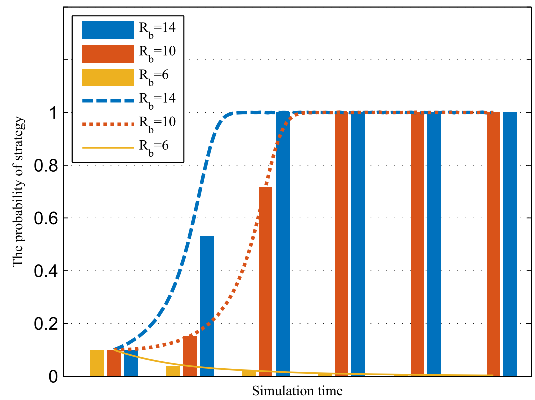

FIGURE 9. Effect of R_b on strategy choices in Group B.

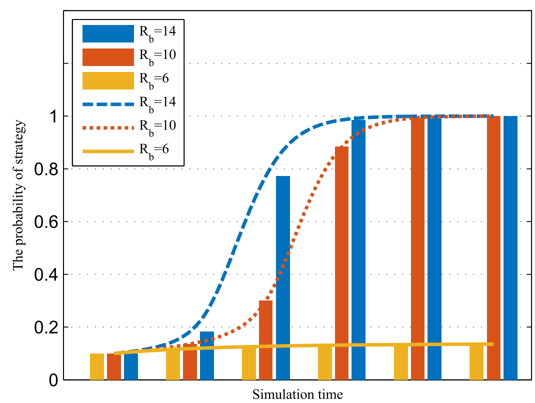

FIGURE 10. Effect of R_b on strategy choices in Group C.

It can be seen that when the income is small, the probability of selecting b_1 in group B is gradually reduced, and the selection strategy c_1 in group C is not basically increased. When the income is large, the ratio of the selection strategies b_1 and c_1 in the two groups increases with time and stabilizes at 1.

When the revenue R_s of the vehicle for data sharing is 2, 4 and 6, the remaining variables are unchanged. As time passes, the percentage of vehicles that choose strategies

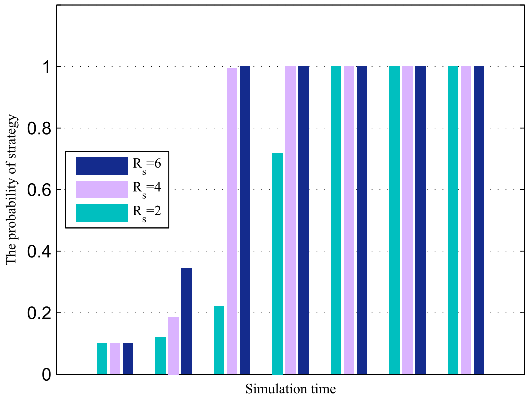

FIGURE 11. Effect of R_S on strategy choices in Group *B*.

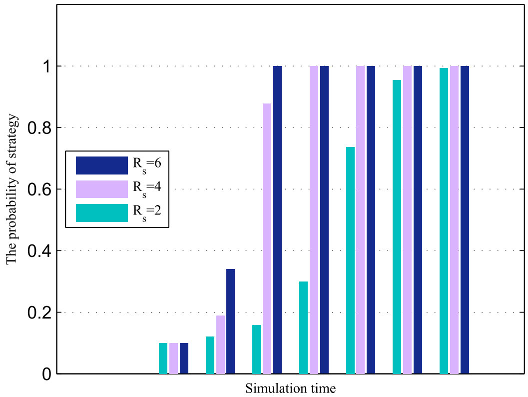

FIGURE 12. Effect of R_S on strategy choices in Group *C*.

b_1 and c_1 is as shown in Fig 11 and Fig 12. It can be seen that the more the revenue is, the easier it is to stabilize the vehicle probability of selecting b_1 and c_1 to 100%.

Through the above simulation, we can know that by setting appropriate parameters, the purpose of stimulating vehicles for information sharing can be achieved.

VIII. CONCLUSION

In this paper, we proposed an edge-MapReduce architecture to implement big data acquisition and analysis in IC-IoV to achieve efficient AVs route planning. By introducing a big data processing architecture, we realized data analysis at the network layer and realized the cognitive and active acquisition of traffic data through intelligent networks. Intelligent IC-IoV analyzed traffic data and user needs to get traffic tasks and corresponding driving routes. At the same time, using the evolutionary game model, we have realized the incentive mechanism of task allocation and information sharing. The simulation results showed that our strategy can promote information sharing in IoV and stimulate vehicles to share data. In future research, we will consider providing a wider variety of services to IoV through intelligent networks with big data analysis capabilities. In addition, considering user privacy and traffic safety, edge information protection is also our research direction in the future.

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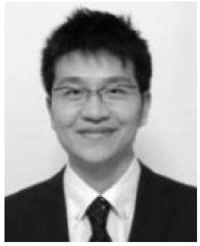

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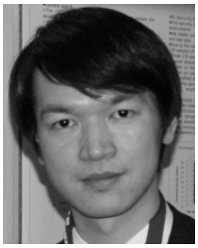

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