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ARTICLE

Adaptive Resource Allocation Algorithm for 5G Vehicular Cloud Communication

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ABSTRACT

The current resource allocation in 5G vehicular networks for mobile cloud communication faces several challenges, such as low user utilization, unbalanced resource allocation, and extended adaptive allocation time. We propose an adaptive allocation algorithm for mobile cloud communication resources in 5G vehicular networks to address these issues. This study analyzes the components of the 5G vehicular network architecture to determine the performance of different components. It is ascertained that the communication modes in 5G vehicular networks for mobile cloud communication include in-band and out-of-band modes. Furthermore, this study analyzes the single-hop and multi-hop modes in mobile cloud communication and calculates the resource transmission rate and bandwidth in different communication modes. The study also determines the scenario of one-way and two-way vehicle lane cloud communication network connectivity, calculates the probability of vehicle network connectivity under different mobile cloud communication radii, and determines the amount of cloud communication resources required by vehicles in different lane scenarios. Based on the communication status of users in 5G vehicular networks, this study calculates the bandwidth and transmission rate of the allocated channels using Shannon's formula. It determines the adaptive allocation of cloud communication resources, introduces an objective function to obtain the optimal solution after allocation, and completes the adaptive allocation process. The experimental results demonstrate that, with the application of the proposed method, the maximum utilization of user communication resources reaches approximately 99%. The balance coefficient curve approaches 1, and the allocation time remains under 2 s. This indicates that the proposed method has higher adaptive allocation efficiency.

KEYWORDS

5G vehicular networks; mobile cloud communication; resource allocation; channel capacity; network connectivity; communication radius; objective function

1 Introduction

The rapid development of the electronic information and communication industry continues to drive swift changes in the social economy and people's lifestyles. In this context, the transportation industry has also encountered new development opportunities, presenting a promising prospect for the collaborative development of an intelligent transportation system that integrates "human-vehicle-road-cloud" [1,2]. 5G vehicle network mobile cloud communication technology, a product of integrating advanced sensors, data transmission, and other functional control technologies, is applied to all vehicles to provide higher quality services for intelligent transportation systems [3]. The sharing of mobile cloud communication resources provides reliable communication resources for vehicles on the road, becoming an important support technology for people's travel [4]. However, in the vehicle networking environment, the resources required for vehicle communication, such as bandwidth and spectrum resources, are dynamically affected by environmental factors. For instance, changes in road traffic flow, changes in the speed and direction of vehicle movement, and differences in signal strength in different regions can impact the utilization of communication resources [1]. Simultaneously, a large number of vehicles communicating at the same time in the 5G vehicle cloud communication system results in an increase in network load and heightened resource competition. To ensure communication quality and avoid network congestion, efficient resource allocation, and capacity management are required. Therefore, studying the communication resource allocation method to dynamically adjust according to the real-time environment and adapt to the ever-changing communication needs is crucial for the rational use of resources.

Therefore, researchers in this field have designed many solutions for cloud communication resource allocation and have achieved significant results [5]. Zhang et al. [6] designed a Vehicle-to-everything (V2X) communication resource allocation algorithm based on fuzzy logic for 5G networks. The algorithm focuses on vehicle communication in 5G cellular networks. However, 5G vehicle networks are highly dynamic, with vehicle movement trajectories, network topologies, and communication channel conditions constantly changing. The fuzzy logic algorithm has some limitations when dealing with this dynamic nature. It is difficult to fully consider the real-time state and dynamic demand of the network, resulting in resource allocation that is not flexible or timely. Shan et al. [7] proposed a cellular device-to-device communication resource allocation algorithm with partial channel state information. In this algorithm, they suggest that in Vehicle-to-everything scenarios, cellular device-to-device communication cannot only improve system capacity and spectrum utilization but also reduce communication load and delay. Although communication between vehicles and everything can enhance system capacity and spectrum utilization, factors such as rapid vehicle movement and fluctuating channel conditions can increase communication delay. Especially in high-speed movement scenarios, it becomes challenging to transmit channel state information promptly, affecting real-time resource allocation. Le et al. [8] analyzed the advantages of the V2X communication wireless resource allocation scheme in the 5G communication system. They pointed out that intelligent transportation systems, which use the Internet and cellular technology to provide safe and autonomous services on the road, are becoming increasingly important. In a complex environment, the lack of network coverage can lead to a deterioration in communication quality or a failure to meet real-time communication needs. This affects the stability and reliability of the intelligent transportation system. Pei et al. [9] proposed a method for unmanned aerial vehicles (UAV) cooperative integrated communication resource allocation. This method uses sensors to calculate the position of the received target and controls the resource transmission power to minimize system power. However, its application in UAV cooperative communication increases the transmission power of resources, leading to signal interference and affecting communication quality and stability. Rathod et al. [10] proposed an autoencoder to achieve efficient resource allocation. This method calculates the communication data rate between cellular and device-to-device (D2D) users, obtaining the rate matrix by considering the channel gain. However, employing autoencoders for resource allocation necessitates a substantial amount of computing resources and time, particularly when calculating the communication data rate between cellular and D2D users. This complexity arises from the consideration of various factors such as complex channel gain, resulting in a high computational burden on the algorithm. Mahbub et al. [11] built a two-layer HetNet for communication transmission, which includes a small cell base station layer and a macro cell and realized the allocation of communication resources by calculating multi-access edge computing (MEC). However, the MEC calculation and communication resource allocation algorithm adopted performed well in certain situations but was not applicable or limited in other scenarios. The effect of communication resource allocation is not ideal. Ravikumar et al. [12] adopted the Ebola-optimized search algorithm to optimize the time and power of communication transmission. They adopted the integrated support vector machine method to deal with the dynamic and complex ultra-dense network environment assisted by drones to realize the allocation of communication resources. Although the Ebola-optimized search algorithm and integrated support vector machine method are adopted, they show good performance in specific data sets or scenarios, but their generalization has problems. This means that in other data sets or scenarios, the performance of the algorithm will decrease.

Based on previous research, this paper investigates an adaptive allocation algorithm for mobile cloud communication resources in 5G vehicular networks. The objective is to improve communication quality in these networks. By analyzing the components of the 5G onboard network architecture, we can determine the performance of different components. This understanding allows us to see each component's contribution to the overall network performance and identify opportunities for optimization. The goal is to achieve more efficient and reliable onboard network communication. We consider both in-band and out-of-band communication modes to improve resource utilization and meet the needs of vehicles for different types of data transmission. The transmission rate and bandwidth of resources in different communication modes were calculated, and single-hop or multi-hop mode was selected to balance network delay and transmission performance, so as to improve communication efficiency and reliability. With the introduction of the Shannon formula and objective function, we calculate the width and rate of the distribution channel based on the user's communication state, achieving adaptive distribution of mobile cloud communication resources.

2 Design of Adaptive Resource Allocation Algorithm for 5G Vehicular Cloud Communication

2.1 5G Vehicular Networks Architecture Analysis

By analyzing the architecture of 5G vehicle networking, one can gain a comprehensive understanding of the system's components, functional modules, and their interrelationships. This understanding assists in designing and planning suitable communication resource allocation schemes to meet the needs of connected vehicle applications. The 5G vehicle networking architecture provides a means for multi-level, multi-access technologies (such as cellular networks, vehicle-to-vehicle communication, etc.) to work together. By analyzing the architecture, differences in resource utilization between various levels and access technologies can be identified, and resource allocation and utilization efficiency can be optimized based on the characteristics of resource requirements in the vehicle networking scenario. The resource allocation in 5G vehicular networks for mobile cloud communication is a process based on Vehicle-to-everything. Therefore, this paper first establishes the architecture of the 5G vehicular networks as the starting point of the research, and then carries out further research on this basis. The architecture of 5G vehicular networks primarily consists of three components: the perception layer, the 5G network layer, and the application layer. The specific structure of the 5G vehicle network is shown in Fig. 1.

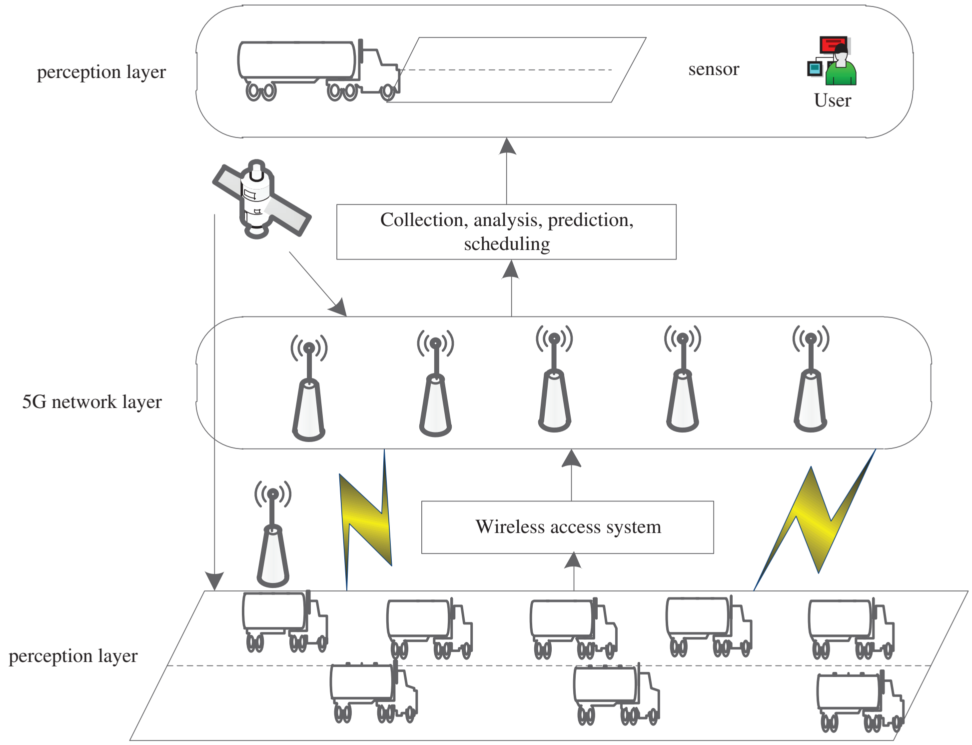


Figure 1: 5G vehicular networks architecture

As can be seen from the structure of the 5G vehicle network in Fig. 1, the sensing layer includes vehicle sensors for sensing the surrounding environment of the vehicle and other RF devices. The 5G network layer communicates through a network of network base stations, road equipment, and vehicle equipment. Application layer includes some basic equipment, through the collection of some vehicle data to judge the state of the vehicle.

In the aforementioned 5G vehicular network architecture, the general V2X adoption of new technology enhances the communication performance of 5G vehicular networks, specifically the non-orthogonal multiple access technology. This technology supports orthogonal time-domain, frequency-domain, etc. It also supports non-orthogonal resource allocation among vehicle users in V2X by increasing the complexity of vehicle receivers, a prerequisite for 5G vehicular networks' mobile cloud communication. This technology allows multiple users to share the same communication resources and differentiates V2X users in different regions through power differences. When it supports multiple users to communicate in the 5G mobile channel uplink, the capacity of its access channel is expressed as:

$$\sum_{i=1}^{n} A_i \leq e \lg \left\{ 1 + \frac{\sum_{i=1}^{n} p_i}{h_i e} \right\} \tag{1}$$

In formula (1), e represents bandwidth, p_i represents transmission power of communication signal, h_i represents Gaussian noise, and A_i represents capacity of access channel.

In the 5G Vehicle-to-everything mobile communication, if the channel has declined and the scheduled receiver has learned the current channel status, then the communication power of each V2X user is the same. The total capacity of the entire Vehicle-to-everything uplink [13–15] is expressed as:

$$C_{all} = W\left\{\lg\left(1 + \frac{\sum_{k=1}^{n} |a_k|^2 p_j}{h_i}\right)\right\} \tag{2}$$

In formula (2), p_j represents the average power of the j user communication, a_k represents the number of k independent base station antennas, and C_{all} represents the total capacity of the uplink of the 5G vehicular networks. W represents the random probability of channel fading. In the 5G vehicle network, due to the rapid speed of the vehicle and the complex, ever-changing channel environment, the channel conditions between the vehicle and the base station will constantly change. This includes effects from multi-path and shadow fading. Therefore, the channel state exhibits a certain level of randomness. Even when the receiving end has acquired knowledge of the current channel state, the channel capacity from the vehicle to the base station remains subject to random fluctuations.

In the 5G vehicular networks architecture analysis, this study examines the components of the 5G vehicular networks architecture to assess the performance of different component modules. The study also evaluates the performance of non-orthogonal multiple access technology to understand its role in the channel capacity change in 5G vehicular networks communication. This lays the foundation for the resource allocation of the subsequent 5G vehicular networks mobile cloud communication.

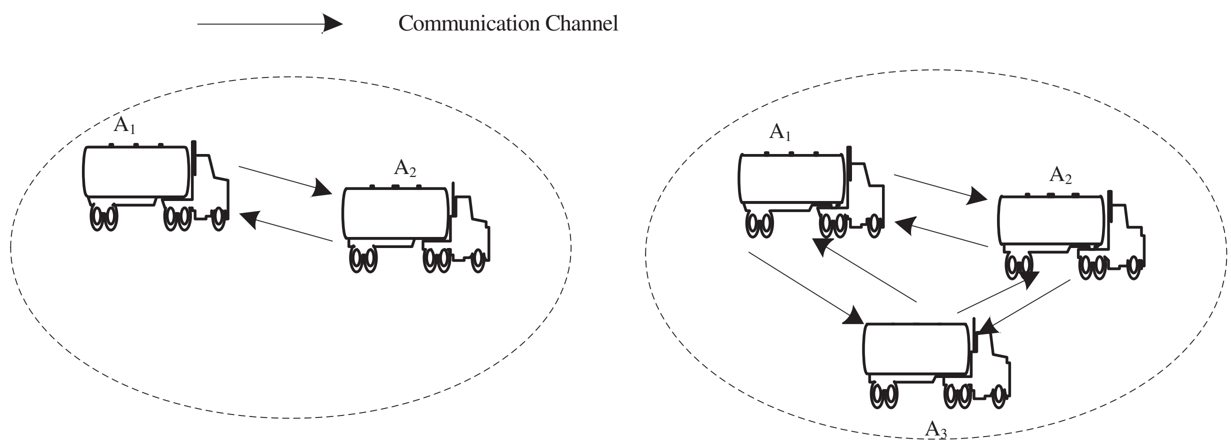
2.2 Analysis of 5G Vehicular Networks Mobile Cloud Communication Mode

In vehicle networks, there is typically a need for two-way communication, including vehicle networking applications and vehicle-to-vehicle communication. Given the need for bidirectional communication, upstream channel resources form the basis, making it essential to allocate resources reasonably. The uplink channel resource is a crucial channel for multiple vehicles to access the base station simultaneously. Through the allocation of upstream channel resources, we can satisfy the requirements of inter-vehicle communication, realize effective resource sharing and utilization, and improve overall communication efficiency. 5G vehicle-connected mobile cloud communication describes how the mobile cloud mode in vehicle-connected communication collaborates with the communication between the vehicle end and the cloud. The 5G vehicle-connected mobile cloud communication model offers large-scale connectivity and communication capabilities between vehicles and the cloud. By analyzing the 5G vehicle networking mobile cloud communication mode, we can better understand the communication needs and interaction modes between vehicles and the cloud. This understanding then allows us to design scalable and flexible resource allocation strategies to adapt to different scales and changes in vehicle networking deployment. Based on the analyzed 5G vehicular networks architecture, we further analyze the 5G vehicular networks mobile cloud communication mode to clarify the characteristics of adaptive resource allocation under this communication mode. Mobile cloud communication in 5G vehicular networks primarily involves communication utilizing the cloud network structure comprising vehicle cloud, roadside cloud, and central cloud. This cloud network structure boasts high resource allocation efficiency in communication. The onboard cloud in this structure is a local cloud established based on cooperative vehicles, which contributes its own idle computing, storage resources, and virtual resource pool through vehicles in the Vehicle-to-everything network for use by other vehicle scheduling. A roadside cloud is a cluster of adjacent roadside units connected by a dedicated server and roadside protocols, enabling cloud communication through the vehicle end. The central cloud is accessed through communication resources or information service infrastructure centers, platforms, and other networks such as cellular networks [16].

The 5G vehicular networks mobile cloud communication mode exchanges information between vehicles and the outside world through the access of different end cloud modes. This primarily includes communication modes between vehicles, vehicles and infrastructure, vehicles and the Internet, and vehicles and pedestrians. Currently, a more convenient and faster communication mode between vehicles and the Internet offers more user-friendly services for end users. Among them, the communication modes in 5G vehicular networks mobile cloud communication include in-band and out-of-band modes [17].

In-band mode allows devices to communicate with authorization, primarily including Underlay and Overlay communication. In Underlay communication, users share the same channel resources with other users, which can have a certain negative impact on the communication link [16]. Out-of-band mode allows cellular users and other users to engage in spectrum communication without authorization, generally leading to uncontrolled spectrum resource authorization and affecting normal communication. Of these two communication modes, in-band communication is more conducive to improving the quality of cloud communication.

In the 5G vehicular networks mobile cloud communication mode, communication between vehicles includes single hop mode and multi hop mode [17], as shown in Fig. 2.



(A) Single hop mode communication (B) Multi hop mode communication

Figure 2: (A) Single hop mode communication. (B) Multi hop mode communication. Schematic diagram of single hop and multi hop modes for mobile cloud communication between vehicles

As shown in Fig. 2A, the single hop mode of mobile cloud communication between vehicles involves direct interaction between two vehicles, and the communication resource signal can be represented as:

$$S_1 = \sqrt{H_{A_1}}\, Ex_1 + n_1 \quad (3)$$

$$S_2 = \sqrt{H_{A_2}}\, Ex_2 + n_2 \quad (4)$$

In the above formula, x_i represents the signal resources transmitted between vehicle communication vehicles, H_{A_i} represents the transmission power, n_i represents Additive white Gaussian noise, and E represents the channel gain.

When the transmission power of vehicles in mobile cloud communication between vehicles is the same, the maximum rate at which resource data can be transmitted is:

$$R_A = \frac{w}{2} \lg \left(1 + \frac{p_A \left| H \right|^2}{w v_0} \right) \tag{5}$$

In formula (5), R_A represents the maximum achievable communication resource transmission rate, w represents the communication resource bandwidth, H represents the inter vehicle channel gain, and v_0 represents the power spectral density value.

As shown in Fig. 2B, during mobile cloud communication in multi hop mode between vehicles, the source vehicle node signal is forwarded multiple times to reach the destination vehicle. When vehicle A_1 passes through the communication resource forwarding between vehicles A_3, the communication resource reaches A_2, and the channel gain between A_1 and A_3 is G_i, then the communication resource signal obtained by A_3 is:

$$S_3 = \sqrt{H_{A_1}} G_i x_1 + \sqrt{H_{A_2}} G_j x_2 + n_3 \tag{6}$$

In formula (6), n_3 represents additional Gaussian noise.

Due to the fact that the mobile cloud communication resource signal received by A_3 is a mixed signal, it is necessary to reconstruct and analyze the communication resource signal of A_3 to obtain:

$$\begin{aligned} & x_3 = \alpha S_3 \\ & \alpha = \sqrt{1/\left(H_{A_1}\right) \left|G_i\right|^2 + \left(H_{A_2}\right) \left|G_j\right|^2 + w v_0} \end{aligned} \tag{7}$$

In formula (7), α represents the power ratio factor, and x_3 represents the simplified result of communication resource signal reconstruction.

In the analysis of 5G Vehicle-to-everything mobile cloud communication mode, we analyze the communication mode in 5G Vehicle-to-everything mobile cloud communication, including in-band and out-of-band modes. We determine the authorization quality of cloud communication resources, analyze the single hop and multi hop modes in mobile cloud communication, and calculate the resource transmission rate and bandwidth in different communication modes. This completes the analysis of 5G Vehicle-to-everything mobile cloud communication mode, and determines the information source for the subsequent adaptive allocation of mobile cloud communication resources.

2.3 Algorithm Design

Vehicle connectivity impacts the quality and stability of the communication link between the vehicle and the cloud. Optimal connectivity is essential to ensure a reliable communication environment and facilitate smooth interaction between the vehicle and the cloud. Therefore, when addressing mobile cloud communication resource allocation in vehicle networking, it is necessary to consider the assurance of vehicle networking connectivity to enhance communication reliability. According to the 5G vehicular networks mobile cloud communication mode, the source of resource data in mobile cloud communication is determined. To achieve adaptive allocation of 5G vehicular networks mobile cloud communication resources, it is crucial to further determine the vehicle network connectivity in mobile cloud communication. In other words, analyze the network accessibility of communication vehicles in 5G vehicular networks, and conduct adaptive allocation of mobile cloud communication resources based on its connectivity [18–20]. This entails assessing the amount of cloud communication resources needed by different vehicles according to their communication accessibility, with the aim of achieving adaptive allocation of cloud communication resources.

In this analysis of vehicle network connectivity in 5G vehicular networks mobile cloud communication, two mobile cloud communication base stations are deployed along the road. Each vehicle is assigned a fixed mobile cloud communication radius. Compared with the radius of mobile cloud communication base stations [21,22], the constraints met are:

$$r_1 < r_2 < 2r_1 < R \tag{8}$$

In formula (8), r represents different vehicle communication radii, and R represents the radius of cloud communication base stations.

Considering the safe operation of vehicles, the safety distance for general vehicles is set to L, and the proportion of vehicles driving on the road is:

$$Z = \sum \frac{Lr_i}{R} \tag{9}$$

In formula (9), Z represents the proportion of vehicle road trips in 5G Vehicle-to-everything.

According to the set radius of 5G Vehicle-to-everything mobile cloud communication base station and vehicle communication radius, we determine the different cloud communication resources required for vehicle mobile cloud communication in different lanes. In road traffic, vehicles can be divided into one-way traffic and two-way traffic. There are also significant differences in the connectivity of mobile communication in different driving lanes [23–25]. Therefore, we analyze the connectivity of mobile communication based on the driving in different lanes.

The scenario of one-way lane mobile cloud communication network connectivity is shown in Fig. 3.

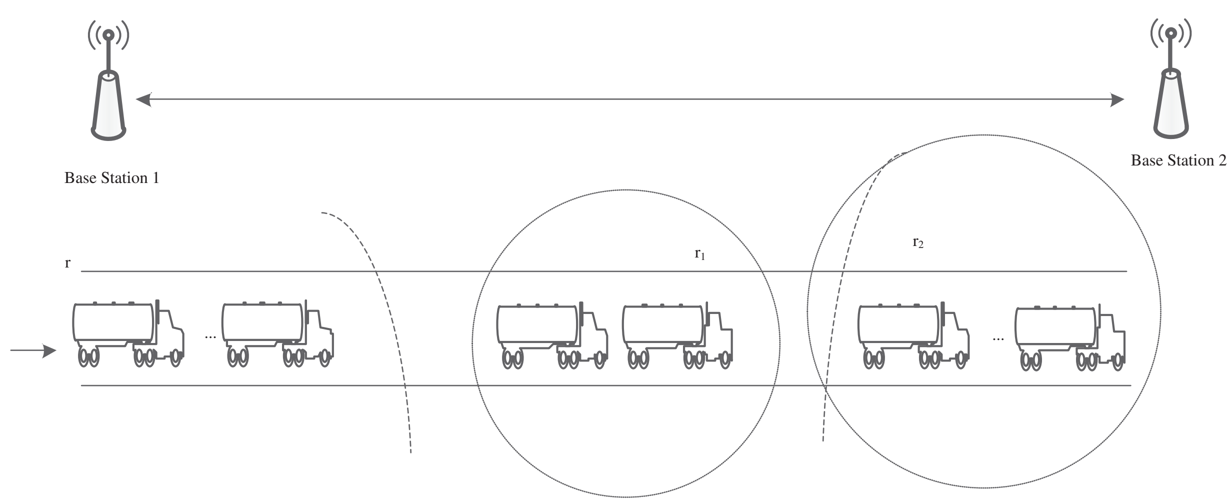


Figure 3: Schematic diagram of one-way lane mobile cloud communication network connectivity scenario

In 5G Vehicle-to-everything mobile cloud communication, when a vehicle is traveling in a one-way lane and its communication radius is $0 < r \leq 2R$, the network connectivity probability of the vehicle traveling in a one-way lane is:

$$G_c = 1 \tag{10}$$

In formula (10), G_c represents the network connectivity probability of vehicles traveling in a one-way lane.

In 5G Vehicle-to-everything mobile cloud communication, when a vehicle is traveling in a one-way lane and its communication radius is $2R < r \leq 2R + r_2$, the vehicle in the lane can be connected to any mobile cloud communication base station. At this time, the network connectivity probability of the vehicle traveling in a one-way lane is:

$$\beta_1 = \frac{(r - 2R)}{r} (1 - \rho) \rho_i \tag{11}$$

In formula (11), when the communication radius of β_1 is $2R < r \leq 2R + r_2$, it represents the network connectivity probability of vehicles traveling in a one-way lane, ρ represents the initial one-way lane density, and ρ_i represents the total density of vehicles in a one-way lane.

When a vehicle is driving in a one-way lane with a communication radius of $r \leq 2R + r_1$, the vehicle on that lane can connect to any mobile cloud communication base station. At this time, the network connectivity probability of the vehicle driving in a one-way lane is:

$$\beta_2 = \frac{(r - 2R)}{r} (1 - \rho)\ \rho \tag{12}$$

The scenario of bidirectional lane mobile cloud communication network connectivity is shown in Fig. 4.

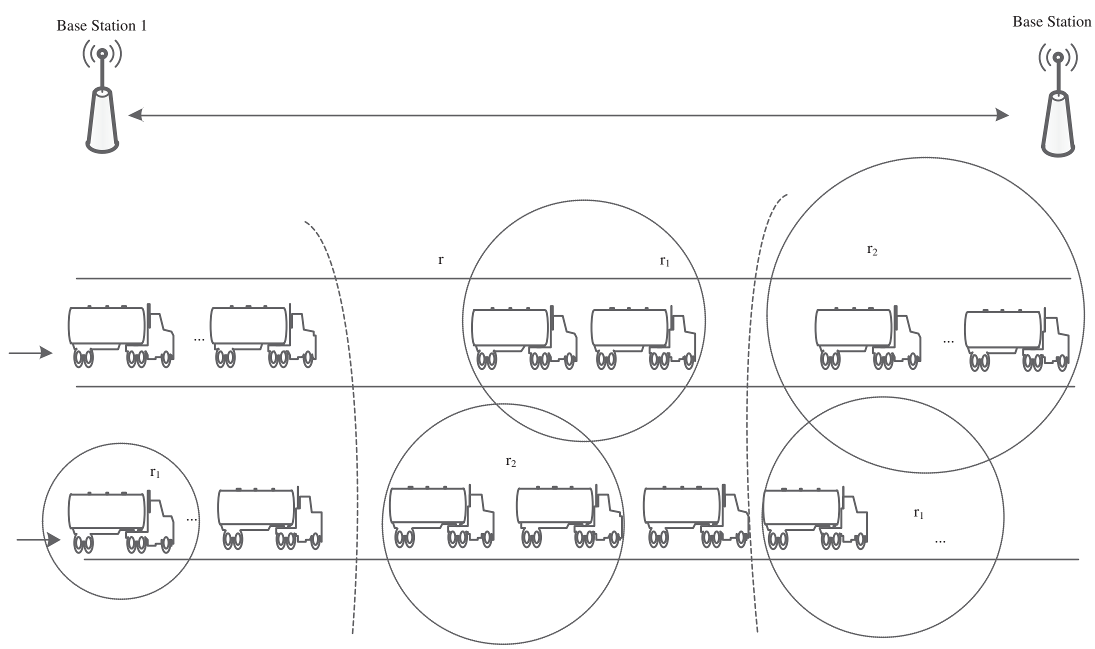


Figure 4: Schematic diagram of bidirectional lane mobile cloud communication network connectivity scenario

When using bidirectional lane mobile cloud communication, when $0 < r \leq 2R$, the connectivity probability of the mobile cloud communication network on the bidirectional lane is equal to that of the unidirectional lane network, both of which are 1.

When the communication radius of the vehicles on the lane is $2R < r \leq 2R + r_2$, the vehicles on the lane can connect to any mobile cloud communication base station, and the probability analysis method for network connectivity on the bidirectional lane is the same [26].

When the communication radius is $r \leq 2R + r_1$, vehicles on that lane can have mobile cloud communication connections with vehicles on adjacent lanes. At this time, the network connectivity probability of vehicles traveling in the bidirectional lane is:

$$\beta_{1-3} = \frac{(r - 2R)}{r} (1 - p) \tag{13}$$

After determining the network connectivity probability of vehicles traveling in the bidirectional lane, it is found that the total amount of vehicle communication in the bidirectional lane is higher than that in the unidirectional lane. This requires a larger amount of mobile cloud communication resource allocation. Therefore, the total probability of vehicle mobile cloud communication network connectivity for further bidirectional lane travel [27] is obtained as follows:

$$\beta_{all} = \sum \frac{2R}{r} p (1 - p) \tag{14}$$

In formula (14), β_{all} represents the total probability of the mobile cloud communication network connection of vehicles traveling in both lanes, and p represents the frequency of vehicles traveling in the lane.

In the vehicle network connectivity analysis of 5G Vehicle-to-everything mobile cloud communication, we determine the one-way lane and two-way lane cloud communication network connectivity scenarios. We calculate the vehicle network connectivity probability under different mobile cloud communication radii, and determine the cloud communication resources required by vehicles under different lane scenarios.

2.3.1 Algorithm Implementation

Based on the vehicle network connectivity in the 5G Vehicle-to-everything mobile cloud communication determined above, a 5G Vehicle-to-everything mobile cloud communication resource adaptive allocation algorithm is designed. The adaptive allocation method can be dynamically adjusted according to the real-time communication environment and network load to adapt to different communication requirements and scenarios. In vehicle communication, due to the changes in vehicle moving speed, communication distance, channel quality, and other factors, the traditional static resource allocation method may not be able to effectively deal with, but the adaptive allocation method can flexibly adjust the resource allocation strategy to meet the actual communication needs. In this adaptive allocation algorithm design, it is assumed that there is one base station in the 5G Vehicle-to-everything mobile cloud communication, M vehicle communication user in the Vehicle-to-everything, n vehicle to vehicle communication relays in the mobile cloud communication network, and the communication between vehicles in the mobile cloud communication includes a sending end and a receiving end. At this time, the communication user's channel in the cloud communication is accessed to the base station in the orthogonal frequency-division multiple access mode, and the 5G

Vehicle-to-everything mobile cloud communication resources are allocated by multiplexing the uplink channel.

The set of vehicle communication users in 5G Vehicle-to-everything mobile cloud communication is:

$$B = \{b_1, b_2, \ldots b_m, \ldots b_M\} \tag{15}$$

The channel set of 5G Vehicle-to-everything mobile cloud communication resources is:

$$K = \{1, \ldots k, \ldots K\} \tag{16}$$

The initial set of resources when vehicles communicate in this network is represented as:

$$D = \{d_1, \ldots, d_i, \ldots, d_n\} \tag{17}$$

The relay set is represented as:

$$F = \{f_1, \ldots f_l, \ldots f_F\} \tag{18}$$

Based on the above settings, the signal is directly transmitted to the other end through the sending end, and in relay mode, communication resource data is transmitted through decoding and forwarding. At this time, resources are adaptively allocated according to the demand for 5G Vehicle-to-everything mobile cloud communication resources.

When 5G Vehicle-to-everything users communicate separately, mobile cloud communication resources are transmitted via uplink on the user multiplexed channel [28], and the adaptive allocation formula is as follows:

$$\varphi_{b_M}^{K} = \vartheta^2 \frac{d_n \left|\eta_{b_M}^{K}\right|^2}{F^2} \upsilon \tag{19}$$

In the formula, $\varphi_{b_M}^{K}$ represents the adaptive allocation result when the user communicates alone, ϑ^2 represents the signal transmission power of the communication resource, $\left|\eta_{b_M}^{K}\right|$ represents the status of the communication base station when the resource is allocated, and υ represents the Gaussian noise power value.

In this state, when allocating mobile cloud communication resources, the width of the allocated channel is determined through the Shannon formula, and the rate of the allocated channel is expressed as:

$$V(x) = B\ \log_2\left(1 + \varphi_{bm}^{K}\right) \tag{20}$$

When 5G Vehicle-to-everything users communicate, the mobile cloud communication resources change in the user-multiplexed channel. The communication resources received by the base station are proportional to the resource demand between users. At this time, its adaptive allocation formula is expressed as:

$$\varphi_{b_M}^{K(D)} = \vartheta^2 \frac{d_n \left|\eta_{b_M}^{K}\right|^2}{\upsilon + F^2 \times d_n} \tag{21}$$

When 5G Vehicle-to-everything users communicate by relay, the communication objects share a unified communication channel, and the amount of resources sent and received by these users is almost equal. At this time, the adaptive allocation formula is expressed as:

$$\varphi_{b_M}^{K(1)} = \sum \frac{d_n \left| \eta_{b_M}^K \right|^2}{\upsilon + F^2 \times |d_n|^2} \tag{22}$$

In the mentioned three scenarios, the 5G Vehicle-to-everything mobile cloud communication resource adaptive allocation algorithm has three distinct states. However, ensuring simultaneous adaptive allocation of cloud communication resources for all communication links presents a challenge. Therefore, based on the above designed allocation algorithm, this article further optimizes it. The adaptive allocation of 5G Vehicle-to-everything mobile cloud communication resources is directly related to its communication power parameters [29,30]. Hence, this article introduces an objective function to calculate the optimal solution for allocation [31–33], achieving optimization of cloud communication resource adaptive allocation algorithms. The introduced objective function is represented as:

$$\mu(X) = \max_{\tau(X)} \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{i=1}^{N} \left(\zeta_{b_M}^{d} + \xi_{d_i k}^{d} \right) \tag{23}$$

In formula (23), $\tau(X)$ represents a linear function, d represents the proportion of multiplexing channels, and ζ_{d_i} represents the initialized resource allocation.

Calculate the optimal solution of the above objective function to optimize the adaptive allocation algorithm for cloud communication resources, and the resulting structure is represented as:

$$U[\mu(X)] = \varpi \arg \mu(X) \sum_{k=1}^{K} \zeta_{d_i} \tag{24}$$

In formula (24), $U[]$ represents the optimal solution for adaptive allocation of cloud communication resources, and ϖ represents the proportion of cloud communication resource allocation.

The specific flow of the 5G vehicle-mounted network mobile cloud communication resource adaptive allocation algorithm is illustrated in Fig. 5.

This paper comprehensively considers the in-band and out-of-band communication modes of 5G vehicle-based networks for mobile cloud communication, and analyzes the resource transmission rate and bandwidth in single-hop and multi-hop communication modes. By comparing the performance of the two communication modes, it provides a comprehensive technical analysis of mobile cloud communication. The scenarios of unidirectional and bidirectional lane cloud communication network connectivity are determined, and the probability of vehicle network connectivity under different mobile cloud communication radii is calculated, and the amount of cloud communication resources required by different vehicles is further determined. By considering the communication requirements in different scenarios, a more practical and operable resource allocation scheme is provided. The distribution channel width and rate are calculated by the Shannon formula, and the adaptive allocation of cloud communication resources is determined. Adaptive resource allocation is completed by introducing the optimal solution after the objective function is allocated. This resource allocation strategy combined with mathematical optimization methods can help the system to use communication resources more efficiently, and improve transmission efficiency and system performance.

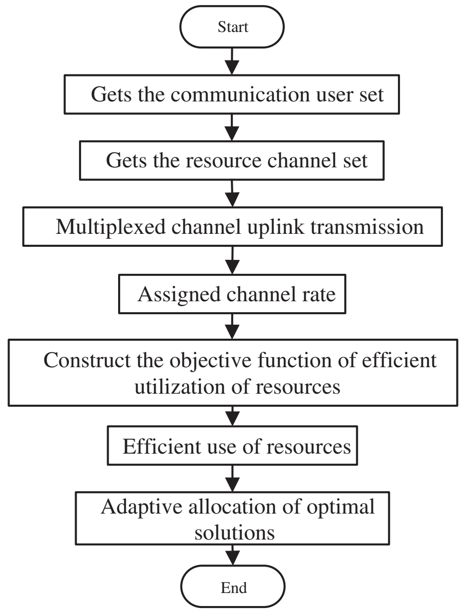


Figure 5: Flow chart of adaptive allocation algorithm for communication resources

3 Experimental Analysis

3.1 Experimental Environment and Parameter Setting

In this experimental study, we assume that the mobile cloud communication scenario of 5G vehicular networks is a fully connected network. The basic cloud communication network facilities include 10 communication processors, operating at an appropriate delivery rate. Among them, the VNF category is 8, and the demand coefficient of cloud communication resource allocation is set to 0.1. In this context, the number of communication vehicle users in 5G vehicular networks is set to 10, and the target bit error rate is a unified value. The transmission rate of vehicle users in mobile cloud communication is consistently 50. For this experiment, to ensure its effectiveness, the selected test section is a central road in a city. The road has two-way lanes, and the test time is from 8:00 to 9:30 in the morning. During this time period, the rationality of resource allocation for networked mobile cloud communication is tested. The specific experimental parameters set are shown in Table 1.

Table 1: Test parameters

Parameter	Value
Communication bandwidth/MHz	10
Noise power spectral density/dBm/Hz	–164
Maximum communication transmission rate/dBm	45
Cloud communication resource nodes	15
Time slot length/s	0.1
Number of intersections/piece	4
Routing communication delay/s	1
Discount factor	0.5

(Continued)

Table 1 (continued)

Parameter	Value
Communication link request delay/s	10
Signal-to-noise ratio/dB	10
Communication radius/m	350
Iterations	100

According to the experimental environment and parameters set above, the indicators selected for this experiment are user communication resource utilization rate, balance coefficient of allocated resource amount, and adaptive allocation time consumption in 5G vehicular networks mobile cloud communication resource allocation. To highlight the feasibility of the method proposed in this paper, the experiment selected and compared two other algorithms. They are the communication resource allocation algorithm based on fuzzy logic [5] and the partial channel state communication resource allocation algorithm [6].

3.2 Analysis of Experimental Results

The experiment initially employs the proposed algorithm, the communication resource allocation algorithm based on fuzzy logic [5], and some channel state communication resource allocation algorithms [6]. These are used to analyze the utilization rate of user communication resources in the 5G vehicular networks' mobile cloud communication resource allocation. In this experiment, 10 vehicle communication users were selected for efficiency analysis of their utilization, and the results are shown in Table 2.

Table 2: The utilization rate of user communication resources in 5G Vehicle-to-everything mobile cloud communication resource allocation/%

Vehicle communication user number	Proposed algorithm	Communication resource allocation algorithm based on fuzzy logic	Partial channel state communication resource allocation algorithm
1	98	90	91
2	98	90	90
3	97	90	90
4	98	87	89
5	98	87	90
6	99	86	88
7	99	85	88
8	98	84	91
9	98	85	90
10	99	87	90

The analysis of the test results in Table 2 shows that the proposed algorithm, the fuzzy logic-based communication resource allocation algorithm [5], and some channel state communication resource allocation algorithms [6] have certain differences in the utilization of user communication resources in the allocation of 5G vehicle-based mobile cloud communication resources. In this paper, the peak user communication resource utilization of the algorithm is as high as 99%. The utilization rate of the other two methods is low. The maximum utilization rate of the fuzzy logic-based communication resource allocation algorithm is only 90%, and the maximum utilization rate of the partial channel state communication resource allocation algorithm is 91%. The feasibility of this research method is verified. This is because the research method in this paper determines the in-band and out-of-band communication modes of 5G vehicle networks for mobile cloud communication, as well as the single-hop and multi-hop communication modes, and the research takes into account the resource requirements and transmission efficiency under different modes. According to the performance evaluation of various communication modes, the resource allocation scheme is optimized to improve the efficiency of resource utilization.

The experiment employs the proposed algorithm, the communication resource allocation algorithm based on fuzzy logic [5], and the communication resource allocation algorithm based on partial channel status [6]. These are used to analyze the 5G vehicular networks' mobile cloud communication resource allocation balance coefficient. The coefficient value ranges between [0,1]. A higher value indicates a better balance in allocation. The results are shown in Fig. 6.

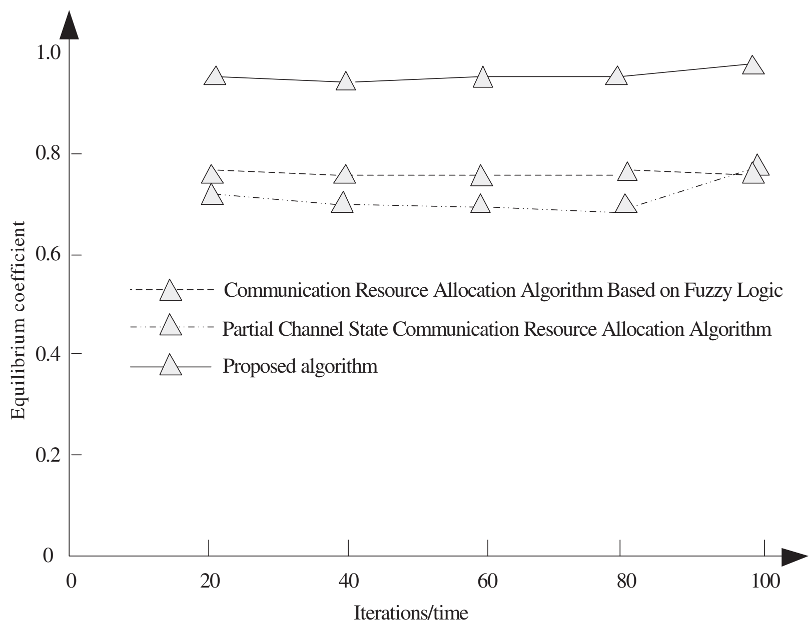


Figure 6: Balance coefficient result of 5G Vehicle-to-everything mobile cloud communication resource allocation

Analysis of the test results in Fig. 6 shows that the balance coefficient results of the three methods of cloud communication resource allocation vary to some extent with the change in 5G vehicular networks mobile cloud communication resource allocation times. Among them, the balance coefficient curve of the communication resource allocation algorithm based on fuzzy logic [5] and the partial channel state communication resource allocation algorithm [6] is lower than that of the proposed method, and the maximum balance coefficient of the two methods is only 0.8, while the balance coefficient curve of the method studied in this paper is closest to 1, which is relatively improved by 0.2. The feasibility of this method is demonstrated. This is because the research method in this paper introduces the objective function to optimize resource allocation, and on the basis of considering various communication modes, scenarios and user communication conditions, makes resource allocation more balanced as far as possible, so that the final result is closest to 1.

Finally, the experiment analyzed the time consumption of the proposed algorithm, communication resource allocation algorithm based on fuzzy logic [5], and partial channel state communication resource allocation algorithm [6] in cloud communication resource allocation. The results obtained are shown in Fig. 7.

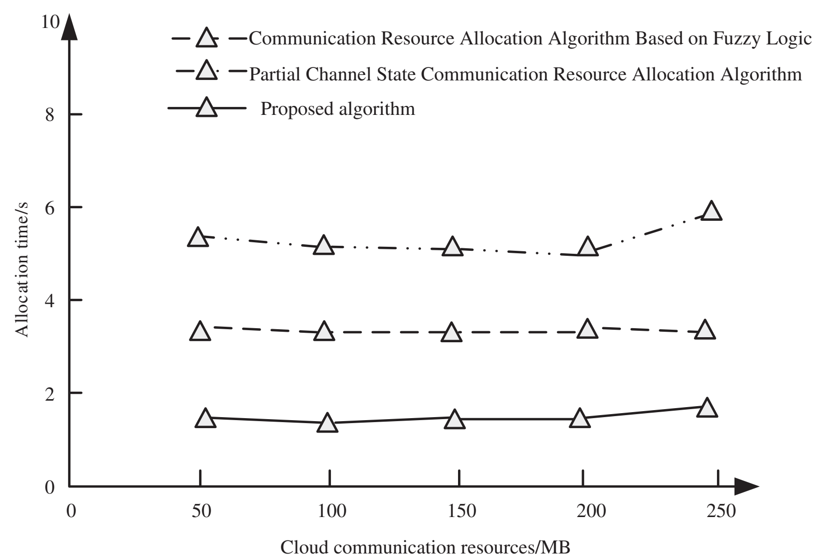


Figure 7: Time consuming result of 5G Vehicle-to-everything mobile cloud communication resource allocation

From the test results in Fig. 7, it can be seen that the proposed method has the shortest allocation time for 5G vehicular networks and mobile cloud communication resources. This is followed by the communication resource allocation algorithm based on fuzzy logic [5], and finally, the communication resource allocation algorithm based on part of the channel status [6]. In contrast, the allocation time of the proposed method is kept below 2 s, which indicates that the adaptive allocation efficiency of the proposed method is higher. This is because the adaptive resource allocation algorithm is introduced to dynamically adjust the resource allocation strategy according to the real-time user communication condition and network environment. This algorithm can quickly respond to network changes, so that resource allocation can be completed within 2 s, maintaining a high timeliness, indicating that this method has high efficiency and flexibility in adaptive resource allocation, and can quickly adapt to different communication scenarios to achieve effective use of resources. It can be inferred that the delay effect is better. Because the short allocation time means that the resource is allocated in a timely manner, the communication delay is reduced, and the system performance and user experience are improved.

Throughput is an indicator that directly reflects the amount of data a method can process per unit of time. In vehicle-connected communication, the performance of the resource allocation method under different load conditions can be better understood through the evaluation of throughput. The higher the throughput, the better the resource allocation effect of the method. Using throughput as the evaluation index, different data transmission amounts are set as the load, and each vehicle transmits data of different sizes such as 10 and 20 MB/s to test the performance of the system under different loads. The throughput results for testing different method references are shown in Fig. 8.

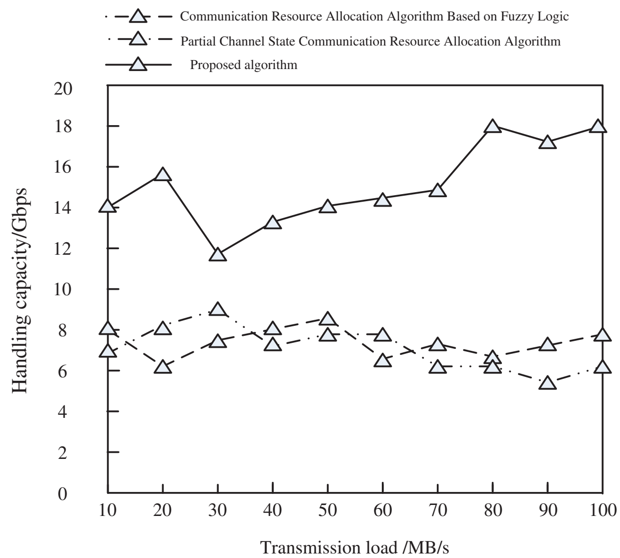


Figure 8: Comparison of throughput results of different methods

As shown in Fig. 8, under different loads, the throughput of the proposed method ranges from 12 to 18 Gbps, which is higher than other methods. The throughput of the other two algorithms is only up to 10 Gbps, which indicates that the maximum numerical throughput and resource allocation of the method have a positive impact on the 5G mobile cloud vehicle network communication test. The width and rate of the distribution channel are calculated using the Shannon formula, based on the communication state of 5G vehicle network users. This helps determine the adaptive allocation amount of mobile cloud communication resources. An objective function is introduced to obtain the optimal solution after allocation. This adaptive resource allocation method can better adapt to changes in the actual communication environment, improve resource utilization efficiency, and obtain higher throughput.

In-vehicle cloud communication systems are often powered by mobile devices, so the analysis and optimization of energy consumption can help improve the energy efficiency of the system, extend the use time of the device, and reduce the frequency of charging, thereby improving the user experience and system stability. The lower the energy consumption, the more energy efficient the method. Communication transmission two-layer HetNet method [11] and Ebola optimization search method was introduced as a comparison of the research methods in the paper [12]. In this experiment, the data transmission volume was continuously increased up to 100 MB/s, and the energy consumption of each method was obtained as shown in Table 3.

Table 3: Comparison of communication resource allocation and energy consumption of each method

Data transfer capacity/MB/s	Textual method	Refer to [11] method	Refer to [12] method
10	50	61	70
20	50	64	74
30	50	68	74
40	51	69	76
50	52	70	80
60	52	71	84
70	52	71	85
80	53	72	85
90	53	73	86
100	55	78	89

According to the results in Table 3, the energy consumption of the proposed method is relatively low and stable under different data transmission volumes and has always been balanced at 53 MJ. With the increase in data transmission volume, energy consumption increased slightly, but the overall change was not large. This shows that the method in this paper can control energy consumption well in the aspect of resource allocation, and has a certain efficiency of energy saving. The energy consumption of references [11,12]'s methods gradually increases with the increase of data transmission volume, and the increase is more obvious. At higher data transmission volume, the energy consumption is relatively high and shows a trend of gradual increase. It can be seen that the research method in this paper has certain advantages.

4 Conclusion

In order to improve the allocation efficiency of 5G vehicle-mounted cloud communication resources, an adaptive allocation algorithm of 5G vehicle-mounted cloud communication resources is designed. Through the analysis of the performance of each component module of the 5G vehicle network structure, the communication requirements, transmission rate, and other performance parameters of each module are determined. This contributes to a better understanding of connected vehicle systems and provides a basis for subsequent resource allocation. Considering the complexity of vehicle Internet mobile cloud communication, in-band and out-of-band modes are distinguished in the analysis. Furthermore, the single-hop and multi-hop modes are analyzed, and the key indexes such as resource transmission rate and bandwidth are calculated under different communication modes. According to the actual application environment of vehicle Internet mobile cloud communication, the amount of cloud communication resources required by the vehicle is calculated. This is done by determining the case for one-way and two-way lanes. Combined with mobile cloud communication radius and vehicle network connectivity probability, the connectivity problem of vehicle Internet is comprehensively considered. Based on considering the communication state and quality requirements of vehicle network users, the Shannon formula is used to calculate the bandwidth and rate of the allocated channel, and the reasonable adaptive allocation of cloud communication resources is determined. At the same time, the objective function optimally allocates the resources and obtains the optimal solution.

In the future, we will verify the effectiveness and performance of the existing algorithm in this complex environment, aiming at the challenges in the background of non-orthogonal multiple access (NOMA) in vehicle networks, especially the problems such as the increased complexity of vehicle receivers caused by NOMA and efficient channel state information (CSI) transmission in high-speed scenarios. The future research will focus on the feasibility of the proposed solution and its application prospects in the vehicle network, including further optimization algorithms in the NOMA scenario to improve the connectivity and resource utilization efficiency of the vehicle network.

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Availability of Data and Materials: Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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