Research Article

Research on Optimization Algorithm for Resource Allocation of Heterogeneous Car Networking Engineering Cloud System Based on Big Data

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A big data-based heterogeneous Internet of Vehicles engineering cloud system resource allocation optimization algorithm is proposed for the sake of meeting the needs of Internet of Vehicles applications and improving the rationality and efficiency of cloud system resource allocation. Based on taking the minimum cloud system delay as the resource allocation target, a multislot cloud system delay optimization model and its indicative function are constructed, the probability distribution function is derived according to the obtained multidimensional probability distribution function set, and the available channels of the vehicle in different time periods are determined. In this way, the matching degree between the vehicle and the channel is solved, the delay optimization model is turned into a convex optimization problem with independent variables, and the resource allocation algorithm for different task offload destinations is optimized. Meanwhile, by building a heterogeneous vehicle network simulation system, the performance of the algorithm is evaluated from the perspectives of resource rental cost, weighted resource utilization, and bit loss rate. As can be learned from the simulation results, the proposed algorithm can effectively reduce the cost of resource rental, and at the same time, the advantages of resource utilization and bit loss rate are relatively significant, so it has certain effectiveness and practicability.

1. Introduction

With the continuous progress of intelligent transportation, car networking technology has received more social attention. Based on intravehicle networking, intervehicle networking, and in-vehicle mobile networking, car networking [1] is a large-scale network that conducts wireless communication and information exchange and cooperates with high-efficiency communication terminals to improve traffic efficiency and improve driving safety. Mobile communication technology is the foundation of communication networks, so its digitization, informatization, and intelligence will inevitably promote the popularization and development of car networking. In this progress, resource allocation is the most likely to become the bottleneck, so this problem has gradually evolved into a hot research topic in related studies.

Aiming at the problem of resource sharing of car networking in dynamic scenarios, Dong and Wu [2] proposed an optimized resource allocation method in an on-board cloud computing system, which can improve task offloading capability by using an infinite time-domain semi-Markov decision process and combining it with the departure of busy vehicles. In order to solve the congestion of car networking, Tang et al. [3] constructed a cloud-fog mixed method for the algorithm of car networking resource allocation. Based on the standard secondary constraint secondary programming problem of the resource optimization model, the overflow probability estimation model of offloaded users’ access to the incoming request queue was established so as to minimize the resource costs.

For the sake of enhancing the network capacity and spectrum utilization in the unit area, heterogeneous car networking has emerged at the right moment, but it also brings more serious and complex interference problems. In
response to effectively solve these problems, an optimized algorithm for resource allocation of a heterogeneous car networking engineering cloud system is proposed. By means of the cross-entropy algorithm, the time delay optimization model was transformed, the algorithm calculation was accelerated, and the algorithm calculation process was simplified; the KKT condition was quoted to get close to the actual application situation and improve the reliability of the distribution result; the classification was performed according to the task offloading destination so as to obtain the corresponding cloud system resource allocation strategy and make the allocation result more reliable as well as accurate.

2. Optimized Algorithm for Resource Allocation of Heterogeneous Car Networking Engineering Cloud System Based on Big Data

2.1. Server Vehicle and Channel Preference Sequence Acquisition. Through the network edge server [4] and the vehicle architecture, a heterogeneous car networking engineering cloud system is established based on big data. Assuming that I vehicle has the ability to offload data, \( F_{\text{mec}} \) is the processor operation cycle per second of the algorithm, the cloud system channel set of K orthogonal channels is \( K = \{1, 2, ..., K\} \), and the vehicle and the channel must correspond one-to-one, \( \alpha_i \) and \( \beta_i \) each is the data volume and data calculation volume of the i th vehicle, and the local processor cycle per second of the vehicle terminal is \( F_{ue}^i \). When the data calculation task is executed locally, the execution delay expression of the i th vehicle is as follows:

\[
    t_{ij}^\theta = \frac{\beta_i}{F_{ue}^i}.
\]

If the computing power per second and the uplink transmission rate of the server of i th vehicle are \( F_{mec}^i \) and \( R_{mec}^i \), respectively, when the data computing task is executed in the cloud, the execution delay of the i th vehicle is as follows:

\[
    t_{ij}^1 = \frac{\alpha_i}{R_{mec}^i} + \frac{\beta_i}{F_{mec}^i}.
\]

The uplink transmission rate \( R_{mk}^i \) of the vehicle on the channel k is solved by the following calculation formula:

\[
    R_{mk}^i = B \log_2 \left( 1 + \left( P \|H_{i,k}\| \sigma^2 / d \gamma \right) \right),
\]

where the bandwidth of each channel and vehicle transmission power are B and P, respectively, the channel k gain of the vehicle i is \( H_{i,k} \), the background noise power is \( \sigma^2 \), and the path loss between the vehicle and the base station is \( d \gamma \), in which the distance between the vehicle and the server is d, the path loss index is \( \gamma \).

The task offloading method of vehicle i is \( m_i \), and the value is 0 when the task is processed locally and is 1 when the task is on the server. Therefore, the following minimum cloud system average delay is set as the resource allocation target:

\[
    \min (i) = \sum_{i=1}^{I} t_{ij}^m_i.
\]

where \( t_{ij}^m_i \) represents the average time delay of the cloud system of the vehicle i. Suppose that when the vehicle i uses the server to offload in time slots j and \( j + 1 \), the state information interaction delay between the vehicle and the base station is \( \theta_i \), and \( \mu \) is the interaction delay when not using server in time slot \( \mu \) but using in time slot \( j + 1 \) for offloading. If the heterogeneous vehicle networking engineering cloud system contains J time slots, then the time delay optimization model of the cloud system based on multiple time slots is as follows:

\[
    \min \{ \sum_{i=1}^{I} t_{ij}^m_i + \sum_{i=1}^{I} \sum_{j=2}^{J} \left[ \mu(m_{i,j-1})H(m_{i,j}) + \theta H(m_{i,j-1})H(m_{i,j}) \right] \},
\]

where \( H \) is the mean value of delay. The constraint equation system is as follows

\[
    \begin{align*}
    \sum_{i=1}^{I} t_{ij}^m_i &= F_{mec}, \quad \forall j \in \{1, 2, ..., J\}, \\
    m_{i,j} &= 0, 1, \quad \forall i \in \{1, 2, ..., I\}, \quad \forall j \in \{1, 2, ..., J\}.
    \end{align*}
\]

In order to speed up the algorithm operation rate and simplify the algorithm operation process, the cross-entropy algorithm [5] is used to transform the delay optimization model into a combined optimization problem. The combination strategy finite-state set is \( M \), where any combination mode is \( m \). Given that \( \{m_1, m_2, ..., m_n\} \) is the N groups of samples of set \( M \), \( m_{n,i,j} \) is the element of the n th group of samples, the quantization threshold is expressed by the parameter \( \eta \), and the indicative function Q of the model is defined through the following conditional expression:

\[
    Q(G(m_n) \geq \eta) = \begin{cases} 1, & G(m_n) \geq \eta, \\ 0, & G(m_n) < \eta. \end{cases}
\]

If the probability value vector is \( \omega = [\omega_{1,1}, \omega_{1,2}, ..., \omega_{L,T}] \), the expression of a set of multidimensional probability distribution function set \( f(m_n; \omega) \) based on the state set binary variable sample \( m_n \) is as follows:

\[
    f(m_{n}; \omega) = \prod_{i=1}^{I} \prod_{j=1}^{J} \omega_{n,i,j} (1 - \omega_{n,i,j})^{m_{n,i,j}}.
\]

All elements of the sample \( m_n \) are independent variables. According to a clear vehicle time slot and channel, the server vehicle and channel preference sequence are obtained from two aspects, namely, channel delay and vehicle offloading amount and it is expressed as follows:

\[
    \begin{align*}
    \mathbf{p}(m_{n,i,j} = 1) &= \omega_{n,i,j}, \\
    \mathbf{p}(m_{n,i,j} = 0) &= 1 - \omega_{n,i,j},
    \end{align*}
\]

The probability \( \omega_{n,i,j} \) is described through the following equation:
\( \omega_{i,j} = \sum_{n=1}^{N} Q(G(m_n) \geq \eta)m_{n,i,j} + \sum_{n=1}^{N} Q(G(m_n) \geq \eta). \) (10)

2.2. Optimized Algorithm for Resource Allocation of Cloud System. After obtaining the corresponding amount of cloud system resources through the vehicle channel rate and allocating them to the vehicle channels offloaded by the application server, all vehicle channels are arranged in ascending order of channel delay so as to establish a vehicle preference sequence; under the condition of small offloading amount and delay while better channel, all channels are arranged in descending order according to the amount of vehicle offloading, so that the channel preference sequence is obtained. By means of the GS (Gale–Shapley) algorithm, the matching degree between the vehicle and the channel is solved, and the resource allocation result is updated.

Since the actual task offloading process is affected by many factors such as resource sharing and interference management, in order to get closer to the real situation and make the distribution result more reliable, KKT (Karush–Kuhn–Tucker conditions) [6] is applied to transform the delay optimization model into a convex optimization problem about the independent variable \( m \) [7], and its goal is to solve the \( m^* \) combination that minimizes the value of \( G \). Assuming that the minimum value is \( \varphi^* \), then the expression formula is as follows:

\[ G(m^*) = \min_{m \in \mathcal{M}} G(m). \] (11)

The KKT conditional expression is as follows, which is a general optimization problem:

\[ KKT = \min_{x} f(x). \] (12)

The following formula is the corresponding constraint:

\[ \begin{align*}
\alpha_j(x) & \leq 0, \\
\beta_j(x) & = 0.
\end{align*} \] (13)

By converting formula (5) into Lagrange multiplier function [8–10], the following expression is obtained:

\[ L(G, \omega, u, F_{mec}, F_{ue}) = T(y^0, G, \omega) + u \left( \sum_{i=1}^{i} G(i) - 1 \right) + F_{mec} \left( \sum_{i=1}^{i} \omega_{i} - F_{mec} \right) + F_{ue} \left( \sum_{i=1}^{i} \omega_{i} - F_{ue} \right). \] (14)

The independent variables \( G_i \) and \( \omega_i \) are derived by gradient operation, and the corresponding derivation results of the following variables are obtained separately:

\[ (1 - m_i) \left( -\frac{\alpha_i}{G^2 R_{mec}^i} \right) + m_i \left( -\frac{\alpha_i}{G^2 R_{k}^i} \right) + u = 0, \] (15)

\[ -\beta_i/\omega_i^2 + F_{mec} m_{n,i,j} + F_{ue} \omega_{n,i,j} = 0. \]

The following equation is derived from equation (18):

\[ \frac{-\alpha_i}{G^2} \left( \left( \frac{1 - m_i}{R_{mec}^i} \right) + \frac{m_i}{R_{k}^i} \right) + u = 0. \] (16)

As can be concluded from the above formula, the equation can be established only when \( G_i \) is infinity and \( u \) takes the value 0 [11]. Since the value range of \( G_i \) is 0−1, the condition that \( u \) is 0 is excluded, and the following equation is obtained:

\[ \sum_{i=1}^{i} G_i - 1 = 0. \] (17)

Let \( G_i = \sqrt{\alpha_i ((1 - m_i/R_{mec}^i) + m_i/R_{k}^i)} \) to simplify the calculation steps, and then the following expression is set:

\[ G_i = G_i \sqrt{\frac{\alpha_i}{u}} \] (18)

After combining the above two formulas, the following expression is obtained, and the solution value \( (\sum_{i=1}^{i} G_i)^2 \) of \( u \) is derived:
After merging with formula (22), the expression is obtained as follows:

\[ F_{\text{mec}} = \left( \sum_{i=1}^{\omega_i \neq F_{\text{mec}}} \frac{W_i}{F_{\text{mec}}} \right)^2. \]  

(23)

Let us set \( F_{\text{mec}} = 0 \) and \( F_{\text{ue}} = 1 \), similarly, the \( F_{\text{ue}} \) expression whose task unloading destination is local is obtained as follows:

\[ F_{\text{ue}} = \left( \sum_{i=1}^{\omega_i \neq F_{\text{ue}}} \frac{W_i}{F_{\text{ue}}} \right)^2. \]  

(24)

In summary, the corresponding cloud system resource allocation strategy is obtained according to the task offload destination [14, 15], which makes the allocation result more reliable and accurate.

### 3. Experimental Analysis

#### 3.1. Building of Experiment Environment

With the purpose to verify the effectiveness and feasibility of the algorithm in this paper, the simulation experiment environment is built according to the overall structure of the heterogeneous car networking communication simulation system and its development environment parameters. The system framework consists of two main parts: the DSRC (dedicated short-range communication) communication submodule and the LTE (long term evolution) communication submodule, which are responsible for vehicle communication and vehicle information collection, respectively. Among them, the LTE communication submodule takes charge of issuing the MAC mechanism to the vehicle for switching information and time slot resource information. After balancing the advantages and disadvantages of open source software, the SUMO (simulation of urban mobility) software developed by the German Aerospace Center that supports microscopic and continuous simulation functions is used to create vehicle trajectory files containing variable information such as speed and position. The file information changes with time the trajectory file is used as the system input, and the simulation data result is obtained through the simulating system. The overall structure of the heterogeneous car networking communication simulation system is shown in Figure 1 and Table 1 shows the corresponding development environment parameters:

In the designed modular structure of the heterogeneous car networking simulation system, the system is divided into the following modules: vehicle trajectory file setting, communication interface, parameter configuration, LTE subsystem, DSRC subsystem, and statistical results. Among them, the result statistics module can make corresponding settings based on the actual simulation scenario.

#### 3.2. Simulation Effect of Optimized Algorithm for Cloud System Resource Allocation

By substituting the methods in [2, 3] and the algorithm in this paper into the constructed heterogeneous car networking simulation system, the performance of the algorithm is evaluated from three perspectives, which are resource rental cost, weighted resource utilization, and bit loss rate.

##### 3.2.1. Comparison of Average Resource Cost

Figure 2 presents the result of comparing the sum of resource rental costs of each algorithm under different cloud system resource quantities.

It can be seen that the cost of the literature method has been increasing at a rate as it ignores dynamic changes, which results in a greater difference between resource allocation and actual demand matching. In contrast, by means of changing the delay optimization model into the convex optimization problem with an independent variable \( m \) through KKT conditions, the necessary conditions for determining the optimal solution are established in this paper, and the derivation results of the respective variables are obtained via gradient operation. Based on the historical period load information, the potential load change of the cloud system in the future period is predicted, and targeted cache resource configuration is conducted in advance, so that the cache resources are reserved and resource waste is prevented.
3.2.2. Comparison of Weighted Resource Utilization. The trend of the weighted resource utilization curve of each algorithm is shown in Figure 3.

As can be observed from Figure 3, all of the algorithms have better transmission and allocation performance for a small number of system resources, and their time-frequency resources can basically meet the transmission needs. However, with the increasing number of resources, limited time-frequency resources are competed with by many other resources. Although the resource utilization rate of the algorithm in this paper shows a small increase, it always shows a continuous upward trend. On the contrary, the increase in the literature algorithm is extremely small, which is basically stable in the later period. This is because the algorithm in this paper converts the time delay optimization model into a combined optimization problem based on the cross-entropy algorithm, which simplifies the algorithm calculation process. According to a set of multidimensional probability distribution functions, the probability distribution function and probability are derived; in line with the clear vehicle time slots and channels, the server vehicle and channel preference sequence are constructed, the matching degree between the vehicle and the channel is obtained, and the resource allocation result is updated; with the help of introducing KKT conditions, the effective resource allocation is realized, so that resources are fully utilized.

![Figure 3: Curve of weighted resource utilization of each algorithm.](image)

3.2.3. Comparison of Average Bit Loss Rate. The curve of the average bit loss rate of each algorithm is shown in Figure 4.

According to Figure 4, continuous increasing resource utilization will lead to insufficient resources as well as serious bit loss. Although literature [2] has a low bit loss rate, it can be seen from Figure 3 that its weighted resource utilization is poor. The algorithm in the literature [3] configures a fixed amount of periodic time-frequency resources instead of considering actual needs, so that some system resources always appear idle, thereby causing excessive or insufficient resource allocation. In contrast, the algorithm in this paper uses the cross-entropy algorithm to transform the delay optimization model into a combined optimization problem. On this basis, a group of multidimensional probability distribution function sets and a probability distribution function of the binary variable sample in the state set are obtained, and the dynamic adjustment of the channel and offloading method is completed. Accordingly, from the two aspects of channel delay and car offloading, the server vehicle and channel preference sequence are built, the matching degree between vehicles and channels is obtained, and the resource allocation results are updated. Meanwhile,
the Lagrangian function is adopted to convert the delay optimization model and bring good adaptive adjustment capabilities so that the buffer resources are reserved in advance according to possible load changes, and the ideal bit loss rate is acquired.

4. Conclusions

In the context of the big data era, it is necessary to maximally satisfy the service resource demand and guarantee the full utilization of resources so as to ensure fair and impartial resource allocation and scheduling. The main components of the current telematics engineering cloud system are multiple heterogeneous servers. Based on this structure, the reasonable allocation of resources is facing a big challenge due to the diversified server configuration and resource supply. Based on the heterogeneous telematics engineering cloud system, a resource allocation optimization algorithm is designed based on big data, which realizes performance analysis mainly through simulation technology. Featured by low resource rental cost, high weighted resource utilization, and small bit loss rate, this algorithm can give vehicle users a low-latency, high-reliability service experience.

In future research, SDN (software-defined network) and NFV (network function virtualization) technologies should be used to architect the system on the NS3 platform and complete the software control of the algorithm. In general, there is a limit on the number of users’ access, and the algorithm of the number of vehicles exceeding the capacity of the LTE module needs to be explored in depth to maximize the capacity, so the optimal solution of random and sequential allocation of heterogeneous vehicle network simulation system should be the focus of the next stage of research.

Data Availability

Simulation data and our model and related parameters used are provided within the article.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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