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Retraction

Retracted: Edge Computing Resource Allocation and Optimization Method and Its Application in Internet of Vehicles Environment

Security and Communication Networks

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Geng, "Edge Computing Resource Allocation and Optimization Method and Its Application in Internet of Vehicles Environment," *Security and Communication Networks*, vol. 2022, Article ID 7333068, 10 pages, 2022.

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Research Article

Edge Computing Resource Allocation and Optimization Method and Its Application in Internet of Vehicles Environment

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With the emergence of new vehicle-mounted services, such as autonomous driving and augmented reality, the computing capability at the edge of the Internet of vehicles (IoV) has become increasingly demanding, and the edge computing of the IoV has also emerged. With the rise of the IoV, new vehicle-mounted applications keep emerging. Vehicle-mounted applications need to process the sensor data of themselves and other vehicles around them. The amount of data is huge, and processing these sensor data requires powerful computing power. But typical vehicles have limited computing power, so such computation-intensive tasks need to be uploaded to a data center for processing. The MEC (Mobile Edge Computing) technology is a good choice to solve this problem. This paper advocates reasonable scheduling of parked vehicles to cooperate with edge servers for collaborative edge computing and studies the resource scheduling scheme under the target of user relative satisfaction. This paper describes the main entities and related functions in the network and proposes a secure and reliable protocol for interaction between entities. The serviceability of different parked vehicles in collaborative edge computing was evaluated to select stable task performers and solve the resource scheduling optimization problem between parked vehicles and edge servers. The simulation results show that the proposed scheme has better customer satisfaction and maximum overhead than the existing scheme that only considers using edge server to perform tasks. Therefore, the method of this paper has important theoretical significance and potential practical value.

1. Introduction

With the rapid development of city size and the continuous increase of population, the number of cars on the road has also increased significantly. With the advent of the Internet of Things era and the popularization of wireless communication technology, the research and development of intelligent vehicle industry and its related application have attracted extensive attention from all parties. The development of intelligent vehicles makes the demand for network services in the mobile environment increase day by day. Vehicles need to complete path navigation, road analysis, and video-on-demand applications through wireless network access so as to provide more convenient driving services and comfortable ride experience for drivers and passengers [1, 2]. In the IoV, the vehicle can be used as a sensing terminal for information perception and data collection and then sent to the cloud server or base station for real-time processing, and the results are sent to the vehicle user. In this case, only relying on cellular network access (such as 3G and LTE) to ensure the network connection of the IoV will cause serious network traffic overload and reduce the data transmission efficiency, thus greatly weakening the service performance of on-board terminals and the network experience of on-board users. IoT applications are increasingly diverse and complex, and most end devices have limited computing and communication capabilities. Therefore, a cloud platform is required to assist terminal devices in information processing and message dispatch to meet the requirements of related applications. The development of cloud computing technology breaks the limitation of time and space of resource request, and the information processing capability of IoT system can be greatly improved through the huge computing resources and

data center of cloud [3]. However, due to the increasing amount of data and the high transmission delay between the remote cloud platform and the terminal device, the centralized service with cloud computing as the core has insufficient real-time performance [4].

These computation-intensive applications often require low latency response, so more computing and communication resources are required to meet the quality of service (QoS) requirements of these applications. This poses great challenges for vehicles with limited resources. Due to the limitation of vehicle computing resources, if the vehicle executes these new computation-intensive applications locally, it will produce a large delay, so it is difficult to meet the quality of service of these applications. In order to solve the above problems, some existing work uses cloud computing to help the unloading of vehicle tasks and offloads the computing-intensive tasks of vehicles to the processing cloud server with sufficient computing resources for execution. Although this can improve computing efficiency to a certain extent, the distance between the vehicle and the remote cloud server is far. However, cloud distance transmission also has its own disadvantages: transmission delay and transmission loss, which greatly affect the quality of service in the vehicle network environment. Mobile Edge Computing (MEC) is a promising technology to solve this problem. MEC was established by The European Telecommunications Standards Institute (ETSI) in 2014. MEC servers are located near the edge of the user network. It can greatly shorten the distance between the vehicle and the server and provide communication resources for the vehicle in close range. As shown in Figure 1, Mobile Edge Computing is located at the side of the roadside unit. At the same time, the MEC server has much more computing resources than the vehicle local resources, which can provide a good solution to the time-delay sensitive problem of computation-intensive tasks [5].

Through the SDN controller, enterprises, carriers, or network administrators can centrally manage the entire network without having to individually access each switch and then configure the switch, thus greatly simplifying the network design and operation [6]. Because SDN is realized based on software, it can run on general equipment, and there is no need to customize special network equipment. Various network protocols and standards can also be processed through software programming, making the network simple. SDN can now achieve logical centralized control over distributed network nodes and mobile devices. The research of SDN has been very comprehensive: SDN controller, network function layout, and SDN applications (such as real-time flow code and multipath routing) have a lot of research.

In the edge computing scenario, users generate a large amount of data or application requests. Due to different request types and requirements, edge devices have different computing and storage capabilities, and communication and network resources vary in different application scenarios. Therefore, effective edge resource scheduling is necessary for successful application of edge computing in reality. Generally speaking, edge resources include computing resources, communication resources, and storage resources [7, 8]. Resource scheduling in edge computing includes two layers: (1) task-centered scheduling: due to users' different resource demands and target demands, scheduling to edge server requires extra energy, communication, and delay, so it is necessary to develop an optimal scheduling strategy; (2) resource-centered scheduling: because edge resources are limited and the load of user requests changes dynamically, edge resources should be allocated and configured appropriately. It includes the deployment of edge resources and the migration of computing between edges and the intelligent placement of services in the edge system to adapt to the changes in user application requirements and improve resource utilization and user quality of service. The common three-tier architecture of edge computing consists of user layer, edge layer, and cloud computing layer. The IoT devices in the user layer are constantly collecting all kinds of data, which can be uploaded directly or processed and uploaded as input to application services. The cloud computing layer consists of powerful computing centers and storage units. The edge layer accesses the cloud computing layer through the core network. In the cloud-edge-end joint computing architecture, cloud computing is the most powerful data processing center. Data reported by the edge layer is stored in the cloud computing center. In this framework, resource scheduling studies of edge computing mainly focus on unloading decisions and resource allocation, which mainly studies how to allocate communication resources, computing resources, and storage resources in the edge system to complete unloading and task processing in the process of computing unloading. In order to realize the reasonable scheduling of edge computing resources and achieve the desired performance index, it needs reasonable scheduling strategy and technology. In recent years, many resource scheduling technologies have emerged and can be divided into centralized and distributed resource scheduling according to whether the control center needs to collect global information [9, 10].

With the development of intelligent connected vehicles towards the goal of building a more intelligent transportation system, more and more new on-board applications are emerging. The subsequent massive task data processing requirements have brought some challenges to the communication computing and storage capabilities of the former vehicle Internet system. With the help of gradually mature edge computing technology, the edge computing architecture of IoV composed of intelligent connected vehicles combined with edge computing technology can overcome the limitations of single vehicle processing and cloud computing processing to a certain extent, but it cannot deal with resource scheduling and optimization problems. This paper is based on the edge computing system of the IoV for the general direction and hot issues of the development of intelligent transportation. Aiming at reasonably scheduling edge resources to meet different service demands of vehicle users, a utility maximization-oriented resource allocation and scheduling architecture was established to reasonably schedule edge computing resources of vehicle network to meet service
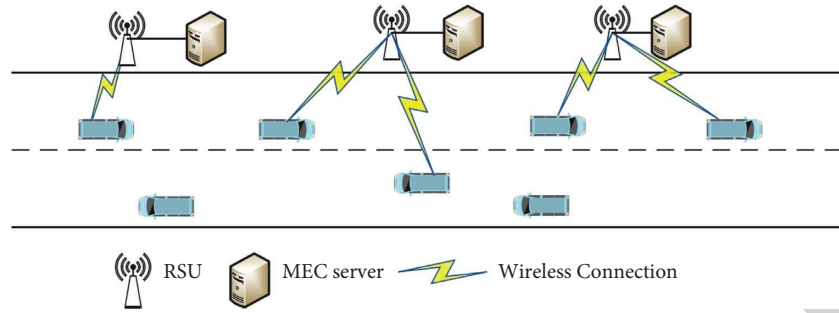
FIGURE 1: Mobile Edge Computing in IoV.

demands of vehicle users. Since resource scheduling is a means to achieve the respective goals and interests of vehicle users and service providers, this research can provide strong support for the realization and actual deployment of edge computing system of IoV [11]. The key technologies of centralized data processing represented by cloud computing model can no longer efficiently and timely process the data generated by edge devices. To solve this problem, the edge computing model with resource optimization as the core idea arises at the historic moment.

2. Related Work

Due to the characteristics of MEC, such as short distance, low latency, and high resources, this paper introduces MEC technology into vehicle network so that vehicles can unload computation-intensive and delay-sensitive applications to MEC server to seek better service quality [12, 13]. A number of applications have been made using the idle resources of parked vehicles for different scenarios, such as parked vehicles as small data centers, relay nodes for packet forwarding, content delivery, and storage nodes for content storage. Currently, academia and industry are focusing on the use of parked vehicles as communication, computing, and storage infrastructure. The authors of literature [14] describe the model of parked vehicles to help unload vehicles and use contract theory to manage idle resources in parked vehicles. Literature [15] proposed a novel multilayer vehicle-mounted data cloud platform by using cloud computing and Internet of Things technology and proposed intelligent parking cloud service and vehicle-mounted data mining cloud service under the Internet of Things environment. From the above literature, we can see that there are many existing works using idle resources of parked vehicles as storage infrastructure. Therefore, we thought that idle resources in parking lots can be used as backup resources of MEC servers to help unload tasks [16, 17]. As MEC server is located at the edge of the network and has strong computing capacity, it can solve the problem of limited computing resources of mobile vehicles to some extent, and it cannot process computation-intensive tasks with low delay and low energy consumption. From the above literature, we can see that there have been many efforts to apply MEC technology to the IoV. However, it seems that the problem of limited MEC resources has not been well solved at present. Some articles consider

using cloud servers as backup resources for MEC servers, but telecommuting issues remain.

The IoV is an important application scenario in the 5G era. It supports the implementation of vehicle-related applications through the IoV. Some of these applications require a stable communication environment, and some require low-delay data transmission, which puts forward the relevant requirements of high-throughput support for the construction of the IoV [18]. To ensure the safety and accuracy of vehicle application execution, IoV requires advanced mobile communication systems to ensure timely response of information and efficient calculation of vehicle tasks. General system applications mainly serve individuals in the IoV and solve the needs of individual vehicles or the IoV itself, such as vehicle safety driving, vehicle entertainment projects, and traffic flow management. Smart city applications provide services for tens of thousands of individuals in smart cities from a macro perspective, aiming to provide efficient information collection and storage services by pooling all available resources. The application of traffic system based on safety is to reduce the number of accidents by detecting the potential collisions of vehicles in the process of driving. It mainly establishes Collision Avoidance Systems (CAS) from three aspects of vehicles, road structure, and pedestrians to ensure traffic safety [19, 20]. In CAS, vehicles regularly receive event-driven information and broadcast their own real-time information to other vehicles to perceive the movement status of nearby vehicles, traffic conditions, and potential dangers. Comfort-based transportation system applications aim to provide more comfortable and relaxed driving experience for drivers and passengers. They provide more comfortable and convenient driving services for people in vehicles from the aspects of driving environment, destination information, and route navigation. Smart city-related applications aim to meet the requirements of massive data collection, transmission, and processing in smart city construction by building the IoV [21, 22]. Compared with traditional Wireless Sensor Networks (WSNs), IoV-based solutions are efficient and economical. Compared with traditional WSN, IoV can make use of mobile vehicles as intelligent nodes or objects, which play four roles in smart city environment: (1) cooperate with other terminal nodes to establish and maintain IoV connection and data transmission, (2) act as a client to undertake some services in IoV and Internet, (3) act as a data collection node to collect and transmit data from other smart nodes to the data center in

the city, and (4) act as a distributed computing resource to supplement the processing capacity of some resource-constrained devices.

In recent years, with the rapid increase in the number of motor vehicles, there have been traffic congestion, environmental pollution, traffic safety, and high energy consumption problems. In order to solve the above problems, the industry and academia have carried out research on the IoV. In addition, IoV applications are becoming popular in people's daily life. Globally, there are two different communication technologies in the field of IoV [23, 24]: (1) C-V2X based on cellular network and (2) Dedicated Short-Range Communications (DSRC) based on Wi-Fi. Among them, C-V2X based on cellular network is mainly developed by Chinese enterprises while DSRC is mainly developed by European and American enterprises. The downside of C-V2X, however, is the relaying nature of the cellular infrastructure, which can be a security risk in delay-sensitive vehicle applications. DSRC, as an IoV communication technology promoted by the United States and Europe, is characterized by high-speed data transmission and low delay and interference of communication links. However, it is currently in need of perfect facilities deployment. In the communication scenario of the IoV, the network topology of the IoV changes rapidly due to the high mobility of vehicles. Communication channels are highly time-varying, and communication services are more complex, which are the urgent problems to be solved in communication resource allocation of IoV. In multilink IoV, in order to solve the problem that centralized resource management cannot meet the rapid change of channels, resource sharing in IoV is modeled as a multiagent reinforcement learning problem of distributed execution, and then, deep Q network method based on fingerprint is used to solve this problem. This improves the transmission capability of the link and enhances the privacy of the link [25]. To sum up, the challenges facing the IoV in the future are as follows: centralized resource management, joint optimization management of multidimensional resources such as computing, storage and communication, and efficiency of resource allocation algorithm in the complex and changeable communication environment. From the above discussions, we know that the main contribution of this paper is as follows:

(1) This paper is the first to introduce the edge resource optimization method into the application field of the Internet of vehicles

(2) The research in this paper not only has good theoretical results but also has great potential application value.

3. The Edge Computing and Resource Optimization

3.1. Interaction Protocol. It is necessary for different entities to communicate with each other in the process of computational offloading when collaborative edge computing is enabled. In particular, parked vehicles are employed by a third-party service provider to act as task enforcer in the computational unload service, and for security and privacy reasons, communication between them must meet the following requirements. First, parked vehicles need to ensure anonymous communication. Secondly, messages transmitted between parked vehicles and service providers should be encrypted and signed for secure communication and protection against tampering attacks and masquerading attacks. Finally, after interactive communication, the service provider and the parked vehicle should agree on the facts of the computation of loads, rewards, and other tasks to prevent malicious entities from denying the receipt and giving of rewards. Based on the above requirements, this paper carefully designs an interaction protocol between different network entities as shown in Figure 2, where both Step 1 and Step 5 are all "submit a calculation tasks" since they do it in parallel.

3.2. Evaluation of Serviceability of Parking Vehicles. In the networked edge computing of jointly parked vehicles, parked vehicles are scheduled to assist the MEC server to undertake computing tasks. However, considering the mobility of parked vehicles, the remaining parking time is different, which means that some parked vehicles may not have the conditions for reliable calculation. Therefore, the serviceability of parked vehicles must be assessed in real time to facilitate the selection of suitable parked vehicles to act as stabilizers. In addition, some MEC servers are deployed around parking lots by service providers to seek for target parking vehicles and arrange them to participate in collaborative edge computing as needed. To recruit stable task performers, the MEC server monitors the vehicles currently parked in the parking lot to assess their serviceability to provide computational unload services externally at this time.

When a certain parking vehicle is predicted, a higher resource supplies stability and is able to perform reliable calculation, and thus, it is considered that its serviceability to bear the calculation load is also higher. This indicates that if the task is assigned to the parked vehicle, there is the possibility of subsequent computing task migration, thus greatly avoiding the extra workload caused by the task migration. Therefore, this paper evaluates the probability of parking vehicles remaining stationary continuously during the whole time cycle as a key indicator to measure the serviceability of parking vehicles participating in collaborative edge computing.

MEC servers support running a wide variety of data analysis methods in the field of data mining. Through continuous data recording and complex algorithm analysis, the probability density function of the parking time t of parked vehicles can be obtained and denoted as $f(t)$. Its cumulative distribution function is

$$F(t) = \int_0^t f(t)\mathrm{d}t, \quad 0 \le t \le t^{\max}. \tag{1}$$

Then, in the following whole resource scheduling time cycle, the probability that it always stays in the stopped state can be expressed as
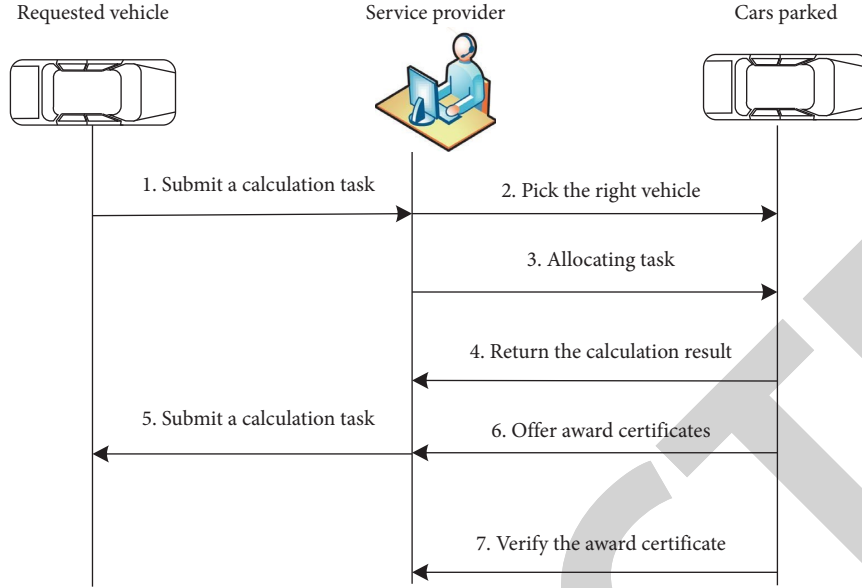
Figure 2: An interaction protocol in mutual communication.

$$p_i^j = P = P\left(t \geq at_i^j + T | t \geq at_i^j\right), \tag{2}$$

where T is the length of the entire time period and t is the specific time sampling point. To further calculate the above results, the cumulative distribution function needs to be solved first

$$F\left(t, t > at_i^j\right) = \begin{cases} F(t), & t > at_i^j, \\ 0, & t \leq at_i^j. \end{cases} \tag{3}$$

According to Bayes' theorem,

$$F\left(t | t > at_i^j\right) = \frac{F\left(t, t > at_i^j\right)}{1 - F\left(at_i^j\right)} = \frac{F(t)}{1 - F\left(at_i^j\right)}, \quad t > at_i^j. \tag{4}$$

Since formula (4) is a probability function, it ranges from 0 to 1. The conditional probability density function can be solved by taking the derivative of the conditional probability distribution function according to t

$$f\left(t | t > at_i^j\right) = \frac{f(t)}{1 - F\left(at_i^j\right)}, \quad t > at_i^j. \tag{5}$$

Finally, the conditional probability in formula (2) can be calculated according to the following formula:

$$p_i^j = \int_{at_i^j + T}^{t_{\max}} \frac{f(t)}{1 - F\left(at_i^j\right)} \mathrm{d}t = \frac{1 - F\left(at_i^j + T\right)}{1 - F\left(at_i^j\right)}. \tag{6}$$

The service provider predicts the probability that all parked vehicles in the parking lot will continue to stay for the following whole period of T and selects the appropriate parked vehicles to act as the stable executor in the calculation of unloading. With the above high predicted probability, the parked vehicles have better serviceability and are more likely to continuously contribute idle resources to the requesting users, thus being suitable for recruitment to perform computing tasks. In practice, there is a trade-off issue in setting threshold of p_i^j. When the threshold is low, the number of parked vehicles that can be selected will definitely increase. However, the overall reliability of these parked vehicles for performing tasks becomes weak. As time goes by, it becomes increasingly difficult to ensure that all vehicles can perform tasks stably.

3.3. Reward and Cost Functions in Resource Scheduling. The optimization algorithm proposed in this paper is not used to optimize the parameters of the model but to optimize the objective function of evaluating the service quality of the Internet of vehicles under certain constraints. Vehicle V sends a computational unload request to the service provider, and its computational tasks can be partially unloaded to the parked vehicle and partially unloaded to a MEC server. Each parked vehicle chooses to perform a subtask with a different computational load. During computing offload, if the total computing load is too large, part of it is allocated to the MEC server. n_k is the measurement parameter of negative impact, which is related to the calculated load-bearing state of parked vehicles at this time.

$$n_k = \frac{y_k}{y_k^{\max}}, \tag{7}$$

where y_k is the current calculated load of the vehicle and $y_k^{\max}$ is the maximum calculated load the vehicle can tolerate. The complete utility function is equivalent to the income gained by participating in the task minus the negative impact on the vehicle service which is given as follows:

$$U_k^V = \left(r_k^V - c_k\right)x_k^V - \omega_k n_k\left(x_k^V\right)^2, \tag{8}$$
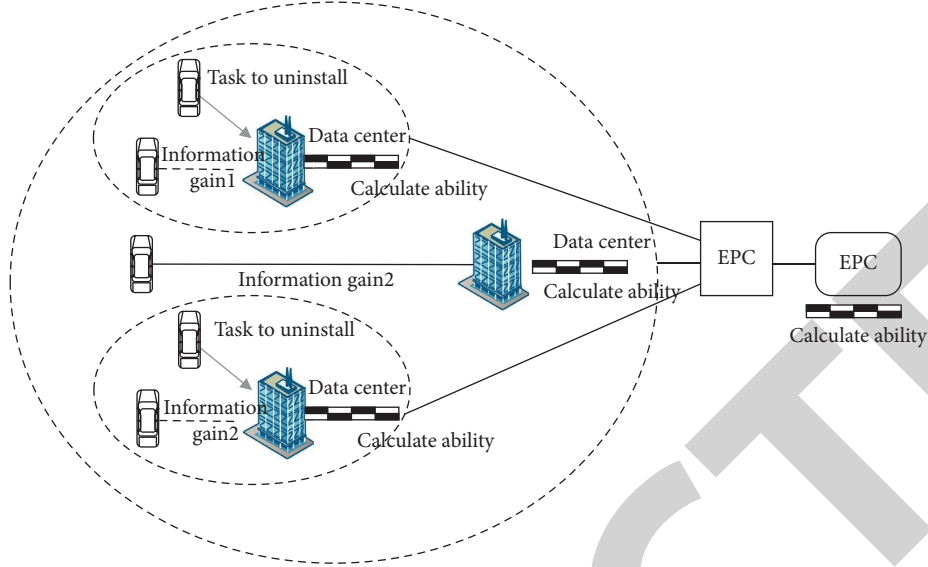
FIGURE 3: Diagram of resource usage in MEC system.

where ω_k is a weight coefficient to weigh economic benefits and negative effects. The service cost of MEC server processing per computing load is f_0. Therefore, the service cost of the vehicle requested during unloading can be expressed as

$$C_V = f_0 \left(W - \sum_{k \in \mathcal{K}} x_k^V \right) + \sum_{k \in \mathcal{K}} r_k^V x_k^V. \tag{9}$$

The cost minimization problem with feasibility constraints is expressed as

$$\min_{\{z_k^\gamma\}_{k \in \mathcal{K}}} C_V,$$
$$\text{s.t.} \sum_{k \in \mathcal{K}} x_k^V \leq W, \tag{10}$$
$$\sum_{k \in \mathcal{X}} x_k^V \geq \rho_V W.$$

In this paper, we consider the system shown in Figure 3. Resource allocation considers wireless channel resources and data center computing resources. Because wired networks can expand their bandwidth by laying more optical fibers, wired bandwidth is often not a bottleneck that limits the deliberate uploading of tasks, while wireless transmission limits the uploading rate due to the limited spectrum. In terms of resource allocation in data center, the allocation of computing resources plays a decisive role in the delay of task processing, so this paper mainly considers the allocation of server computing resources, assuming that memory and cache resources are sufficient. As can be seen from Figure 3, the coverage areas of macro station and micro base station overlap, which will interfere with each other and reduce the transmission rate. Data centers in different locations also have different computing resources and loads, the former depending on the deployment of the operator and the latter depending on the current traffic flow and user request density at the

site. Reasonable task unloading decision and resource allocation scheme can greatly improve resource utilization efficiency, reduce service request rejection rate, and improve user satisfaction, which is essential for the whole system.

4. Experimental Results and Analysis

4.1. Experimental Data Introduction. In this paper, the simulation is completed on the Python platform. The vehicle density in cities is 500–2000 vehicles/km^2, in suburbs 300–800 vehicles/km^2, and in expressways 100–500 vehicles/km^2. In different scenarios, the coverage of base station will be different. And take both urban and city environment as an example.

This paper assumes that the total rate of base station is about 20 Gbit/s, in line with the requirements of 5G base station rate. In addition, we assume that the signal transmission delay from the micro base station to the macro station data center is 0.002 s, the transmission delay from the macro base station to the Internet data center is 0.5 s, and the transmission delay from the micro base station to the Internet data center is 0.2 s.

4.2. Experimental Results' Analysis. Figure 4 shows the change of reward under different number of iterations, from which the convergence performance of the proposed algorithm can be observed. In this paper, there are 200 training steps in each iteration, and the cumulative rewards and rewards for all training steps in each iteration are set. According to the figure analysis, with continuous training iterations, the reward value gradually increases. When the training reaches 200 iterations, the proposed algorithm begins to converge. Due to the high mobility of vehicles, the network topology will change rapidly, resulting in numerical fluctuations during algorithm convergence. Thus, the

stability of the proposed method is proved. It should be noted that although a small number of sampling points in Figure 4 have a sudden increase, the main reason may be that the sampling points contain noise and other disturbances, but it does not affect the overall increasing trend of reward.

Figure 5 shows the performance comparison of average delay when the proposed algorithm is used to obtain the optimized resource allocation scheme compared with the conventional algorithm. The curves of the proposed algorithm and the conventional algorithm are shown in dark blue and light blue bars, respectively. The horizontal coordinate in the figure indicates service requests of different priorities, where type 1 indicates real-time and traffic security service requests, type 2 indicates real-time service requests, type 3 indicates non-real-time and nonsecurity service requests, and type 4 indicates real-time and non-traffic security service requests. It can be seen from the figure that when the service request type is type 1, the average delay between the proposed algorithm and the conventional algorithm is about 400 ms. When the service request type is 3, the average delay between the proposed algorithm and the conventional algorithm is 800 ms. This is because higher priority service requests can allocate more spectrum resource blocks to obtain higher system utility. The lower latency of real-time and traffic safety service requests means that vehicles can receive traffic safety-related information in a timely manner (for example, collision avoidance messages, traffic accident reports, and warning messages), which can greatly enhance traffic safety. In addition, Figure 5 also shows that the proposed algorithm has a shorter time delay than the conventional algorithm, mainly because the proposed algorithm has faster convergence, which further reduces the time delay. In a real connected car environment, though, there are many different types of service requests. However, only the four most representative service types (Type 1, Type 2, Type 3, and Type 4) are selected here to verify the validity of the proposed method.

Figure 6 shows the computing task charging impacts on network operators' earnings in city and country. As can be seen from the figure, no matter in urban or rural areas, with the increase in computing task charges, the resource allocation scheme proposed in this paper can bring higher benefits to operators. This is because when the charge of computing tasks increases, the benefits of the system performing computing offloading also increase. When allocating resources, the system of IoV tends to perform computation-intensive tasks. At the same time, we can also see that in the case of no computing offloading, different computing task charging prices have no impact on edge caching schemes. In conclusion, it can be seen from the results of Figure 6 that the proposed method achieves good resource allocation and optimization results in both towns and cities, thus proving the effectiveness and universality of the proposed method.

Figure 7 shows the system throughput with different parameters, the threshold value is set as 20, the number of vehicles changes from 0 to 2500, and the weight parameter w changes from 0.1 to 0.5. It can be seen from the figure that under various conditions with different weight parameters, the throughput of the system increases with the increase in
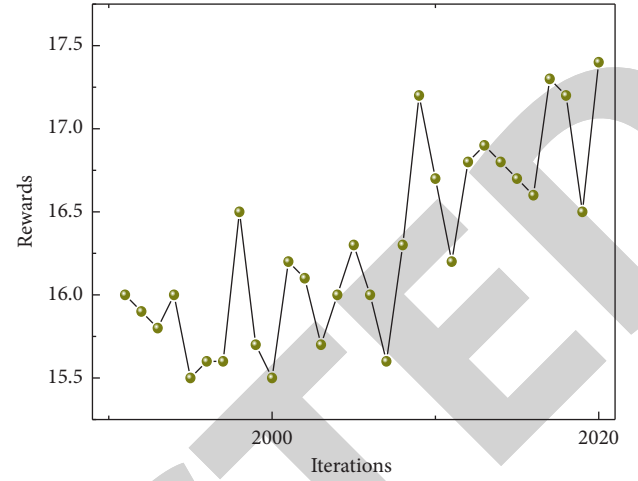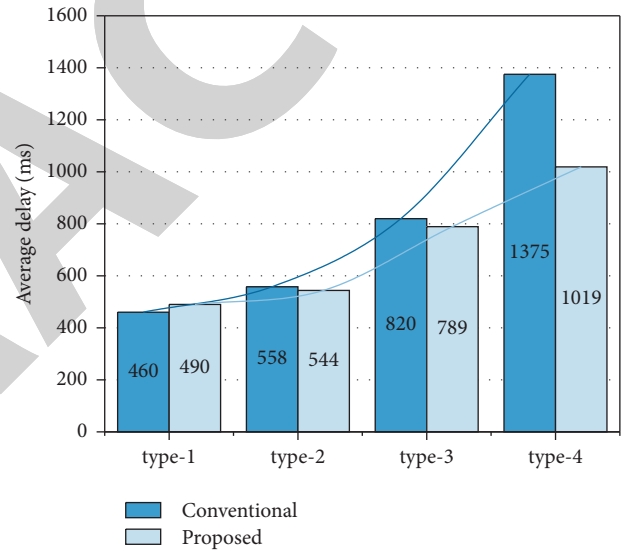

FIGURE 4: The convergence of the algorithm.

FIGURE 5: The performance comparison of average delay.

the number of vehicles. This is because the system throughput is the sum of the throughput of all requesting vehicles in retrieving the request content, and as the number of vehicles increases, the system throughput increases accordingly.

Figure 8 shows how the time cost of processing a task varies with the intensity of computation. As can be seen from the figure, with the increase in calculation intensity, the cost of processing tasks increases. However, when the calculation intensity reaches a certain level, the cost shows a downward trend, mainly due to the overfitting of the model. However, the algorithm proposed in this paper has the lowest computational overhead and shows the best performance under the same computational intensity.

In terms of resource allocation and optimization strategies in the Internet environment mentioned above, Figure 9 shows the distribution of user satisfaction. As can be seen from the figure, user satisfaction basically presents a normal
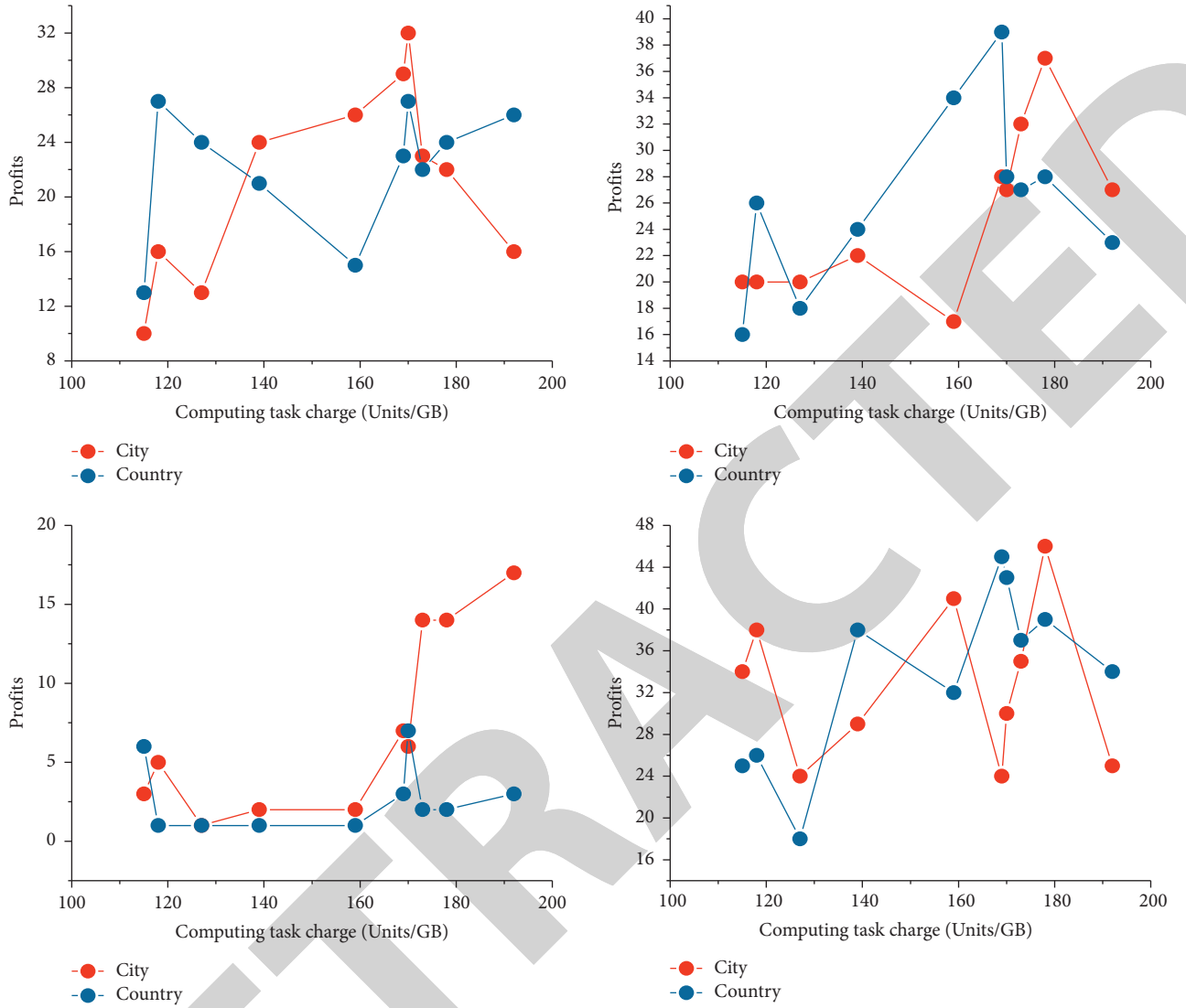
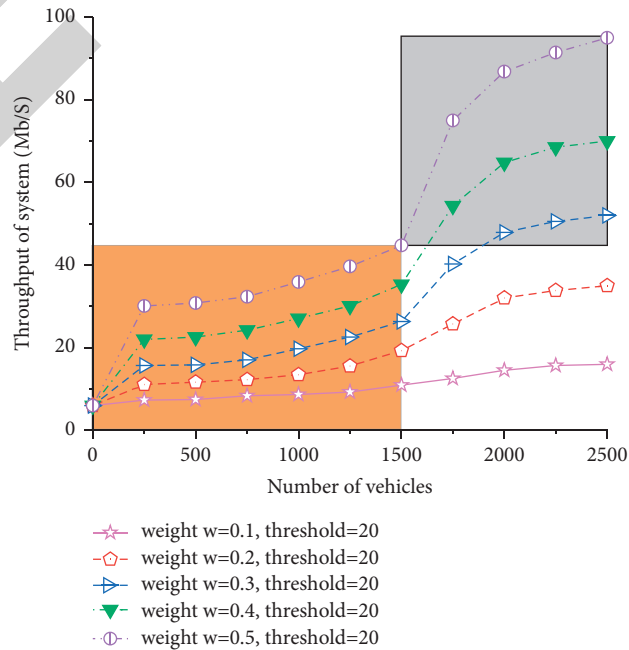Figure 6: Computing task charging impacts on network operators' earnings in city and country.

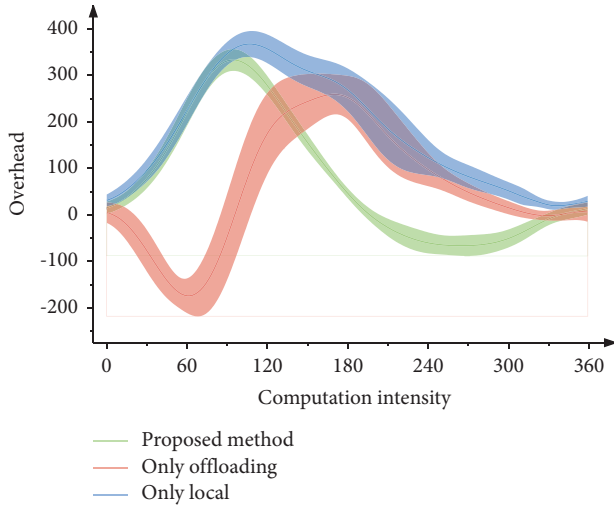Figure 7: System throughput with different parameters.

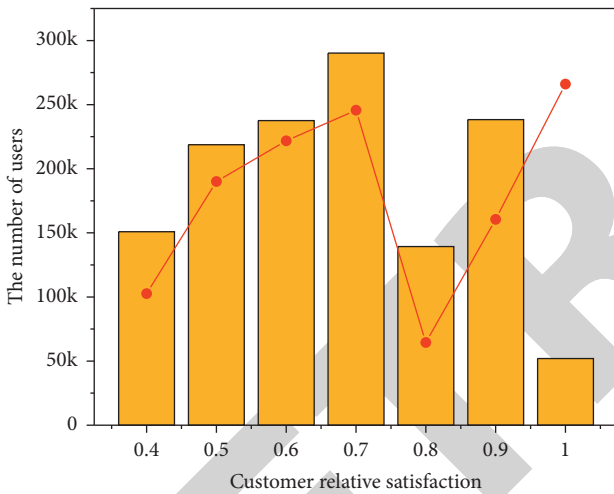Figure 8: The relationship between cost and computational intensity.

Figure 9: The distribution of user satisfaction in terms of resource allocation and optimization.

distribution. Most of them are satisfied, which shows the effectiveness of the method in this paper.

5. Conclusion

As we all know, with the rapid development of the global economy in recent decades, car ownership continues to increase all over the world, which also leads to frequent traffic jams and accidents. With more powerful computing and storage capacity, IoT devices can not only efficiently obtain current road condition information but also process data at a faster speed and give early warning to vehicles and pedestrians. Faced with a variety of complex businesses, how to allocate resources of different sizes and priorities for vehicles according to business types is the focus of many research works.

This paper proposes a resource allocation and optimization method based on edge computing to evaluate the

serviceability of different vehicles in collaborative edge computing and solve the resource scheduling optimization problem between vehicles and edge servers. Simulation results show that this scheme has higher customer satisfaction and maximum cost compared with existing schemes that only consider using edge servers to perform tasks. Therefore, the method of this paper has important theoretical significance and potential practical value. Although the method in this paper has achieved good theoretical and experimental results, it is still a conventional machine learning model. In the face of big data scenarios, depth-based resource optimization methods will be the focus of future research.

Data Availability

The data used to support the findings of this study are available from the author upon request.

Conflicts of Interest

The author declares there are no conflicts of interest or personal relationships that could have appeared to influence the work reported in this paper.

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