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A Novel Utility Based Resource Management Scheme in Vehicular Social Edge Computing

FUHONG LIN[1], XING LÜ[1], ILSUN YOU[2], (Senior Member, IEEE), AND XIANWEI ZHOU[1]
[1]School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing 100083, China
[2]Department of Information Security Engineering, Soonchunhyang University, Asan 31538, South Korea

Corresponding author: Ilsun You (ilsunu@gmail.com)

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ABSTRACT Vehicular network aims at providing intelligent transportation and ubiquitous network access. Edge computing is able to reduce the consumption of core network bandwidth and serving latency by processing the generated data at the network edge, and social network is able to provide precise services by analyzing user's personal behaviors. In this paper, we propose a new network system referred to as vehicular social edge computing (VSEC) that inherits the advantages of both edge computing and social network. VSEC is capable of improving the drivers' quality of experience while enhancing the service providers' quality of service. In order to further improve the performance of VSEC, the network utility is modeled and maximized by optimally managing the available network resources via two steps. First, the total processing time is minimized to achieve the optimal payment of the user to each edge device for each kind of the required resource. Second, a utility model is proposed, and the available resources are optimally allocated based on the results from the first step. The two optimization problems are solved by the Lagrangian theory, and the closed-form expressions are obtained. Numerical simulations show different capacities in different scenarios, which may provide some useful insights for VSEC design.

INDEX TERMS Edge computing, network utility, social activity, vehicular network.

I. INTRODUCTION

Nowadays, vehicles are playing more and more important roles in people's daily routine work. They can offer convenient transportation for people to visit anywhere at any time. With the development of information technology, the internal space of vehicles are significantly changed comparing with last decade. More and more electronic devices are equipped inside, such as GSP, PAD, road deceleration devices and cameras. The communication technologies among these devices have sprung up a new area for in-vehicle service providing. Usually, the produced data needs to be transmitted to a remote cloud computing center for processing, and then the feedback will be utilized to guide the intelligent transportation management, in-vehicle entertainment, and so on. Due to the centralized structure of cloud computing, the distance between vehicles and data centers is large. Therefore, the cost of data transmission is very high. Since most vehicles need to exchange the information with the cloud computing center for service providing, the waste of core network bandwidth and long latency should be carefully focused.

To solve the above-mentioned issues, vehicular edge computing was proposed [1]. The main idea of this paradigm is to create a vehicle network at the network edge. Based on the electronic devices equipped inside vehicles, new mechanisms can be proposed to connect them automatically and securely [2]. Then, large proportion of data will not need to be uploaded and processed in the cloud computing center. On the contrary, it will be locally handled in vehicular edge computing. However, if a user wants to record the results with high priority, the processed outcomes can be stored inside the cloud computing center as well. Such processing scheme does not require much core network bandwidth consumption and can reduce the average Time to Live (TTL). Moreover, it can support location-aware applications and contribute to the solutions for reliable transmissions [3]–[5].

The next developing way of vehicular network is social activities based vehicular social network. The infrastructure of the vehicular network is composed by lightweight devices. They have weak calculating or processing ability and small storage spaces. Lots of challenging and open problems exist in making this network to work well. A key aspect is that there should be a cooperative mechanism to incentive users sharing there available resources [6], [7]. How to achieve better cooperation needs suitable payment incentives. Until now, lots of incentive schemes are proposed to deal with this thing in vehicular network [8]. So the social cooperation further improves the performance of vehicular network and it can be treated as vehicular social network.

This paper firstly proposes the architecture of vehicular social edge computing (VSEC) and then focuses on improving its performance via resource managing.. To process a certain task, different services provided by the applications need different resources. So optimally allocating available resources is an important issue. In this study, we just consider three kinds of resources in the vehicular social edge computing, namely CPU, RAM, and STORAGE SPACE. The final aim is to provide better services so as to improve user' QoE. We use minimal processing time delay as a first stage optimizing object, then the maximum utility of the VSEC is set as the second stage optimizing object. In the first stage, the total budget and the tasks are constant. According to the VSEC work mechanism, a processing time delay model is proposed. To solve the built model, Lagrangian method is used. The optimal payment of a user to each edge device for CPU, RAM, and STORAGE SPACE required by a task is gotten. On the second stage, according to the outcome of the first stage and the edge device capacity, a utility model is proposed. In order to get optimal utility, Lagrangian method is used again which gives out the optimal resource allocation scheme to make vehicular social edge computing utility being the largest. To demonstrate the good performance of the proposed scheme, we carry out a series of numerical simulations. The identical or hierarchical price scenarios are considered in the first stage simulation and we find that increasing each kind of resource requirement will decrease the payment share of other resources, the increasing of total budget will increase the payment share of all the resources, and the payments in identical or hierarchical price scenarios have little difference. In the second stage simulation, the identical or hierarchical capacities scenarios are considered. The conclusions are: the user allocated resources are different and the resources sharing trends are more or less the same under different user payment of each resource, and user allocated resources shares have no difference in hierarchical and identical capacities Scenarios.

The following sections are organized as follows. In section 2, related work is briefly described. In section 3, the resource management models are built and they are solved in section 4. Numerical simulation is carried out in section 5. A final conclusion is drawn in section 6.

II. RELATED WORK

In an earlier work in vehicular network, the Christian proposed ad-hoc networking based the concept in [9]. The main idea was to process the local event within a certain area other than forwarding it to the central data center. After this work, lots of researches have been carried out in the vehicular network. In this Section, we will state the achievements in resource management of vehicular network from three different aspects: traditional resource management, edge computing based resource management and social activities based resource management. Nicola *et al.* [10] studied the resources allocation problem with primary and secondary users in vehicular network. A network utility based model was proposed to optimally manage the cognitive resource. Simulation showed that this scheme has outstanding performance. Based on the centralized network architecture of vehicular network, Yu *et al.* [11], [12] proposed a resource management scheme using cloud computing technologies. The cloud computing has centralized computation, storage or bandwidth resources. An optimal resource management scheme should be implemented. They built a resource competition model and solved it using game theory. Simulation showed that the proposed scheme has good performance when virtual machine migration occurs. Cordesch *et al.* [13] studied the reliable adaptive resource management in cloud computing based vehicular network. The background problem was how to efficiently offload the traffic of resource-limited devices (which is one of the vehicular network features) to the cloud center. They built a suitable stochastic network utility model under constrained condition to solve the abrupt changes produced by cars' mobility. This scheme provides a good reference to allocate resources in resource-limited conditions. Ramon *et al.* [14] researched on the resource management in dynamic vehicular environments, for a variety of accessing technologies is proposed nowadays. The concept of software defined network was used to cope with this tough task. A redesigned architecture was proposed to fit the dynamic vehicular networks. Sadip *et al.* [15] studied the resource allocation problem in cloud architecture based vehicular network. A three-layer cloud computing structure was proposed, namely vehicular cloud, roadside cloudlet and centralized cloud. Different resources are optimally allocated among these three cloud layers. They claimed that this architecture could shorten the task response time and reduce the energy consumption. Lin *et al.* [16] studied the resource fairly allocation in edge computing environment. They proposed a multi-resources simultaneously allocating scheme. This scheme could improve the resource allocating efficiency while keeping the fairness. Wang *et al.* [17] proposed a resource allocation scheme based on the service characteristics in vehicular networks. Network virtualization was used to support different applications. According to the smart identifiers, cars autonomously entered into different serving groups based on the services that they want to get. The simulation showed that this scheme had better performance comparing with the traditional schemes in long-term acceptance ratio and average revenue. Xiong *et al.* [18]–[20] studied the performance improvements in high speed vehicular network, which sheds some light on the investigation of traditional vehicular network.

These researches only focused on the resource management in traditional vehicular network and did not consider optimize the performance using edge computing technologies. Next, we will survey the achievements in edge computing based vehicular networks.

Kumar *et al.* [1] proposed a mobile edge network considering vehicles with high mobility. In order to shorten time delay in transmission, response or communication, most of the tasks were assigned to the edge node. This scheme shows one of the advantages of edge computing. Lai *et al.* [21] stated that centralized and decentralized vehicular networks could work together. To combine the advantages of them, an edge computing concept was proposed. They designed cooperation schemes and scheduling methods to organize the vehicle nodes. Using the real-world dataset, the good performance of the proposed scheme was verified. Song *et al.* [22] studied a smart caching scheme in fog or edge computing which can be used to in vehicular network. It could further shorten the serving time delay. Huang *et al.* [23] improved vehicular network computing capacity. They designed a reputation management scheme to keep the vehicular network being a cooperate environment. The reputation, treated as feedback, was used to guide the resource allocation. Liu *et al.* [24] proposed a software defined vehicular network using the edge computing techniques. It could provide short time delay and high reliability services. According to the real world application test, this architecture worked very well. Huang *et al.* [25] focused on the mobility of vehicular network. The 5G and software defined network technologies were used to meet the vehicles' communicating requirements. Mobile edge computing was used to strengthen the network control. Zhang *et al.* [26] studied the optimal computation offloading problem in vehicular network using mobile edge computing techniques. Based on the sparse dense of cars, they proposed hierarchical cloud-based framework to guarantee the network performance. Feng *et al.* [27] proposed an autonomous vehicular edge to deal with computation task at vehicle edge. Further, they researched the resource caching scheme to assist service providing. This scheme could improve the performance of vehicular network.

These researches focused on edge computing technologies used in vehicular network. As mentioned above the social network could also improve the performance of vehicular network. Next, we introduce the related achievements in this aspect.

Xu *et al.* [28] studied the incentive scheme in mobile social network. They pointed out that most of users are selfish and do not want to share. A bargain game was used to decide the incentive price of the services. Kong *et al.* [29] studied the dataset management in vehicular social network, and collected raw data from the flowing cars. A three-step data process scheme was introduced. Using the actual traffic data, the proposed scheme was verified. Lin *et al.* [30] researched on the user access management scheme based on network pricing. The incentive scheme decided which wireless network is the best one that the users could access. The simulation showed this scheme could work efficiently. Faye *et al.* [31] and Eze *et al.*[32] studied the human activities when using the wearable devices which give us some insight of solving the drivers' behaviors. Lin *et al.* [33] researched the analysis of social big data produced by vehicular network. They proposed a clustering model to classify the vehicles into different groups according to the social relationships. The location prediction was used to guide the global localization achievement. The simulation showed that the proposed scheme had better performance comparing with other schemes. Liu *et al.* [34] researched on the welfare maximization problem in vehicular social network and proposed a novel control method. They gave each vehicle a strategy to control its behaviors and maximize the social welfare. Real environment experiment demonstrated that the proposed scheme was efficient. Song *et al.* [35] proposed a data collection strategy considering the mobility in vehicular social network. Some of the collected data were useless and needed to be discarded. So the priority assignment concept was used. According to the real dataset testing, the proposed scheme was effective and efficient. Tang *et al.* [36] studied the service serving in vehicular social network using the device-to-device communication technique. The contents were stored in a data center and vehicles retrieved them according to their requirements. Turning to the parked vehicles, this service's providing ability could be enhanced.

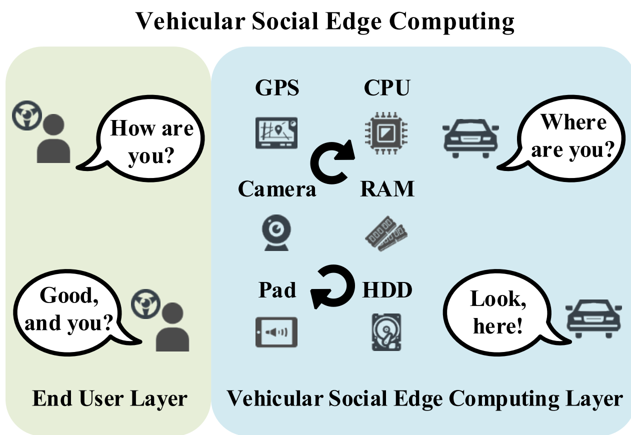


FIGURE 1. The VSEC architecture.

From the above statements, we can get that there are so many achievements in edge computing and social network based vehicular network. However, merging these two technologies into the vehicular network has not been studied. In the following section, we will research on the resource management in this kind of network.

III. THE RESOURCE MANAGING MODELS IN VSEC

In this section, firstly, the vehicular social edge computing mechanism is introduced. Then, two models are built to minimize the vehicular social edge computing process time delay and to maximize its utility.

A. THE VSEC DESCRIPTION

The architecture of VSEC is consisted of two layers (Shown in figure 1), namely vehicular social edge computing layer and end user layer. The vehicular social edge computing layer, which is at the network edge, is formed by a number of vehicles who have electronic devices with higher processing, storage or computing ability comparing with end user devices, such as GSP, PAD, road deceleration devices or cameras. The edge user layer is formed by users who want to get services for the vehicular social edge computing layer. The reason why users want to get service from vehicular social edge computing layer can be summarized as: firstly, the processing requirements are high, but the storage and processing ability of their devices are weak and cannot meet the requirements. So users can offload the tasks to the vehicular social edge computing layer to process. After processing, the vehicular social edge computing layer returns the outcomes to end users. Secondly, some resources are very popular, such as a new movie or a famous song which are high in demand. So these resources can be pre-pushed or cached at the vehicular social edge computing layer and users can get these resources without consuming the core network bandwidth. Thirdly, some services are time sensitive, such as automatic drive. If they are calculated at the vehicular social edge computing layer, users can fetch them with a very small time delay which can improve the users' QoE. This work focuses on the resource management in stationary situation. During a short period of time, the relative locations of the vehicles keep unchanged. So the topology of the VSEC does not change.

The VSEC can be used various kinds of vehicle environments, such as intelligent transportation, in-car entertainment, and computation offloading. A representative application Scenario is as follows. The movie "Avatar" is released and stored in the data center, e. g. amazon cloud. A large number of the people want to watch it. In the VSEC scheme, this movie can be firstly download to one device in a car, e. g. PAD. Owing to the VSEC being a connected structure, all the devices in different vehicles (in a certain range) are networked. The users in these vehicles who want to watch this movie can download it from the PAD rather than from the amazon cloud. This action can bring down the load of data center while shortening the downloading time delay.

B. THE RESOURCE MANAGING MODELS

The different services, provided by the VSEC, need different resources (CPU, RAM, and STORAGE SPACE), and this paper mainly focuses on the maximizing the utility of VSEC network. This can be further divided into following two problems. The first one is minimizing the VSEC total processing time with constraint budget and the second one is optimally allocating available resources to maximize the VSEC utility. The Scenario is as follows. The devices in each vehicle are connected forming an edge node and the kinds of resources in it form a resources edge pool. Also the all the edge nodes are networked to process the tasks cooperatively. In the VSEC, there are M devices in the vehicular social edge computing layer. The i'th device has maximum capacities

TABLE 1. Parameters used in the model.

Symbol	Notation
w_{ij}^{cpu}, w_{ij}^{ram}, $w_{ij}^{storage}$	Payment of user i to edge device j for CPU, memory, storage space required by a task, respectively
x_{ij}^{cpu}, x_{ij}^{ram}, $x_{ij}^{storage}$	CPU, memory, storage space of edge device j allocated to user i, respectively
C_j^{cpu}, C_j^{ram}, $C_j^{storage}$	The maximum capacity of CPU, memory, storage space of edge device j
ξ_j^{cpu}, ξ_j^{ram}, $\xi_j^{storage}$	The price of CPU, memory, storage space of edge device j per unit of resource
I_i^{cpu}, I_i^{ram}, $I_i^{storage}$	The total tasks of CPU, memory, storage space of user i
B_i	The budget of user i

of CPU, RAM, and STORAGE SPACE which donate C_j^{cpu}, C_j^{ram}, $C_j^{storage}$ and the unit prices of these resources donate ξ_j^{cpu}, ξ_j^{ram}, $\xi_j^{storage}$. There are N users in the end user layer. Each one wants to get services from the vehicular social edge computing layer. Each one has a task to process. To process the tasks of user i, the resource consumption is I_i^{cpu}, I_i^{ram}, $I_i^{storage}$ and his total budget is up to B_i. Each user can get service from any edge device. So w_{ij}^{cpu}, w_{ij}^{ram}, $w_{ij}^{storage}$ are the payments of user i to edge device j for CPU, RAM and STORAGE SPACE required by a service, and x_{ij}^{cpu}, x_{ij}^{ram}, $x_{ij}^{storage}$ are the CPU, RAM and STORAGE SPACE of edge device j required by a service for user i, respectively. The detailed explanation of each parameter is shown in table 1.

A certain task is divided into pieces and assigned to every device. So the time delay for process one task is $\sum_j \left(I_i^{cpu}\xi_j^{cpu}/w_{ij}^{cpu} + I_i^{ram}\xi_j^{ram}/w_{ij}^{ram} + I_i^{storage}\xi_j^{storage}/w_{ij}^{storage} \right)$. There are N tasks needing to process, so the total processing time can be modeled as:

$$\begin{aligned} &\textbf{Min} \sum_i \sum_j \left(\frac{I_i^{cpu}\xi_j^{cpu}}{w_{ij}^{cpu}} + \frac{I_i^{ram}\xi_j^{ram}}{w_{ij}^{ram}} + \frac{I_i^{storage}\xi_j^{storage}}{w_{ij}^{storage}} \right) \\ &\text{Subject to } \sum_j \left(w_{ij}^{cpu} + w_{ij}^{ram} + w_{ij}^{storage} \right) \le B_i, \quad i \in I \\ &\text{Over } w_{ij}^{cpu}, w_{ij}^{ram}, w_{ij}^{storage} \ge 0, \quad i \in I,\ j \in J \end{aligned} \tag{1}$$

If this model is solved, the optimal payment of each user to each edge device for CPU, RAM, and STORAGE SPACE required by one task is gotten.

The VSEC utility is related to the optimal payment, the resource consumption, the number of devices, and the number of users. The services provide by the VSEC are elastic services. According to the service model mentioned in [37], The VSEC utility can be built as:

$$\begin{aligned}
&\textbf{Max} \sum_i \sum_j \begin{pmatrix} w_{ij}^{\text{cpu}} \log(x_{ij}^{\text{cpu}}+1) + w_{ij}^{\text{ram}} \log(x_{ij}^{\text{ram}}+1) \\ + w_{ij}^{\text{storage}} \log(x_{ij}^{\text{storage}}+1) \end{pmatrix} \\
&\text{Subject to } \sum_i x_{ij}^{\text{cpu}} \le C_j^{\text{cpu}}, j \in J \\
&\qquad \sum_i x_{ij}^{\text{ram}} \le C_j^{\text{ram}}, \quad j \in J \\
&\qquad \sum_i x_{ij}^{\text{storage}} \le C_j^{\text{storage}}, \quad j \in J \\
&\text{Over } x_{ij}^{\text{cpu}}, x_{ij}^{\text{ram}}, x_{ij}^{\text{storage}} \ge 0, \quad i \in I,\ j \in J
\end{aligned} \tag{2}$$

The two key models are built. In the next Section, they will be solved to get the optimal solutions.

IV. THE SOLVING PROCESS OF THE BUILT MODELS

This Section mainly processes the built models. Analyzing the characteristics of the model in equation (1), we can get that it is a convex programming problem. The objective function is a concave function and the constraint condition is linear. The globally unique optimum ($w_{ij}^{\text{cpu}*}$, $w_{ij}^{\text{ram}*}$, $w_{ij}^{\text{storage}*}$) can be obtained through Lagrangian method.

According to the Lagrangian theory, the Lagrangian function of equation (1) can be written as

$$\begin{aligned}
L^{user} &= \sum_i \sum_j \left(\frac{I_i^{\text{cpu}} \xi_j^{\text{cpu}}}{w_{ij}^{\text{cpu}}} + \frac{I_i^{\text{ram}} \xi_j^{\text{ram}}}{w_{ij}^{\text{ram}}} + \frac{I_i^{\text{storage}} \xi_j^{\text{storage}}}{w_{ij}^{\text{storage}}} \right) \\
&\quad + \sum_i \lambda_i \left(\sum_j \left(w_{ij}^{\text{cpu}} + w_{ij}^{\text{ram}} + w_{ij}^{\text{storage}} \right) - B_i \right)
\end{aligned} \tag{3}$$

Solving this Lagrangian function (see the Appendix A), the globally unique optimal outcome of $w_{ij}^{\text{cpu}*}$, $w_{ij}^{\text{ram}*}$, $w_{ij}^{\text{storage}*}$ can be gotten as:

$$\begin{cases}
w_{ij}^{\text{cpu}*} = \dfrac{\left(I_i^{\text{cpu}} \xi_j^{\text{cpu}}\right)^{1/2} B_i}{\varphi} \\
w_{ij}^{\text{ram}*} = \dfrac{\left(I_i^{\text{ram}} \xi_j^{\text{ram}}\right)^{1/2} B_i}{\varphi} \\
w_{ij}^{\text{storage}*} = \dfrac{\left(I_i^{\text{storage}} \xi_j^{\text{storage}}\right)^{1/2} B_i}{\varphi}
\end{cases} \tag{4}$$

where

$$\varphi = \sum_j \left(\left(I_i^{\text{cpu}} \xi_j^{\text{cpu}}\right)^{1/2} + \left(I_i^{\text{ram}} \xi_j^{\text{ram}}\right)^{1/2} + \left(I_i^{\text{storage}} \xi_j^{\text{storage}}\right)^{1/2} \right)$$

We look into the characteristics of the model in equation (2). The objective function is a concave function and the constraint condition is linear. So the model is a strict convex optimization problem and exists the optimal solution. According to the Lagrangian theory, the Lagrangian function of equation (2) can be written as:

$$\begin{aligned}
L^{fog} &= \sum_i \sum_j \begin{pmatrix} w_{ij}^{\text{cpu}} \log(x_{ij}^{\text{cpu}}+1) + w_{ij}^{\text{ram}} \log(x_{ij}^{\text{ram}}+1) \\ + w_{ij}^{\text{storage}} \log(x_{ij}^{\text{storage}}+1) \end{pmatrix} \\
&\quad + \sum_j \phi_j^{\text{cpu}} \left(C_j^{\text{cpu}} - \sum_i x_{ij}^{\text{cpu}} \right) \\
&\quad + \sum_j \varphi_j^{\text{ram}} \left(C_j^{\text{ram}} - \sum_i x_{ij}^{\text{ram}} \right) \\
&\quad + \sum_j \gamma_j^{\text{storage}} \left(C_j^{\text{storage}} - \sum_i x_{ij}^{\text{storage}} \right)
\end{aligned} \tag{5}$$

Solving this Lagrangian function (see the Appendix B), the globally unique optimal outcome of $\phi_j^{\text{cpu}*}$, $x_{ij}^{\text{cpu}*}$, $\varphi_j^{\text{ram}*}$, $x_{ij}^{\text{ram}*}$, $\phi_j^{\text{storage}*}$, $x_{ij}^{\text{storage}*}$ can be gotten as:

$$\begin{cases}
\phi_j^{\text{cpu}*} = \dfrac{\sum_i w_{ij}^{\text{cpu}}}{C_j^{\text{cpu}} + |I|} \\
\varphi_j^{\text{ram}*} = \dfrac{\sum_i w_{ij}^{\text{ram}}}{C_j^{\text{ram}} + |I|} \\
\phi_j^{\text{storage}*} = \dfrac{\sum_i w_{ij}^{\text{storage}}}{C_j^{\text{storage}} + |I|}
\end{cases} \tag{6}$$

$$\begin{cases}
x_{ij}^{\text{cpu}*} = \dfrac{w_{ij}^{\text{cpu}} \left(C_j^{\text{cpu}} + |I|\right)}{\sum_i w_{ij}^{\text{cpu}}} - 1 \\
x_{ij}^{\text{ram}*} = \dfrac{w_{ij}^{\text{ram}} \left(C_j^{\text{ram}} + |I|\right)}{\sum_i w_{ij}^{\text{ram}}} - 1 \\
x_{ij}^{\text{storage}*} = \dfrac{w_{ij}^{\text{storage}} \left(C_j^{\text{storage}} + |I|\right)}{\sum_i w_{ij}^{\text{storage}}} - 1
\end{cases} \tag{7}$$

Until now, the two built models are solved. In the next Section, the numerical simulations are carried out to show the efficient performance of our proposed method.

V. NUMERICAL SIMULATION AND ANALYSIS

In this Section, numerical simulations will be carried out to show the good performance of the proposed scheme. As mentioned in Section 3.1, we only consider the stationary situation. The network topology keeps the same when serves the users. This assumption is restricted. However, it is make sense, for during a short period of time, the locations of the vehicles do keep unchanged. For longer time, the topology will change by the vehicular mobility. How to optimize the proposed scheme to fit the dynamic condition will be the future research. The evaluations are under different environments and parameters. In the first part, we will simulate the optimal payment of user i to edge device j for CPU, RAM

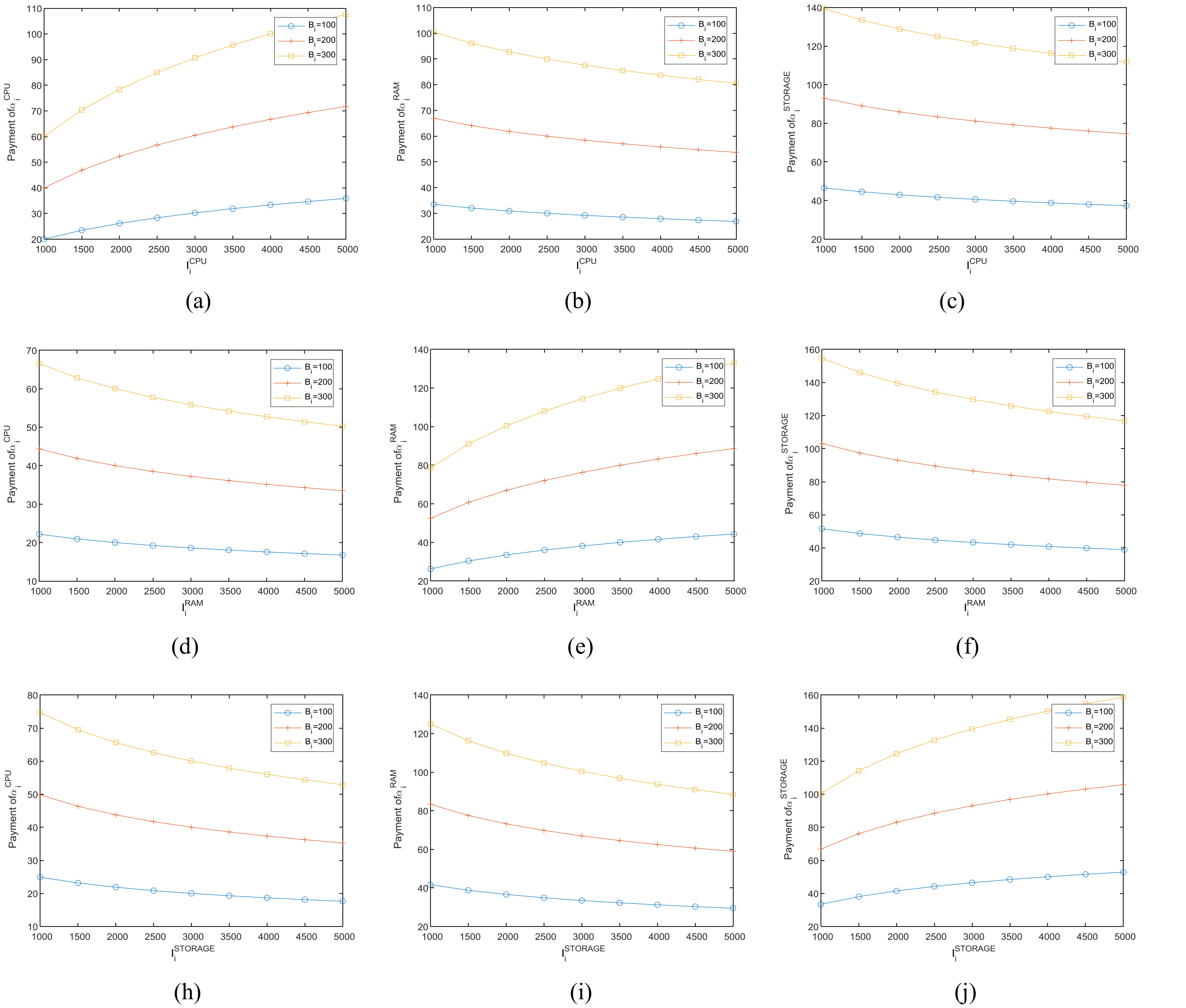


FIGURE 2. **The payment of the user to the edge devices under identical price**

and STORAGE SPACE required by a service. This can be further divided into two parts of sub-simulation. In the first sub-simulation, the price of all the edge devices are identical in CPU, RAM and STORAGE SPACE, respectively, and the second sub-simulation considers the hierarchical price. In the second part, we will simulate the optimal CPU, RAM and STORAGE SPACE of edge device j allocated to user i, respectively. This can be also divided into two parts of sub-simulation with hierarchical or identical prices in CPU, RAM and STORAGE SPACE.

A. THE OPTIMAL PAYMENT OF A USER TO THE EDGE DEVICES

In this sub-section, we will carried out the first simulation. The values of the basic parameters are shown in table 2.

Firstly, the simulation is carried out with considering the price of all the edge devices are identical in CPU, RAM and

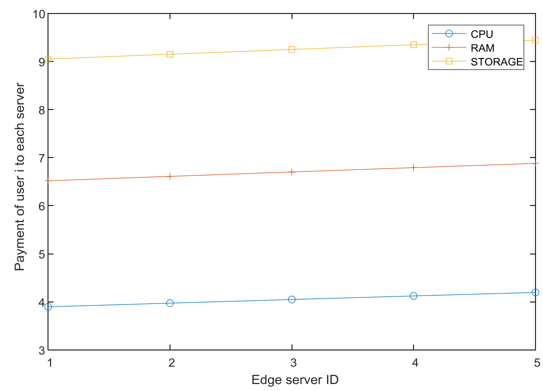


FIGURE 3. **The payment of the user to each edge devices under hierarchical price**

STORAGE SPACE, respectively. The values of the following two kinds of parameters are changing. The value of user

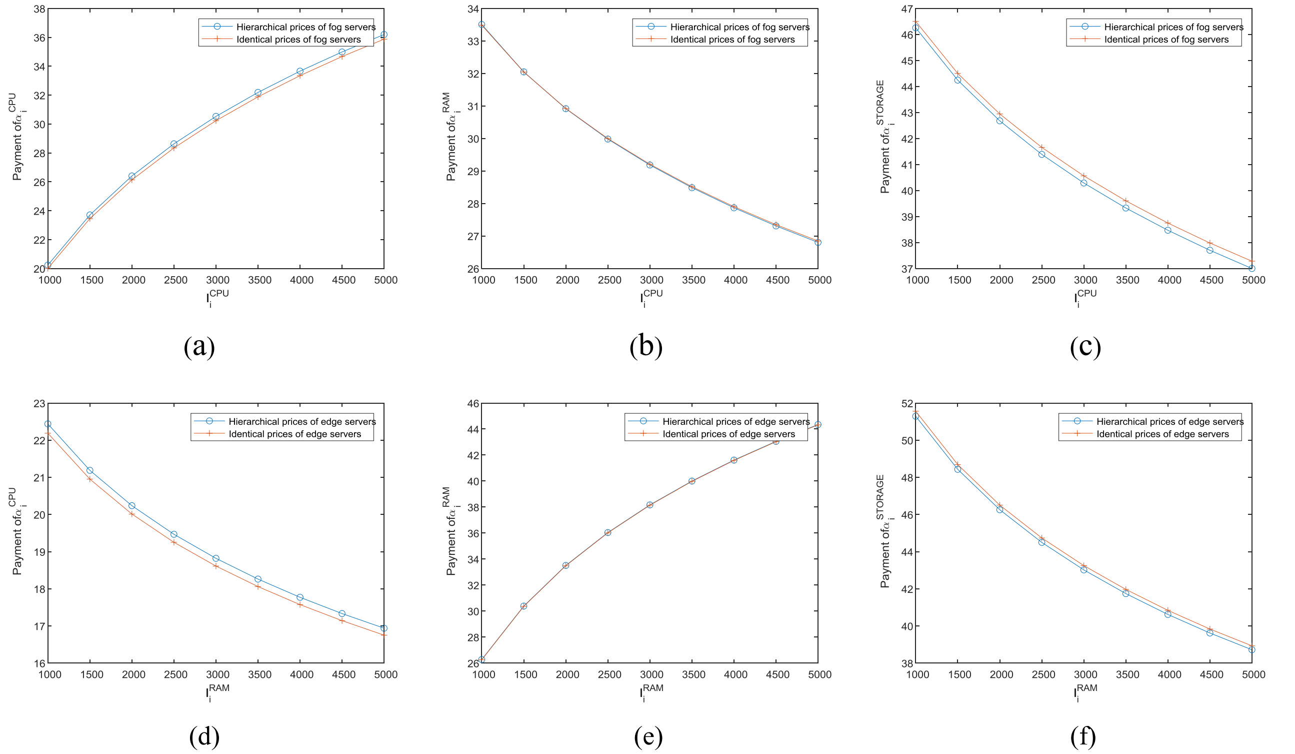


FIGURE 4. **The payment of the user to the edge devices under different Scenarios.**

TABLE 2. **Parameters used in the payment allocation model.**

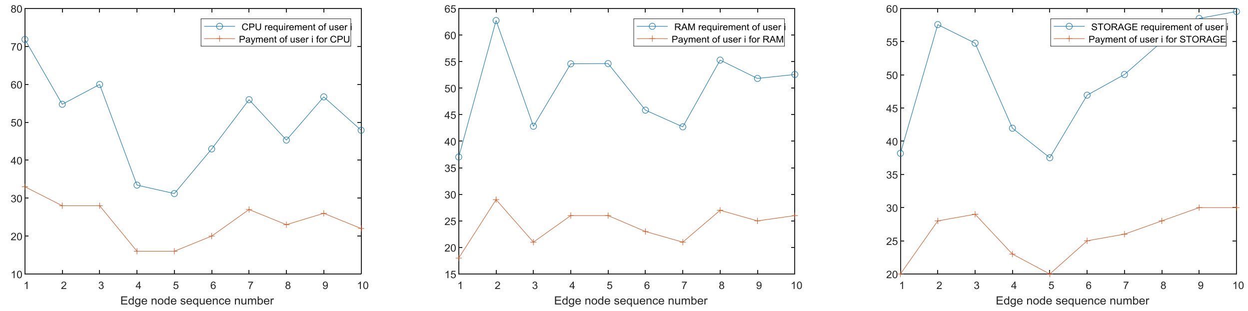
Symbol	Notation	Value
w_{ij}^{cpu} , w_{ij}^{ram} , $w_{ij}^{storage}$	Payment of user i to edge device j for CPU, memory, storage space required by a task, respectively	Needing to be optimized
ξ_j^{cpu} , ξ_j^{ram} , $\xi_j^{storage}$	The price of CPU, memory, storage space of edge device j per unit of resource	5, 7, 9
I_i^{cpu} , I_i^{ram} , $I_i^{storage}$	The total tasks of CPU, memory, storage space of user i	1000, 2000, 3000
B_i	The budget of user i	100
J	The number of edge devices	5

5	8	6	7	7	2	3	4	5	4	2	3	6	4	5
2	9	1	7	9	3	6	7	7	6	6	7	4	2	9
6	7	4	6	5	5	3	6	4	3	6	3	8	9	3
3	4	4	1	4	5	6	1	7	7	5	2	8	6	2
4	6	2	2	2	5	7	6	5	3	4	6	3	5	2
6	2	2	4	6	8	2	4	1	8	6	5	6	6	2
3	8	4	5	7	5	3	8	2	3	6	5	6	5	4
3	8	2	6	4	9	3	1	7	7	6	6	5	6	5
6	8	6	4	2	6	6	5	5	3	6	7	8	5	4
3	3	5	8	3	9	8	4	2	3	9	4	3	7	7
		CPU					RAM					STORAGE		

FIGURE 5. **The values of w_{ij}^{cpu}.**

budget is 100, 200 or 300. The value of each user's total tasks in CPU, RAM and STORAGE SPACE are changing within the range of [1000, 5000]. The outcome is shown in figure 2.

From figure 2, we can get the following conclusions. In figure 2 (a), (b) and (c), the value of each user's total tasks using CPU changes within the range of [1000, 5000] and the value of user budget is 100, 200 or 300. This indicates two points. Firstly, when the total tasks of CPU are increasing, the user should pay more on the CPU. This results in the decreasing of the shared budget of RAM and STORAGE SPACE. The explanation is that the CPU is the dominant resource in this circumstance. Only this budget allocation scheme can reduce the total processing time to minimal. Secondly, when the users' budget is increasing, all the shared budget of CPU, RAM and STORAGE SPACE increase. The reason is that when the user allows a higher budget, he should pay the money as much as possible to bring down the processing time. In figure 2 (d), (e) and (f), the value of each user's total task in RAM changes and in figure 2 (g), (h) and (i), the value



(a) (b) (c)

FIGURE 6. The resource payment and shared resources of each user

of each user's total task in STORAGE SPACE changes. The same conclusion can be drawn as in (a), (b) and (c).

Secondly, the simulation is carried out considering the price of all the edge devices being hierarchical in CPU, RAM and STORAGE SPACE, respectively. The price of the three resources of the first edge device per unit of resource is [5, 7, 9], and the values increase with a step of 0.2. There are 5 edge devices, so the last edge device with the value vector is of [5.8, 7.8, 9.8]. The budget of the user is 100. Figure 3 shows the user payment to each edge device.

From figure 3, we can get that if the edge device increases the price of the three resources, it can get more payment from users. The explanation is that if the user wants to bring down the processing time, he will need to optimally allocate his budget. The more money he spends on expensive resources, the quicker he finishes his tasks. Furthermore, we can see that due to the price decreasing of CPU, RAM and STORAGE SPACE, the allocated payment of the three resources will also decrease.

Next, the hierarchical and the identical price Scenarios are compared. Figure 4 (a), (b) and (c) simulate payments of the users under hierarchical and identical prices. In the hierarchical pricing Scenarios, the value of each user's total task using CPU changes within the range of [1000, 5000] and the value of user budget is 100. Figure 4 (d), (e) and (f) simulate the same parameters with the changing factor being RAM.

From figure 4, we can understand that the payments of the user under hierarchical price and identical price Scenarios are more or less the same. The reason is that from the user's view, the only aim is to process the tasks as quick as possible and the budget should be allocated according to the proportion of CPU, RAM and STORAGE SPACE. In this simulation, the proportion is almost the same under hierarchical price and the identical price Scenarios. The final budget allocations show no much difference.

B. THE OPTIMAL RESOURCE ALLOCATION OF EDGE DEVICES TO USERS

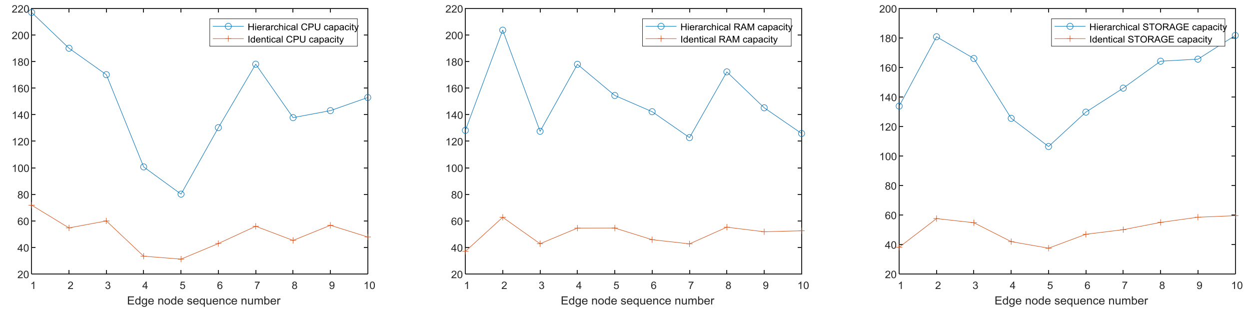
In this sub-section, we carried out with the second part simulation which is the optimal CPU, RAM and STORAGE SPACE of an edge device required by a service for a certain user. The values of the basic parameters are shown in table 3.

TABLE 3. Parameters used in the model.

Symbol	Notation	Value
w_{ij}^{cpu} , w_{ij}^{ram} , $w_{ij}^{storage}$	Payment of user i to edge device j for CPU, memory, storage space required by a task, respectively	Shown in Fig. 5
x_{ij}^{cpu} , x_{ij}^{ram} , $x_{ij}^{storage}$	CPU, memory, storage space of edge device j allocated to user i , respectively	Needing to be optimized
C_j^{cpu} , C_j^{ram} , $C_j^{storage}$	The maximum capacity of CPU, memory, storage space of edge device j	100, 100, 100
N	The number of users	10
j	The number of edge devices	5

Firstly, the simulation is carried out with considering the maximum capacity of all the edge devices being identical in CPU, RAM and STORAGE SPACE, respectively. The payment of the user to an edge device for each resource required by a task is optimally determined according to equation (9) and we assume the values are as in figure 5. The graph's horizontal axis is the edge device and the vertical axis is the user. There are 5 edge devices and 10 users in the VSEC. The first part is the optimal payment of each user to each edge device considering the CPU resource. The second and third parts are the same mean considering RAM or STORAGE resource. According to the equation (7), the optimal resource allocation of edge devices to users can be gotten which is shown in figure 6.

From figure 6, we can get that the allocated resources among the 10 users are different owing to the user's payment is different from each resource while the trends are similar.. The reason is that the optimal user payment for each resource is obtained by using equation (9) aimed at minimizing the



(a) (b) (c)

FIGURE 7. The resource allocation under different Scenarios

time delay. The optimal budget is different, so the allocated resources should be different. If one has more budget, he will have more freedom to get the resources he wants. Then, the trends of resource payment and shared resources are almost the same.

Next, the hierarchical and the identical maximum capacities Scenarios are compared. Figure 7 simulates the optimal resources allocation under hierarchical and identical maximum capacities. In the hierarchical maximum capacities Scenario, the value of each edge device capacities of each resource changes within the range of [100, 500].

From figure 7, we can get that the trends of the hierarchical and identical maximum capacities Scenarios are almost the same and the variance of the hierarchical scheme is higher than the identical one. The reason lies in the optimal resource allocation is determined by optimal user payment. Owing to these two schemes using the same user payment assumption, the trends remain the same. The variance of the hierarchical scheme being higher is caused by different maximum capacities.

VI. CONCLUSION

In this work, we studied the Cloud-enhanced vehicular network, which processes the produced data based on centralized cloud computing modes. Since it might waste core network bandwidth and long latency. The vehicular edge computing is proposed to overcome these shortcomings. Besides, the drivers' social activity is used to further improve the performance of vehicular network. We defined this new paradigm as VSEC. It is noticed that this work mainly focused on how to improve the system performance by maximum the system utility. Moreover, a total processing time minimization problem was studied. By utilizing the Lagrangian method, the closed-form expressions of the optimal solutions were obtained. To verify the efficiency of our novel scheme, numerical simulations were executed, by which different capacities in multiple scenarios were discussed.

In this paper, the resource management is carried out in stationary situation. The mobility of the vehicles does not take into consider. How to optimize the proposed scheme to fit the dynamic environment is the future research.

APPENDIX

A. OPTIMAL SOLUTION OF EQUATION (3)

To solve the function of equation (3), derivatives L^{user} with respect to $w_{ij}^{\text{cpu}^*}$, $w_{ij}^{\text{ram}^*}$, $w_{ij}^{\text{storage}^*}$, λ_i in it are:

$$\begin{cases} \dfrac{\partial L^{user}}{\partial w_{ij}^{\text{cpu}^*}} = \dfrac{I_i^{\text{cpu}}\xi_j^{\text{cpu}}}{\left(w_{ij}^{\text{cpu}^*}\right)^2} - \lambda_i^* = 0 \\ \dfrac{\partial L^{user}}{\partial w_{ij}^{\text{ram}^*}} = \dfrac{I_i^{\text{ram}}\xi_j^{\text{ram}}}{\left(w_{ij}^{\text{ram}^*}\right)^2} - \lambda_i^* = 0 \\ \dfrac{\partial L^{user}}{\partial w_{ij}^{\text{storage}^*}} = \dfrac{I_i^{\text{storage}}\xi_j^{\text{storage}}}{\left(w_{ij}^{\text{storage}^*}\right)^2} - \lambda_i^* = 0 \\ \lambda_i^*\left(B_i - \sum_j \left(w_{ij}^{\text{cpu}^*} + w_{ij}^{\text{ram}^*} + w_{ij}^{\text{storage}^*}\right)\right) = 0 \end{cases} \tag{8}$$

According the first equation in equation (8), the optimal expression of λ_i^* or $w_{ij}^{\text{cpu}^*}$ is:

$$\lambda_i^* = \frac{I_i^{\text{cpu}}\xi_j^{\text{cpu}}}{\left(w_{ij}^{\text{cpu}^*}\right)^2}, \quad or\ w_{ij}^{\text{cpu}*} = \left(\frac{I_i^{\text{cpu}}\xi_j^{\text{cpu}}}{\lambda_i^*}\right)^{1/2} \tag{9}$$

Using this same method, the optimal expression $w_{ij}^{\text{ram}*}$ and $w_{ij}^{\text{storage}^*}$ can be gotten.

Owing to $\lambda_i^* > 0$, according the last equation in equation (8), we can get

$$B_i - \sum_j \left(w_{ij}^{\text{cpu}^*} + w_{ij}^{\text{ram}^*} + w_{ij}^{\text{storage}^*}\right) = 0 \tag{10}$$

Substituting the $w_{ij}^{\text{cpu}^*}$, $w_{ij}^{\text{ram}^*}$, $w_{ij}^{\text{storage}^*}$ into equation (10), and we get:

$$\frac{1}{\left(\lambda_i^*\right)^{1/2}} \sum_j \left(\begin{array}{l} \left(I_i^{\text{cpu}}\xi_j^{\text{cpu}}\right)^{1/2} + \left(I_i^{\text{ram}}\xi_j^{\text{ram}}\right)^{1/2} \\ + \left(I_i^{\text{storage}}\xi_j^{\text{storage}}\right)^{1/2} \end{array}\right) = B_i \tag{11}$$

Solving the equation (11), the optimal value of λ_i^* is

$$\lambda_i^* = \frac{\left(\sum_j \left(\left(I_i^{cpu}\xi_j^{cpu}\right)^{1/2} + \left(I_i^{ram}\xi_j^{ram}\right)^{1/2} + \left(I_i^{storage}\xi_j^{storage}\right)^{1/2}\right)\right)^2}{B_i^2} \quad (12)$$

Substituting the value of λ_i^* into equation (9), the globally unique optimal outcome of $w_{ij}^{cpu^*}$, $w_{ij}^{ram^*}$, $w_{ij}^{storage^*}$ is:

$$\begin{cases} w_{ij}^{cpu^*} = \dfrac{\left(I_i^{cpu}\xi_j^{cpu}\right)^{1/2} B_i}{\varphi} \\ w_{ij}^{ram^*} = \dfrac{\left(I_i^{ram}\xi_j^{ram}\right)^{1/2} B_i}{\varphi} \\ w_{ij}^{storage^*} = \dfrac{\left(I_i^{storage}\xi_j^{storage}\right)^{1/2} B_i}{\varphi} \end{cases} \quad (13)$$

where

$$\varphi = \sum_j \left(\left(I_i^{cpu}\xi_j^{cpu}\right)^{1/2} + \left(I_i^{ram}\xi_j^{ram}\right)^{1/2} + \left(I_i^{storage}\xi_j^{storage}\right)^{1/2}\right)$$

The optimal solution in equation (3) is achieved.

B. OPTIMAL SOLUTION OF EQUATION (5)

To solve the function of equation (5), derivatives L^{fog} with respect to x_{ij}^{cpu}, x_{ij}^{ram}, $x_{ij}^{storage}$ in it are:

$$\begin{cases} \dfrac{\partial L^{fog}}{\partial x_{ij}^{cpu^*}} = \dfrac{w_{ij}^{cpu}}{x_{ij}^{cpu^*}+1} - \phi_j^{cpu^*} = 0 \\ \dfrac{\partial L^{fog}}{\partial x_{ij}^{ram^*}} = \dfrac{w_{ij}^{ram}}{x_{ij}^{ram^*}+1} - \phi_j^{ram^*} = 0 \\ \dfrac{\partial L^{fog}}{\partial x_{ij}^{storage^*}} = \dfrac{w_{ij}^{storage}}{x_{ij}^{storage^*}+1} - \phi_j^{storage^*} = 0 \end{cases} \quad (14)$$

The derivatives of ϕ_j^{cpu}, φ_j^{ram}, $\gamma_j^{storage}$ in equation (5) are:

$$\begin{cases} \phi_j^{cpu^*}\left(C_j^{cpu} - \sum_i x_{ij}^{cpu^*}\right) = 0 \\ \varphi_j^{ram^*}\left(C_j^{ram} - \sum_i x_{ij}^{ram^*}\right) = 0 \\ \gamma_j^{storage^*}\left(C_j^{storage} - \sum_i x_{ij}^{storage^*}\right) = 0 \end{cases} \quad (15)$$

Solving the equation (14), the optimal expression of $\phi_j^{cpu^*}$ and $x_{ij}^{cpu^*}$ are:

$$\phi_j^{cpu^*} = \frac{w_{ij}^{cpu}}{x_{ij}^{cpu^*}+1} \quad or\ x_{ij}^{cpu^*} = \frac{w_{ij}^{cpu}}{\phi_j^{cpu^*}} - 1 \quad (16)$$

Owing to $\phi_j^{cpu^*} > 0$, solving the equation (15), we can get

$$C_j^{cpu} - \sum_i x_{ij}^{cpu^*} = 0 \quad (17)$$

which is

$$\sum_i x_{ij}^{cpu^*} = \sum_i \left(\frac{w_{ij}^{cpu}}{\phi_j^{cpu^*}} - 1\right) = C_j^{cpu} \quad (18)$$

Solving the equation (18), the optimal value of $\phi_j^{cpu^*}$ is

$$\phi_j^{cpu^*} = \frac{\sum_i w_{ij}^{cpu}}{C_j^{cpu} + |I|} \quad (19)$$

where $|I|$ is the number of users.

Using the equation (16) and the optimal value of $\phi_j^{cpu^*}$ in equation (19), the optimal value of $x_{ij}^{cpu^*}$ is gotten as

$$x_{ij}^{cpu^*} = \frac{w_{ij}^{cpu}\left(C_j^{cpu} + |I|\right)}{\sum_i w_{ij}^{cpu}} - 1 \quad (20)$$

Using the same method, the other four optimal values can be gotten as

$$\varphi_j^{ram^*} = \frac{\sum_i w_{ij}^{ram}}{C_j^{ram} + |I|}, \qquad x_{ij}^{ram^*} = \frac{w_{ij}^{ram}\left(C_j^{ram} + |I|\right)}{\sum_i w_{ij}^{ram}} - 1 \quad (21)$$

$$\phi_j^{storage^*} = \frac{\sum_i w_{ij}^{storage}}{C_j^{storage} + |I|}, \qquad x_{ij}^{storage^*} = \frac{w_{ij}^{storage}\left(C_j^{storage} + |I|\right)}{\sum_i w_{ij}^{storage}} - 1 \quad (22)$$

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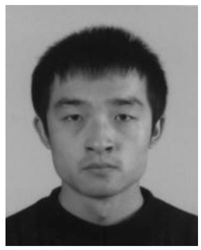
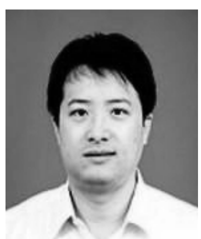
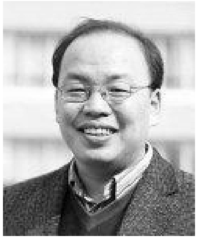


FUHONG LIN received the M.S. degree and the Ph.D. degree in electronics engineering from Beijing Jiaotong University, Beijing, China, in 2006 and 2010, respectively. He is currently an Associate Professor with the Department of Computer and Communication Engineering, University of Science and Technology Beijing, China. His research interests include edge/fog computing, network security, and big data. He has received the Provincial and Ministry Science and Technology Progress Award 2 in 2017. He also received the track Best Paper Award from the IEEE/ACM ICCAD 2017. Two of his papers have received the Top 100 of the Most Influential International Academic Papers in China in 2015 and 2016, respectively. He has served as the Co-Chair of the First and the Third IET International Conference on Cyberspace Technology and the General Chair of the Second IET International Conference on Cyberspace Technology. He was the Leading Guest Editor of the Special Issue *Recent Advances in Cloud-Aware Mobile Fog Computing for Wireless Communications and Mobile Computing*. He serves as Reviewer for over 20 international journals, including the IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, the IEEE ACCESS, *Information Sciences*, the IEEE INTERNET OF THINGS JOURNAL, *The Computer Journal*, and the IEEE CHINA COMMUNICATIONS.



XING LÜ received the Ph.D. degree in computer science and technology from the Beijing University of Posts and Telecommunications, Beijing, China, in 2012. He is currently a Professor with the Department of Communication Engineering, School of Computer and Communication Engineering, University of Science and Technology Beijing, China. His research interests include fog computing, optical soliton communication, and big data.



ILSUN YOU (SM'13) is currently with the Department of Information Security Engineering, Soonchunhyang University. His main research interests include Internet security, authentication, access control, and formal security analysis. He is a fellow of IET. He is the Editor-in-Chief of the *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*. He is on the Editorial Board of *Information Sciences*, the *Journal of Network and Computer Applications*, the *International Journal of Ad Hoc and Ubiquitous Computing*, *Computing and Informatics*, the *Journal of High Speed Networks*, *Intelligent Automation and Soft Computing*, and *Security and Communication Networks*. He has served or is currently serving as a Main Organizer for international conferences and workshops, such as MobiWorld, MIST, SeCIHD, and AsiaARES.

XIANWEI ZHOU received the B.S. degree from the Department of Mathematics, Southwest Normal University, in 1986, the M.S. degree from Zhengzhou University in 1992, and the Ph.D. degree from the Department of Transportation Engineering, Southwest Jiaotong University, China, in 1999. He was engaged in post-doctoral study at Beijing Jiaotong University, China, from 1999 to 2000. He is currently a Professor with the Department of Communication Engineering, School of Computer and Communication Engineering, University of Science and Technology Beijing, China. His research interests include the security of fog computing, network security, and big data.