Learning Cooperation Schemes for Mobile Edge Computing Empowered Internet of Vehicles

Jiayu Cao, Ke Zhang, Fan Wu, and Supeng Leng
School of Information and Communication Engineering
University of Electronic Science and Technology of China
liuda945@163.com, {zhangke, wufan, spleng}@uestc.edu.cn

***Abstract*—Intelligent Transportation System has emerged as a promising paradigm providing efficient traffic management while enabling innovative transport services. The implementation of ITS always demands intensive computation processing under strict delay constraints. Machine Learning empowered Mobile Edge Computing (MEC), which brings intelligent computing service to the proximity of smart vehicles, is a potential approach to meet the processing demands. However, directly offloading and calculating these computation tasks in MEC servers may seriously impair the privacy of end users. To address this problem, we propose federated learning empowered MEC schemes, which utilize onboard computation resources of smart vehicles and road side units for task processing while leveraging road side edge service to improve vehicular computing power in a privacy-protected way. Numerical results demonstrate the effectiveness of our schemes.**

***Index Terms*—Federated Learning, MEC, Vehicular networks**

I. Introduction

By integrating information and communication technologies into traffic management, Intelligent Transportation Systems (ITS) has emerged as an appealing paradigm to bring safe, efficient and sustainable transportation networks [1]. In the operation of ITS, various types of data, such as vehicle driving pattern, pedestrian behavior characteristics and road congestion states, are detected and analyzed, which constitute the information basis of traffic management and scheduling.

Along with the proliferation of smart vehicles and powerful traffic sensors, the amount of gathered data has evolved from terabytes to petabytes [2]–[4]. These massive data sets pose a critical challenge on ITS system to process them efficiently under strict delay constraints. Machine Learning (ML) empowered Mobile Edge Computing (MEC), which offers intelligent computation capabilities at the edge of mobile networks, is a potential approach to meet the data processing demands. In [5], the authors proposed a deep reinforcement learning based edge resource allocation strategy to achieve optimal costs of vehicular networks. In [6], the authors introduced an energy efficient computation task scheduling scheme in an enhanced learning approach. Although ML inspired edge computing brings an efficient approach to alleviate computation burdens of smart vehicles, the implementation of edge service requires task data be directly transmitted to MEC servers, and data privacy may be leaked during this transmission.

Federated Learning (FL) is a promising technique to address the security problem. FL secures data privacy through training learning model across multiple decentralized edge devices holding local data samples, without exchanging their data samples. Recently, a few works have been carried out focusing on FL. In [7], the authors investigated gradient descent based FL and minimized operation costs under resource budget constraints. The authors in [8] used multi-objective evolutionary algorithm to optimize the structure of neural network model in FL. In [9], the authors developed a FL-based communication network with dynamic, heterogeneous, and intermittent resource availability. In [10], the authors applied FL to edge computing system with dynamic workload and radio environment. In [11], the authors proposed a FL-enabled power and resource allocation scheme.

In the above works, FL is rarely used in vehicular networks and the authors always took the assumption that agents of FL are definite. However, as roadside computing and caching resources are distributed between the road side unit(RSU) and the vehicle, there are many options for agents in FL empowered MEC. Considering constrained onboard resources and complex vehicle communication environment, the agent choices may seriously undermine processing delay and costs performance. Thus, aforementioned monotonous calculating and offloading strategies that ignore the complexity of vehicular network are insufficient to accurately make FL empowered MEC agents selection. The main contribution of this work is listed as follows.

- We propose a FL empowered MEC architecture that combines FL with Internet of Vehicles to solve MEC problems.
- We propose an independent-agent selection scheme for FL in vehicular networkS, where the vehicle acts as its own agent.
- We extend independent-agent selection scheme to multi-agent selection scheme, where high-credibility vehicles and RSUs with MEC servers are considered, and design

This work was partly supported by National Key R&D Program of China (No.2018YFE0117500), the Opening Project of Shanghai Trusted Industrial Control Platform (No.2019YY201), the Key R&D Project of Sichuan Province (No.2019YFG0520), and the EU H2020 Project COSAFE (MSCA-RISE-2018-824019)

This is an early open access version, which will be submitted to IEEE WCNC 2020

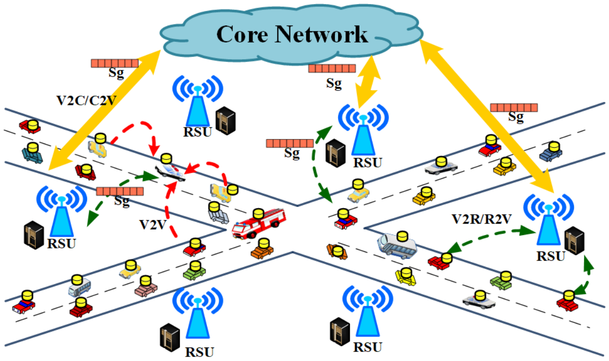

Fig. 1. FL empowered MEC in the vehicular network

an efficient task selection algorithm to minimize its costs.

The rest of the paper is organized as follows. The system model is presented in Section II. In Section III, we propose an independent-agent selection scheme. In Section IV, we propose a multi-agent selection scheme, formulate an optimization problem and design an efficient algorithm to solve it. We present numerical results in Section V and conclude the paper in Section VI.

II. SYSTEM MODEL

Fig. 1 shows the FL empowered MEC in vehicular networks. We consider that there are N vehicles on the road. The computing and caching capacities of each vehicle are denoted as f_v and c_v, respectively. Through real-time communication with surrounding vehicles and roadside sensors, vehicles can obtain much local traffic environment information, such as geographical location, traffic lights, vehicle speed, etc. These local data sets of local traffic environment information can be used by vehicles to model their driving path, driving speed, etc [12].

In addition, M RSUs equipped with MEC servers are randomly distributed along the road. All RSUs can provide computing and caching services for vehicles on the road, and their computing and caching capacities are denoted as $\{f_1^R, ..., f_M^R\}$ and $\{c_1^R, ..., c_M^R\}$, respectively.

In vehicular networks, the local traffic environment around vehicle changes dynamically. Due to the limited communication range of vehicle, the information that vehicle can collect independently is very limited. If vehicle v only processes its own local data set, then the automatic driving model established by vehicle v will be limited and not applicable to the dynamically changing traffic environment. Therefore, compared with the independent modeling of each vehicle, we prefer to use ML empowered MEC approach to merge and process local data sets of different vehicles in various traffic scenarios and give a suitable autonomous driving model for various traffic scenarios [13].

Although a ML empowered MEC approach can reach a good autonomous driving model, it does not protect the privacy of vehicles and may have a large communication costs. Thus, we consider adopting the FL empowered MEC approach to handle autonomous driving tasks in the vehicular networks. Different from other ML, FL is more flexible, more secure and more fault-tolerant, which can also reduce the communication pressure of the whole network. A FL-based autonomous driving task g can be described by four terms as $A_g = \{\sigma_g, \vartheta_g, s_g, T_g^{\max}\}$, where σ_g is the local accuracy of FL, ϑ_g is the global accuracy of FL, s_g is the size of parameters obtained after local training, and $T_g^{\max}$ is the maximum tolerable delay of task g.

The core network acts as the upper-level aggregation of FL and can communicate directly with the RSU. The transmission rates of RSU to the core network (R2C) and the core network to RSUs (C2R) are r_{R2C} and r_{C2R}, respectively. And the communication between the vehicle and the core network requires the RSU's forwarding functions. r_{R2V} and r_{V2R} are the transmission rates of RSUs to vehicles (R2V) and vehicles to RSUs(V2R), respectively. Moreover, different communication methods will generate different communication costs. The communication unit prices between vehicles and vehicles, vehicles and RSUs, and RSUs and core network can be denoted as w^{V2V}, $w_m^{V\leftrightarrow R}$ and $w_m^{R\leftrightarrow C}$ respectively. Due to the different location deployments and transmission distances of RSUs, the contact rates between various RSUs and vehicles are different, which are denoted as $\{\lambda_1^R, ..., \lambda_M^R\}$ respectively. The contact rate between the two vehicles is λ_v.

Since both vehicle and RSU can provide computing and caching resources for task g, they both can act as agents for the task. The different agent selection schemes will be described in detail below.

III. THE VEHICLE ACTS AS ITS OWN AGENT

The training process of FL in the vehicular network is mainly divided into four processes: 1) Agents are selected and each agent individually trains its own local sample data set until it reaches local accuracy σ_g. 2) The result parameters of local calculation are uploaded to the core network by the agent. 3) Each calculated result parameter is integrated in the core network. The new parameters after integration have the same size s_g and are downloaded by each agent for the new local iteration training. 4) Repeat steps 1 to 3 until global accuracy ϑ_g is reached at the core network. And in the local training of step 1, vehicles will provide agents with their local data sets of size d_{vg} for agents to train the model.

In this section, we propose a scheme that the smart vehicles act as their own agents. Each vehicle acts as a FL agent, processing and training its own local data set, and then communicates with the core network via different RSUs to update its training result parameters.

Time for vehicle v to compute its local data set once is

$$T_{self,v}^{comp} = \frac{d_{v,g}}{f_v}. \tag{1}$$

Time for vehicle v to upload the result parameters to the core network via RSU m is

$$T_{self,v,m}^{upload} = \frac{s_g}{r_{V2R}} + \frac{s_g}{r_{R2C}}. \tag{2}$$

Time for vehicle v to download the updated result parameters from the core network via RSU m is

$$T_{self,v,m}^{download} = \frac{s_g}{r_{C2R}} + \frac{s_g}{r_{R2V}}, \tag{3}$$

Thus, total time for vehicle v act as agent to complete task g via RSU m is

$$\begin{aligned} T_{self,v,m}^{total} = \tfrac{F(\vartheta_g)}{1-\sigma_g} \Big[& K\log\left(1/\sigma_g\right) T_{self,v}^{comp} + T_{self,v,m}^{upload} \\ & + T_{self,v,m}^{download} + 1/\lambda_m^R \Big]. \end{aligned} \tag{4}$$

$K\log\left(1/\sigma_g\right)$ is the number of local iterations of the vehicle [5], and positive constant K depends on the data size and condition number of task g. $F(\vartheta_g)/1-\sigma_g$ is the general upper bound on global iterations. And $1/\lambda_m^R$ is the time for the vehicle encountering RSU m.

Costs for vehicle v to complete task g via RSU m is mainly the communication costs, and can be denoted as

$$O_{self,v,m}^{total} = \frac{2F\left(\vartheta_g\right) s_g N}{1-\sigma_g} \left(w_m^{R\leftrightarrow V} + w^{R\leftrightarrow C}\right). \tag{5}$$

The task may have different costs and latency performance due to various parameter communication strategies. And the optimal FL empowered MEC in vehicular networks should minimize the total costs under delay constraint $T_g^{\max}$. Thus, the problem can be formulated as

$$\begin{aligned} \min_{p_{m,v}^{trans}} \quad & \sum_{m=1}^{M} p_{v,m}^{trans} O_{self,v,m}^{total} \\ s.t. C1 \quad & 0 \le p_{v,m}^{trans} \le 1, m \in M \\ C2 \quad & \sum_{m=1}^{M} p_{v,m}^{trans} T_{self,v,m}^{total} \le T_g^{\max} \\ C3 \quad & \sum_{m=1}^{M} p_{v,m}^{trans} = 1, m \in M, \end{aligned} \tag{6}$$

where, $p_{v,m}^{trans} \in \left\{p_{v,1}^{trans}, ..., p_{v,M}^{trans}\right\}$ is the probability that vehicle v selects RSU m to transmit parameters and communicate with the core network. Constraint C1 gives the ranges of decision variable $p_{v,m}^{trans}$. Constraint C2 indicates that vehicle should compute task g under its delay constraint, and constraint C3 indicates that the vehicle should select one of M RSUs as the uploading object. Using the traditional lagrangian multiplier method and KKT condition, the above optimization problem can be solved.

IV. MULTI-AGENT SELECTION SCHEME

In this section, we extend the independent-agent selection to the multi-agent selection scheme. We investigate the effects of multi-agent selection on costs and delay, and design a subgradient descent inspired algorithm to obtain the optimal agent selection and parameter communication strategies.

A. Costs and delay effects with multi-agent selection

Due to the complex communication environment of vehicular networks, as well as the caching and computing resources of RSUs and vehicles, in addition to the vehicle itself, the vehicle with high credibility can also be selected as the agent. We describe different possibilities as follows.

1) High-credibility vehicle as agent: In vehicular networks, there are quite a few vehicles with high social credibility, such as police vehicles, fire trucks, etc., which can act as agents to process data sets collected from surrounding vehicles and communicate with the core network via RSUs to update training parameters. Thus, compared to the scheme proposed in section III, when a high-credibility vehicle acts as the agent, there is an additional data collection process in which each ordinary vehicle will send its local data set to the agent. High-credibility vehicles select themselves as their agents.

Time for high-credibility vehicle n to collect data for task g is

$$T_{mul,v,n}^{collect} = p_{v,n}^{mul} N^* \left(\frac{d_{v,g}}{r_{V2V}} + \frac{1}{\lambda_v}\right), \tag{7}$$

where, $p_{v,n}^{mul}$ is the probability that ordinary vehicle selects high-credibility vehicle n as agent. r_{V2V} is the transmission rate of V2V. Thus, the amount of the vehicle that selects vehicle n as agent is $p_{v,n}^{mul} N^*$, where $N^* = N - N^{tru}$ and N^{tru} is the amount of the high-credibility vehicle. The rest of formula is time taken by vehicle n to collect a data set, and $1/\lambda_v$ is time for vehicle encountering.

Time for high-credibility vehicle n to compute the data set it collected once is

$$T_{mul,v,n}^{comp} = \left[p_{v,n}^{mul} N^* + 1\right] \frac{d_{v,g}}{f_v}. \tag{8}$$

where the upload and download time for high-credibility vehicle n to communicate with core network via RSU m are $T_{mul,v,n,m}^{upload} = \mathrm{s_g}/r_{V2R} + s_g/r_{R2C}$, and $T_{mul,v,n,m}^{download} = \mathrm{s_g}/r_{R2V} + s_g/r_{C2R}$ respectively

Total time for high-credibility vehicle n act as agent to complete task g via RSU m is

$$\begin{aligned} T_{mul,v,n,m}^{total} = \tfrac{F(\vartheta_g)}{1-\sigma_g} \Big[& K\log\left(1/\sigma_g\right) T_{mul,v,n}^{comp} + \\ & T_{mul,v,n,m}^{upload} + T_{mul,v,n,m}^{download} + \tfrac{1}{\lambda_m^R} \Big] + T_{mul,v,n}^{collect}. \end{aligned} \tag{9}$$

When the vehicle acts as its agent independently in section III, it only have to pay the communication costs. However, when the vehicle chooses to select a high-credibility vehicle or RSU as agent, it not only needs to pay the communication costs, but also needs to pay the computing and caching costs. And it is obvious that the selection of choosing a high-credibility vehicle or RSU as agent has significantly less communication costs than choosing vehicle itself as agent.

Total costs for high-credibility vehicle n act as agent to complete task g via RSU m is

$$\begin{aligned} O_{mul,v,n,m}^{total} = & p_{v,n}^{mul}\left(N^*\right) d_{v,g} w_{v,n}^{cache} \\ & + \tfrac{F(\vartheta_g) K \log(1/\sigma_g)}{1-\sigma_g} p_{v,n}^{mul} N^* d_{v,g} w_{v,n}^{comp} \\ & + \tfrac{2F(\vartheta_g) s_g}{1-\sigma_g} \left(w_m^{R\leftrightarrow V} + w^{R\leftrightarrow C}\right) \\ & + p_{v,n}^{mul} N^* d_{v,g} w^{V2V}, \end{aligned} \tag{10}$$

where, $w_{v,n}^{comp}$ is the unit price of computing resource of vehicle n. $w_{v,n}^{cache}$ is the unit price of caching resource of vehicle n. The first and second parts of formula are computing and caching costs when the vehicle chooses vehicle n as the agent. And the third part is the communication costs of this scheme.

2) RSU with MEC server as agent: In the urban traffic environment, many RSUs equipped with MEC servers are distributed around the road, which can provide a variety of computing and caching services for vehicles within their communication range. Thus, these RSUs can also act as the agents to process the data sets collected from surrounding vehicles, and communicate directly with the core network.

Vehicles that choose RSU m as their agent will first send their data sets to RSU m. Time for RSU m to collect data for task g is

$$T_{mul,R,m}^{collect} = p_{R,m}^{mul} N^* \left(\frac{d_{v,g}}{r_{V2R}} + \frac{1}{\lambda_m^R} \right). \tag{11}$$

$p_{R,m}^{mul}$ is the probability that the ordinary vehicle selcects RSU m as the agent.

Time for RSU m to compute the data sets once is

$$T_{mul,R,m}^{comp} = p_{R,m}^{mul} N^* \frac{d_{v,g}}{f_m^R}. \tag{12}$$

The upload and download time for RSU to communicate with core network are $T_{mul,R,m}^{upload} = 1/r_{R2C}$, and $T_{mul,R,m}^{download} = 1/r_{C2R}$ respectively.

Obviously, the effect of RSU acting as agent to handle task g on task delay is

$$\begin{aligned} T_{mul,R,m}^{total} = & \tfrac{F(\vartheta_g)}{1-\sigma_g} \Big[K \log\left(1/\sigma_g\right) T_{mul,R,m}^{comp} + \\ & T_{mul,R,m}^{upload} + T_{mul,R,m}^{download} \Big] + T_{mul,R,m}^{collect}. \end{aligned} \tag{13}$$

The effect of RSU as agent on costs is

$$\begin{aligned} O_{mul,R,m}^{total} = & \tfrac{F(\vartheta_g) K \log(1/\sigma_g)}{1-\sigma_g} p_{R,m}^{mul} N^* d_{v,g} w_{R,m}^{comp} \\ & + \tfrac{2F(\vartheta_g) s_g}{1-\sigma_g} w^{R\leftrightarrow C} + p_{R,m}^{mul} N^* d_{v,g} w_m^{R\leftrightarrow V} \\ & + p_{R,m}^{mul} N^* d_{v,g} w_{R,m}^{cache}. \end{aligned} \tag{14}$$

$w_{R,m}^{comp}$ is the unit price of computing resource of RSU m. $w_{R,m}^{cache}$ is the unit price of caching resource of RSU m. The first and third parts of formula are computing and caching costs when vehicle chooses RSU m as agent. The second part is the communication costs of this scheme.

B. Problem formulation and a sub-gradient descent approach

The task may have different costs and delay performance due to various communication strategies of parameters and agent selection schemes. For task g, costs and delay of FL empowered MEC in the vehicular network can be denoted as

$$\begin{aligned} O_g^{total} = & p_v^{self} \sum_{m=1}^{M} p_{v,m}^{trans} O_{self,v,m}^{total} + \sum_{m=1}^{M} p_{R,m}^{mul} \\ & O_{mul,R,m}^{total} + \sum_{n=1}^{N^{tru}} p_{v,n}^{mul} \sum_{m=1}^{M} p_{n,m}^{trans} O_{mul,v,n,m}^{total}, \end{aligned} \tag{15}$$

$$\begin{aligned} T_g^{total} = & p_v^{self} \sum_{m=1}^{M} p_{v,m}^{trans} T_{self,v,m}^{total} + \sum_{m=1}^{M} p_{R,m}^{mul} \\ & T_{mul,R,m}^{total} + \sum_{n=1}^{N^{tru}} p_{v,n}^{mul} \sum_{m=1}^{M} p_{n,m}^{trans} T_{mul,v,n,m}^{total}, \end{aligned} \tag{16}$$

where, p_v^{self} is the probability that vehicle chooses itself as agent. $p_{v,n}^{mul}$ is the probability that vehicle chooses high-credibility vehicle as agent. And $p_{R,m}^{mul}$ is the probability that vehicle chooses RSU as agent. $p_{n,m}^{trans}$ is the probability that high-credibility vehicle communicates with core network via RSU m.

The minimum costs of FL empowered MEC in vehicular network under maximum tolerable delay constraint can be formulated as

$$\begin{aligned} & \min_{\left\{p_v^{self}, p_{R,m}^{mul}, p_{v,n}^{mul}, p_{v,m}^{trans}, p_{n,m}^{trans}\right\}} O_g^{total} \\ & s.t. C1 \quad 0 \le p_v^{self}, p_{R,m}^{mul}, p_{v,n}^{mul}, p_{v,m}^{trans} \\ & \qquad\qquad , p_{n,m}^{trans} \le 1, n \in N^{tru}, \quad m \in M \\ & \quad C2 \quad T_g^{total} \le T_g^{\max} \\ & \quad C3 \quad \sum_{m=1}^{M} p_{v,m}^{trans} = 1 \\ & \quad C4 \quad \sum_{m=1}^{M} p_{n,m}^{trans} = 1, \quad n \in N^{tru} \\ & \quad C5 \quad p_v^{self} + \sum_{m=1}^{M} p_{R,m}^{mul} + \sum_{n=1}^{N^{tru}} p_{v,n}^{mul} = 1 \\ & \quad C6 \quad p_{v,n}^{mul} N^* d_{v,g} \le c_v, \quad n \in N^{tru} \\ & \quad C7 \quad p_{R,m}^{mul} N^* d_{v,g} \le c_m^R, \quad m \in M. \end{aligned} \tag{17}$$

Constraint C1 gives the ranges of decision variables. Constraint C2 indicates maximum tolerable delay constraint of task g. Constraint C3 and C4 indicate that if the vehicle as an agent wants to communicate with core network, it must be relayed through RSU. Constraint C5 indicates that each vehicle should select an object as its agent within the scope of RSUs, high-credibility vehicles, and itself. Constraints C6 and C7 indicate that the data set collected by vehicles and RSUs should not exceed their maximum caching capacities.

Since the target function in (17) contains the product of multiple variables, it is a non-convex problem. We consider using subgradient descent algorithm combined with lagrangian multiplier method to obtain the minimum costs strategy. The lagrangian relaxation function of target problem takes the form in (18), where $\mathbb{U} = \left\{U^1, U^2, ..., \mathbb{U}^{15}, \mathbb{U}^{16}\right\}, \mathbb{U} \in R, U^1, U^2, ..., \mathbb{U}^{10}, U^{11}, \mathbb{U}^{15}, \mathbb{U}^{16} \ge 0$. And $\mathbb{P} = \left\{p_v^{self}, p_{R,m}^{mul}, p_{v,n}^{mul}, p_{v,m}^{trans}, p_{n,m}^{trans}\right\}, n \in N^{tru}, m \in M$.

The Lagrangian dual problem of (18) under the domain constraint of dual variables can be denoted as

$$\begin{aligned} & \max_{\mathbb{U}} \ g\left(\mathbb{U}\right) = \max_{\mathbb{U}} \ \inf_{\mathbb{P}} \ L\left(\mathbb{P}, \mathbb{U}\right) \\ & s.t. \quad U^1, U^2, U^{11}, U^{12}, U^{14} \in R, \ \mathbb{U}^3, \mathbb{U}^4, \mathbb{U}^5, \mathbb{U}^6, \\ & \quad \mathbb{U}^{16} \in \mathbb{R}^{1\times M}, \mathbb{U}^7, \mathbb{U}^8, \mathbb{U}^{13}, \mathbb{U}^{15} \in \mathbb{R}^{1\times N^{tru}}, \ \mathbb{U}^9, \\ & \quad \mathbb{U}^{10} \in \mathbb{R}^{M\times N^{tru}}, U^1, U^2, \mathbb{U}^3, \mathbb{U}^4, \mathbb{U}^5, \mathbb{U}^6, \mathbb{U}^7, \mathbb{U}^8, \\ & \quad \mathbb{U}^9, \mathbb{U}^{10}, U^{11}, \mathbb{U}^{15}, \mathbb{U}^{16} \ge 0 \end{aligned} \tag{19}$$

By differentiating $L\left(\mathbb{P}, \mathbb{U}\right)$ with respect to p_v^{self}, $p_{R,m}^{mul}$, $p_{v,n}^{mul}$, $p_{v,m}^{trans}$, $p_{n,m}^{trans}$ and let them equal to zero under the constraints, we can get a feasible solution of $\inf_{\mathbb{P}} L\left(\mathbb{P}, \mathbb{U}\right)$ for the given multipliers $\mathbb{U}$. Then we update the multipliers $\mathbb{U}$ by

$$
\begin{aligned}
L(\mathbb{P},\mathbb{U}) = {} & O_g^{total} - U^1\left(p_v^{self}-1\right) + U^2 p_v^{self} - \sum_{m=1}^{M} U_m^3\left(p_{R,m}^{mul}-1\right) + \sum_{m=1}^{M} U_m^4 p_{R,m}^{mul} - \sum_{m=1}^{M} U_m^5\left(p_{v,m}^{trans}-1\right) + \\
& \sum_{m=1}^{M} U_m^6 p_{v,m}^{trans} - \sum_{n=1}^{N^{tru}} U_n^7\left(p_{v,n}^{mul}-1\right) + \sum_{n=1}^{N^{tru}} U_n^8 p_{v,n}^{mul} - \sum_{n=1}^{N^{tru}}\sum_{m=1}^{M} U_{n,m}^9\left(p_{n,m}^{trans}-1\right) + \sum_{n=1}^{N^{tru}}\sum_{m=1}^{M} U_{n,m}^{10} p_{n,m}^{trans} - \\
& U^{11}\left(T_g^{total}-T_g^{\max}\right) + U^{12}\left(\sum_{m=1}^{M} p_{v,m}^{trans}-1\right) + \sum_{n=1}^{N^{tru}} U_n^{13}\left(\sum_{m=1}^{M} p_{n,m}^{trans}-1\right) + U^{14}\left(p_v^{self} + \sum_{m=1}^{M} p_{R,m}^{mul} + \right. \\
& \left.\sum_{n=1}^{N^{tru}} p_{v,n}^{mul}-1\right) - \sum_{n=1}^{N^{tru}} U_n^{15}\left(p_{v,n}^{mul}\left(N-N^{tru}\right)d_{v,g}-c_v\right) - \sum_{m=1}^{M} U_m^{16}\left(p_{R,m}^{mul}\left(N-N^{tru}\right)d_{v,g}-c_m^R\right).
\end{aligned} \tag{18}
$$

subgradient descent to get the maximum value of $g(\mathbb{U})$, which can be denoted as (20),

$$
\begin{aligned}
&U^1(t+1) = \left[U^1(t) - \left(p_v^{self}-1\right)\tau\right]^+, \\
&U^2(t+1) = \left[U^2(t) + p_v^{self}\tau\right]^+, \\
&U_m^3(t+1) = \left[U_m^3(t) - \left(p_{R,m}^{mul}-1\right)\tau\right]^+, \\
&U_m^4(t+1) = \left[U_m^4(t) + p_{R,m}^{mul}\tau\right]^+, \\
&U_m^5(t+1) = \left[U_m^5(t) - \left(p_{v,m}^{trans}-1\right)\tau\right]^+, \\
&U_m^6(t+1) = \left[U_m^6(t) + p_{v,m}^{trans}\tau\right]^+, \\
&U_n^7(t+1) = \left[U_n^7(t) - \left(p_{v,n}^{mul}-1\right)\tau\right]^+, \\
&U_n^8(t+1) = \left[U_n^8(t) + p_{v,n}^{mul}\tau\right]^+, \\
&U_{n,m}^9(t+1) = \left[U_{n,m}^9(t) - \left(p_{n,m}^{trans}-1\right)\tau\right]^+, \\
&U_{n,m}^{10}(t+1) = \left[U_{n,m}^{10}(t) + p_{n,m}^{trans}\tau\right]^+, \\
&U^{11}(t+1) = \left[U^{11}(t) - \left(T_g^{total}-T_g^{\max}\right)\tau\right]^+, \\
&U^{12}(t+1) = U^{12}(t) + \left(\sum_{m=1}^{M} p_{v,m}^{trans}-1\right)\tau, \\
&U_n^{13}(t+1) = U_n^{13}(t) + \left(\sum_{m=1}^{M} p_{n,m}^{trans}-1\right)\tau, \\
&U^{14}(t+1) = U^{14}(t) + \left(p_v^{self} + \right. \\
&\qquad \left.\sum_{m=1}^{M} p_{R,m}^{mul} + \sum_{n=1}^{N^{tru}} p_{v,n}^{mul} - 1\right)\tau, \\
&U_n^{15}(t+1) = \left[U_n^{15}(t) - \left(p_{v,n}^{mul}N^*\ d_{v,g}-c_v\right)\tau\right]^+ \\
&U_m^{16}(t+1) = \left[U_m^{16}(t) - \left(p_{R,m}^{mul}N^*\ d_{v,g}-c_m^R\right)\tau\right]^+,
\end{aligned} \tag{20}
$$

where τ is step size of multipliers in each iterative update, and $[b]^+ = \max(b,0)$. The main steps of proposed optimal agent selection and parameters communication scheme of FL empowered MEC are shown in Algorithm 1.

Algorithm 1 Sub-gradient based multi-agent selection algorithm for FL empowered MEC in the vehicular network

Initializes the lagrangian multiplier sets $\mathbb{U}(t) = \left\{U^1(t), U^2(t), ..., \mathbb{U}^{15}(t), \mathbb{U}^{16}(t)\right\}$, $t=0$ under the constraint of (19)

for The number of iterations $t \in [0,1,2,...,t_{\max}]$ **do**

  Based on the multiplier sets $\mathbb{U}(t)$, solve the following equations,

$$
\begin{cases}
\frac{dL(\mathbb{P},\mathbb{U})}{dp_v^{self}} = \frac{dL(\mathbb{P},\mathbb{U})}{dp_{R,m}^{mul}} = \frac{dL(\mathbb{P},\mathbb{U})}{dp_{v,n}^{mul}} = 0 \\
\frac{dL(\mathbb{P},\mathbb{U})}{dp_{v,m}^{trans}} = \frac{dL(\mathbb{P},\mathbb{U})}{dp_{n,m}^{trans}} = 0 \\
\sum_{m=1}^{M} p_{v,m}^{trans} = 1 \\
\sum_{m=1}^{M} p_{n,m}^{trans} = 1, \quad n \in N^{tru} \\
p_v^{self} + \sum_{m=1}^{M} p_{R,m}^{mul} + \sum_{n=1}^{N^{tru}} p_{v,n}^{mul} = 1.
\end{cases}
$$

  Obtain the feasible solutions p_v^{self}, $p_{R,m}^{mul}$, $p_{v,n}^{mul}$, $p_{v,m}^{trans}$ and $p_{n,m}^{trans}$ of $\inf_{\mathbb{P}} L(\mathbb{P},\mathbb{U})$;

  Update the multiplier set $\mathbb{U}(t+1)$ in next iteration according to (20);

  if $\mathbb{U}(t+1) - \mathbb{U}(t) \le \varepsilon$ **then**

    Return p_v^{self}, $p_{R,m}^{mul}$, $p_{v,n}^{mul}$, $p_{v,m}^{trans}$ and $p_{n,m}^{trans}$;

    Break;

  else

    Continue;

  end if

end for

V. NUMERICAL RESULTS

In this section, we evaluate the performance of proposed independent-agent selection scheme and multi-agent selection scheme. We consider 5 RSUs with various contact rates λ_m^R, whose computing capacities are randomly taken from (250, 500) units. There are 200 vehicles on the road, eight of which are high-credibility vehicles. The computing capacities of these vehicles are uniformly distributed in (50,300) units. For the convenience of calculation, we consider that the global accuracy ϑ_g of generated autopilot task is fixed, and local accuracy σ_g is randomly chosen from (0.2,0.7) units.

Fig.2 compares the costs of task g with different selections of agents. Compared with the independent-agent scheme proposed in III, the random-agent selection and multi-agent selection which consider the effects of different agent choices and communication methods on delays and costs, have lower costs performence. And our proposed multi-agent selection scheme has the lowest costs than the other two schemes with various local accuracy. Thus, extending RSUs and high-credibility vehicles as agent candidates can greatly reduce the communication costs, and can also protect the privacy of vehicles. Moreover, since the global accuracy is fixed, the local accuracy will influence the number of local iterations and global iterations. The higher the local accuracy (closer to 1) is, the greater the number of global iterations will be. It

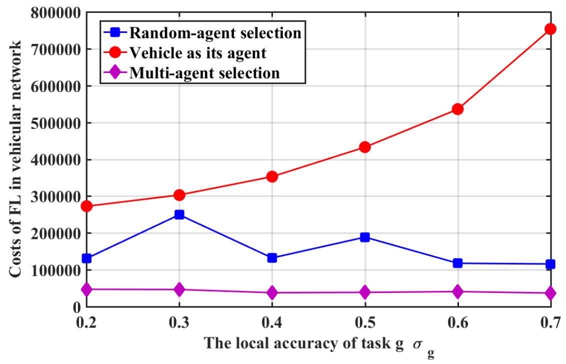

Fig. 2. Comparison on costs performance with different agent selections

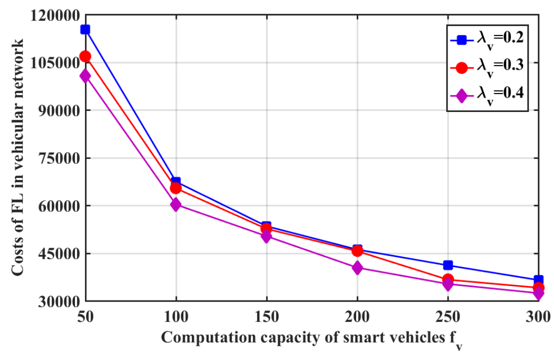

Fig. 3. Costs of task g with different computation capacity of smart vehicles f_v

can be seen from Fig.2 that the local accuracy has a significant impact on the costs of the independent-agent selection scheme, but has little effect on the multi-agent selection scheme, as exorbitant global iterations will lead to expensive communication costs. Therefore, the multi-agent selection scheme has better practicality in the complex vehicular network.

Fig.3 shows the impact of vehicle computing capacity and contact rate on system costs. As the vehicle's computing capacity increases, the task costs decreases. In most realistic scenarios, RSUs and high-credibility vehicles have lower communication costs as agents, but their performance on time delay is very poor and may not satisfy the delay constraint. However, this contradiction can be mitigated as the computing capacities of vehicles increase. Therefore, in this case, the vehicle is more likely to choose the vehicle with high credibility as its agent to obtain the optimal task costs. The performance of agent selection probability with increasing computation capacities of smart vehicles is shown in Fig.4 in detail. With the improvement of the computing capacities of vehicles, the average probability of choosing high-credibility vehicles as agents increases.

VI. CONCLUSION

In this paper, we investigated MEC problem based on FL algorithm in the vehicular network, and proposed two effective FL agent selection schemes. By leveraging subgradient descent algorithm combined with lagrangian multiplier method, we

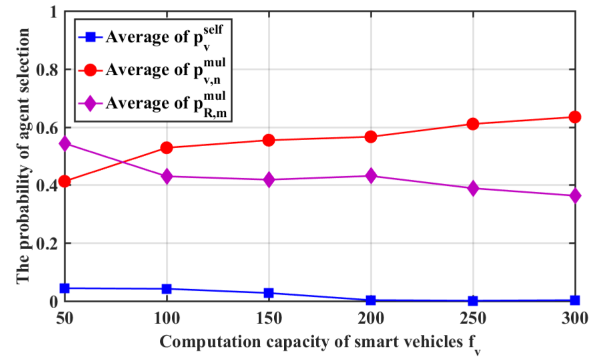

Fig. 4. The performance of agent selection probability with different computation capacity of smart vehicles f_v

indicated the optimal FL agent selection strategy for in the vehicular network. Numerical results demonstrated the improved costs of our proposed schemes.

REFERENCES

[1] L. Qi, "Research on intelligent transportation system technologies and applications," in Proc. Workshop Power Electron. Intell. Transp. Syst, pp. 529–531, 2008.

[2] N. Mohamed and J. Al-Jaroodi, "Real-time big data analytics: applications and challenges," in Proc. Int. Conf. High Perform. Comput. Simulation(HPCS), pp. 305–310, Jul. 2014.

[3] Q. Shi and M. Abdel-Aty, "Big data applications in real-time traffic operation and safety monitoring and improvement on urban expressways," Transp. Res. C, Emerg. Technol., vol. 58, pp. 380–394, Sep. 2015.

[4] L. Zhu, F. R. Yu, Y. Wang, B. Ning, T. Tang, "Big data analytics in intelligent transportation systems: a survey," IEEE Transactions on Intelligent Transportation Systems, vol. 20, pp. 380-398, Jan. 2019.

[5] L. T. Tan, R. Q. Hu, L. Hanzo, "Twin-timescale artificial intelligence aided mobility-aware edge caching and computing in vehicular networks," IEEE Transactions on Vehicular Technology, vol. 66, pp. 4582-4601, Jun. 2017.

[6] Ribal F. Atallah, C. M. Assi, J. Y. Yu, "A reinforcement learning technique for optimizing downlink scheduling in an energy-limited vehicular network," IEEE Transactions on Vehicular Technology, vol. 68, pp. 3086-3099, Apr. 2019.

[7] S. Wang, T. Tuor, T. Salonidis, K. K. Leung, C. Makaya, T. He, and et al., "Adaptive federated learning in resource constrained edge computing systems," IEEE J. Sel. Areas Commun, vol. 37, pp. 1205-1221, Jun. 2019.

[8] N. H. Tran, W. Bao, A. Zomaya, N. M. N.H. and C. S. Hong, "Federated learning over wireless networks: optimization model design and analysis," IEEE Conference on Computer Communications(INFOCOM), 2019.

[9] D. Conway-Jones, T. Tuor, S. Wang and K. K. Leung, "Demonstration of federated learning in a resource-constrained networked environment," IEEE International Conference on Smart Computing(SMARTCOMP), 2019.

[10] J. Ren, H. Wang, T. Hou, S. Zheng and C. Tang, "Federated learning-based computation offloading optimization in edge computing-supported internet of things," IEEE Access, vol. 7, pp. 69194-69201, Jun. 2019.

[11] S. Samarakoon, M. Bennis, W. Saad and M. Debbah, "Federated learning for ultra-reliable low-latency V2V communications," IEEE Global Communications Conference (GLOBECOM), 2018.

[12] G. Cesari, G. Schildbach, A. Carvalho, F. Borrelli, "Scenario model predictive control for lane change assistance and autonomous driving on highways," IEEE Intelligent Transportation Systems Magazine, vol. 9, pp. 23-35, Jul. 2017.

[13] K. Zhang, Y. Zhu, S. Leng, Y. He, S. Maharjan, Y. Zhang, "Deep learning empowered task offloading for mobile edge computing in urban informatics," IEEE Internet of Things Journal, vol. 6, pp. 7635-7647, Oct. 2019.