Resource Cooperation in MEC and SDN based Vehicular Networks

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Abstract—Internet of Things (IoT) systems require highly scalable infrastructure to adaptively provide services to meet various performance requirements. Combining Software-Defined Networking (SDN) with Mobile Edge Cloud (MEC) technology brings more flexibility for IoT systems. We present a four-tier task processing architecture for MEC and vehicular networks, which includes processing tasks locally within a vehicle, on neighboring vehicles, on an edge cloud, and on a remote cloud. The flexible network connection is controlled by SDN. We propose a CPU resource allocation algorithm, called Partial Idle Resource Strategy (PIRS) with Vehicle to Vehicle (V2V) communications, based on Asymmetric Nash Bargaining Solution (ANBS) in Game Theory. PIRS encourages vehicles in the same location to cooperate by sharing part of their spare CPU resources. In our simulations, we adopt four applications running on the vehicles to generate workload. We compare the proposed algorithm with Non-Cooperation Strategy (NCS) and All Idle Resource Strategy (AIRS). In NCS, the vehicles execute tasks generated by the applications in their own On-Board Units (OBU), while in AIRS vehicles provide all their CPU resources to help other vehicles' offloading requests. Our simulation results show that our PIRS strategy can execute more tasks on the V2V layer and lead to fewer number of task (and their length) to be offloaded to the cloud, reaching up to 28% improvement compared to NCS and up to 10% improvement compared to AIRS.

Index Terms-MEC, V2V, CPU resource allocation, IoT, SDN

I. INTRODUCTION

MEC is a technology that extends services to the edge cloud for IoT systems. In MEC-based IoT networks, computational task offloading enhances processing performance for the tasks generated by User Equipments (UEs) of the IoT network. Researchers have been designing offloading strategies to meet diverse performance requirements. However, the dynamically changing characteristics of the location and service requests from the UEs may still lead the fixed edge server deployment to have "service holes" in IoT networks, therefore dynamic communication between the UEs is necessary [1].

The vehicle is a type of UE in IoT system. Today's vehicles are equipped with OBUs with multiple sensors, processing units, localization systems, and radio transceivers. These embedded technologies can facilitate the setup of Vehicular Ad Hoc Network (VANET) [2] across vehicles. However, the processing capacity of vehicles is limited, and it is difficult to execute computationally intense tasks within their own OBUs. Therefore, task offloading to Edge Server (ES) or cloud is considered as an option to increase the availability of processing power [3].

SDN-based technologies can be widely adopted in IoT system, from different networking aspects, e.g., access, edge, core, data center networking [4], and also useful in V2V systems [5] - [6]. The SDN controller inside the MEC server can flexibly construct the network topologies between the vehicles, and realize the V2V offloading dynamicity. Authors in [5] proposed an architecture using SDN and MEC servers, in which the SDN controller can keep calculating and selecting the best V2V routing path between vehicles. In [7], the authors extend the architecture to multi-hop V2V connection and optimize the path base on the SDN controller deployed in MEC for both V2V and V2I task offloading. Authors in [6] proposed a vehicle trajectory prediction model to improve the efficiency of V2V task offloading by utilizing the mobility advantages of vehicles. However, these papers didn't consider the willingness of vehicles for resource sharing, since the computational resources are managed in a centralized way as a resource pool.

Our work integrates V2V, Vehicle to Infrastructure (V2I), and SDN architecture for task offloading, and extends it with the willingness and cooperation of the vehicles. We propose a Game-Theory-based algorithm to optimize resource allocation. We then investigate four different application types in our simulation, which are typical use cases in the IoT-based vehicular networks with different levels of computational task loads [8].

In this paper, our contributions are as follows: (1) We propose a four-tier resource cooperation architecture, which uses SDN for communication control and MEC for task offloading. (2) We propose a cooperation strategy, dubbed PIRS, based on ANBS in Game Theory [9], at V2V layer to reallocate the spare resource of each vehicle, which considers vehicles' cooperation history and willingness. (3) We simulate the task offloading schemes (with cutting-edge simulator Edge-CloudSim [10]) and benchmark our PIRS strategy against two other strategies: non-cooperative NCS strategy and cooperation with all idle resource (AIRS) strategy. The results show an obvious performance advantage of our strategy.

II. SYSTEM MODEL

A. Architecture

Our proposed architecture is shown in Fig. 1. It's a SDNbased four-tier architecture, which includes processing at local vehicle on-board, neighboring vehicles, edge cloud, and remote cloud. We assume each vehicle is equipped with OBU, and has a certain computational ability. The tasks generated by vehicles are prioritized to be executed in the local onboard CPU (i.e., the OBU) first. If the on-board CPU capacity is not sufficient, it cooperates/negotiates with neighboring vehicles by V2V communications, gets resources from them, and sends the remaining task to them to execute. After that, if still not sufficient, the remaining task is offloaded to ESs by V2I communication. Finally, the last option is to offload the remaining task to the remote cloud, in case ESs get congested and do not have enough computational resources, especially when there are many demands coming from a large number of vehicles for the ES. Each ES is associated with an Access Point (AP). In our architecture, V2V connections use the IEEE 802.11p standard, while V2I connections use the IEEE 802.11ac standard [8]. These connections are controlled by SDN. Every vehicle, and ES has an SDN switch. All the connection establishment between them and data transmission are controlled by the SDN controller located in the central office. The procedure of task offloading is handled by the MEC orchestrator, located in the central office as well, adopting architectures such as those defined in [11].

For modeling the mobility of vehicles, we divide the whole map into several areas by AP coverage. When vehicles drive in an AP coverage area for a short period and move out of this area to another location, we define this short period as a dwell time. Different locations are assumed to have different levels of dwell time for the vehicles since different areas have different average driving speeds. We have a randomly distributed vehicle generator to map vehicles into APs, and a dwell time to simulate the mobility of vehicles in areas covered by different APs. Vehicles are assumed to move out of their AP coverage area after the dwell time has expired and move into an adjacent AP coverage area for a new dwell time.



Fig. 1. Proposed MEC architecture.

B. Offloading strategy

As mentioned above, in our architecture, when a task is generated it has four ways to be executed: locally in the vehicle, across neighboring vehicles, on the ES, and on the remote cloud.

1) Local task execution: The strategy where a vehicle V_i always executes the task $K(L_K, D_K)$ on its own OBU

without cooperation with other vehicles, is named NCS. The task length L_K denoted by the number of instructions, $D_K = (D_K^{up}, D_K^{down})$ is the task upload/download data size. We assume every vehicle has the same CPU capacity and the spare CPU resource of the vehicle V_i at time t is represented by $C_i(t)$. The execution time $d_c^l(K)$ is determined by its current spare CPU capacity $C_i(t)$. Since there is no communication delay, the delay $d^l(K)$ only includes the computational delay, shown in Equation (1). The unfinished tasks are directly offloaded to MEC.

$$d^{l}(K) = d^{l}_{c}(K) = L_{K}/C_{i}(t)$$

$$\tag{1}$$

2) Cooperative task execution with neighboring vehicles: When a vehicle V_i finds that the local estimated delay $d^l(K)$ is larger than the task's delay tolerance $d_{limit,K}$, the vehicle carries out a new estimation of the V2V delay $d^g(K)$ if the processing were to be executed on a cooperating neighbouring vehicle. In our scheme, the cooperation has the following steps:

Geographical grouping: Vehicles are grouped by their geographical locations. The SDN controller at the central office collects the information of the vehicle V_i 's neighbors' geographical region and spare CPU resource $C_j(t)$, and sends the neighbor set $N = \{N_1, N_2..., N_j\}$ to the task owner vehicle V_i . All this information is useful for selecting cooperating neighboring vehicles.

Utility Equation: Each vehicle *i* evaluates its utility value when it cooperates with other vehicles. Our utility equation is defined in Equation (2) [12]. It considers the current environment state and the vehicles' willingness to cooperate. The current environment state of vehicle V_i (*i* is the ID index of vehicles) at time t, is denoted by $s = [\theta_0, \theta_1]$. θ_0 means the vehicle V_i has spare resources, while θ_1 means it does not. The risk probability vector $P\theta_i = [P\theta_i(\theta_0, t), P\theta_i(\theta_1, t)]$ represents the probability of the vehicle in a risky (the vehicle might not have enough computing resources left for its own tasks) or safe state (the vechicle does not risk to run out of resources). $P\theta_i(\theta_0, t)$ denotes the probability of the vehicle V_i in risky state θ_0 , and $P\theta_i(\theta_1, t)$ denotes the probability of the vehicle in safe state θ_1 , defined by Equations (3). This equation includes two terms: the first term is the realtime usage $B_i(t)$ spent on real-time resource $C_i^r(t)$. The realtime resource $C_i^r(t)$ is the total resource vehicle V_i has at time t. The real-time spare CPU resources are defined as $C_i(t) = C_i^r(t) - B_i(t).$

The second term represents the willingness of vehicle V_i to join the current round of cooperation. The cooperation willingness probability vector is $\beta_i(t) = [\beta_{i,0}(t), \beta_{i,1}(t)]$, $(\beta_{i,0}(t) \ge 0, \beta_{i,1}(t) \ge 0)$. Here $\beta_{i,0}(t)$ is the 'giving' probability, which denotes the vehicle's willingness to give its resource to other vehicles at a given time, while $\beta_{i,1}(t)$ is the 'getting' probability, which denotes the vehicle's intention to get resources from other vehicles within that same time. Note that $\beta_{i,0}(t) + \beta_{i,1}(t) = 1$ [13], i.e., vehicles are not allowed to both give and get resources within the same time window. The willingness probability vector $\beta_i(t)$ changes after each cooperation round, and depends on all previous cooperation rounds of V_i .

$$U_{i}(s, a, t) = E \{J_{i}(s, a, t)\} = M\theta \cdot P\theta_{i}^{T} \cdot J_{i}(s, a, t)$$
$$= \begin{bmatrix} M\theta_{11}, M\theta_{12} \\ M\theta_{21}, M\theta_{22} \end{bmatrix} \cdot \begin{bmatrix} P\theta_{i}(\theta_{0}, t) \\ P\theta_{i}(\theta_{1}, t) \end{bmatrix} \cdot J_{i}(s, a, t) \quad (2)$$
$$(i, j = 1, 2..., n \quad i \neq j)$$

Where, $P\theta_i$ and $J_i(s, a, t)$ are derived by the following Equations [12]:

$$P\theta_{i}(\theta_{0}, t) = \frac{B_{i}(t)}{C_{i}^{r}(t)} + (\beta_{i,0}(t) - \beta_{i,1}(t));$$

$$P\theta_{i}(\theta_{1}, t) = 1 - P\theta_{i}(\theta_{0}, t)$$
(3)

$$J_{i}(s, a, t) = Pa_{i} \cdot Ma \cdot Pa_{j}^{T}$$

= $[Pa_{i}(a_{0}, t), Pa_{i}(a_{1}, t)] \cdot \begin{bmatrix} Ma_{11}, Ma_{12} \\ Ma_{21}, Ma_{22} \end{bmatrix} \cdot \begin{bmatrix} Pa_{j}(a_{0}, t) \\ Pa_{j}(a_{1}, t) \end{bmatrix}$
(4)

The factor $J_i(s, a, t)$ in Equation (4) reflects the reward that the vehicle can get from its current action [12]. We define a vehicle V_i action space as $a = [a_0, a_1]$ having two action choices, giving out resources to help others, denoted as a_0 , or getting resources from others, denoted as a_1 . The giving probability vector $Pa_i = [Pa_i(a_0, t), Pa_i(a_1, t)]$ represents the probability of the vehicle selecting the give/get action. $Pa_i(a_0,t)$ is the probability that the vehicle gives out its resource. $Pa_i(a_1, t)$ is the probability that the vehicle chooses to get other's resource. In our case, the task owner vehicle joining the cooperation selects a_1 , and its giving probability $Pa_i = [0, 1]$, while its neighboring vehicle who takes part in the cooperation selects a_0 , and $Pa_i = [1,0]$. Based on Game Theory, the payoff matrix Ma and $M\theta$ are defined empirically. The vehicles are encouraged to be rewarded for cooperating with each other to execute the tasks. Therefore, the Nash Equilibrium point, in this case, will be reached when the neighboring vehicles prefer to form a coalition with the task owner vehicle without getting into a risk environment which might lead to a lack of CPU resources to process their own tasks. The central office gives a list of neighboring vehicles sorted by their utilization values to the task owner vehicle V_i .

Selecting and cooperating with neighboring vehicles: After the task owner vehicle V_i gets the cooperation list N^c from the central office, it selects the top utility value neighbors to be cooperating candidates to execute the task $K(L_K, D_K)$, which is generated by vehicle V_i at the time t. The V_i estimates the delay time $d^g(K)$ of the offloading task to those cooperating candidates. This is represented in Equation (5). The delay $d^g(K)$ includes communication delay $d^g_m(K)$ between vehicles and computational delay $d^g_c(K)$. We assume the tasks in the V2V layer can be partitioned. We denoted the communication data rate with b_V . The vehicle V_i selects $min(N^c, N^n)$ neighbors to cooperate. N^n is the maximum number of vehicles that one vehicle can connect to.

If the estimated execution time $d^g(K)$ is less than the task's maximum tolerable time $d_{limit,K}$, the task $K(L_K, D_K)$

will be executed on the V2V layer. In our scheme, each vehicle is an SDN switch and is controlled by the SDN controller located in the central office. The SDN controller can build a temporary connection when the vehicle V_i forms a coalition with selected cooperation candidates. This coalition is temporary. It is formed when the vehicles cooperate to execute a task, and it's cancelled when the task is finished. In Equation (5), L_K denotes the task length and D_K^{up}/D_K^{down} represents task upload/download data size. $C_i(t)$ is the spare CPU resource of V_i , while $\sum_{j=1}^{min(N^c,N^n)} C_j(t)$ is the sum of resources provided by each cooperating neighboring vehicle.

$$\begin{cases} d^{g}(K) = d_{c}^{g}(K) + d_{m}^{g}(K) \\ d_{c}^{g}(K) = \frac{L_{K}}{C_{i}^{r}(t)} \\ C_{i}^{r}(t) = C_{i}(t) + \sum_{j=1}^{\min(N^{c},N^{n})} C_{j}(t) \\ d_{m}^{g}(K) = \frac{D_{K}^{up}}{b_{V}} + \frac{D_{K}^{down}}{b_{V}} \end{cases}$$
(5)

We assume a cooperating neighboring vehicle N_j has $C_j(t)$ spare resource value at the time t. If the vehicle N_j provides all of its spare resources to help process V_i 's offloading task at current time t, we call this reallocation algorithm AIRS. However, the drawback of the AIRS approach is that vehicle N_j might become unable to process its own upcoming tasks so that it has to offload them to other vehicles or even to ES/remote cloud, which would have cost implications.

Here we propose a PIRS algorithm, based on ANBS in Game Theory [9], where neighboring vehicle N_j provides part of its spare resources for cooperation. The task owner vehicle V_i cooperates with neighboring vehicles N_j in the candidate list N^c one by one in descending order of their utility values. In each cooperation round, candidate neighboring vehicle N_j , which adopts the PIRS algorithm does not provide all its spare resources for cooperation, but only part of it to process task owner vehicle V_i 's offloading. We consider this cooperation as a bargain problem and assume both vehicles are rational and intend to maximize their extra resource utility in the bargain.

The set of spare resources in the utility equation in this bargain problem can be described as $\Gamma = \{\gamma_i | i = 1, 2\}\}$, where $\gamma_i = \{(C_i^r(t) - B_i(t)) | i = 1, 2\}$, which is a nonempty compact convex set with boundary [14]. $C_i^r(t)$ is the realtime total CPU resource for each vehicle, including its own CPU resource and the resource it gets externally, while $B_i(t)$ is the real-time resource usage. The cooperation problem is described in Equation (6):

$$\Gamma^{*} = \underset{C_{i}^{r}(t)}{\operatorname{argmax}} \prod_{i} (C_{i}^{r}(t) - B_{i}(t))^{\lambda_{i}(t)},$$

$$s.t. \qquad \sum_{i=1}^{2} C_{i}^{r}(t) = \Phi$$

$$\sum_{i=1}^{2} \lambda_{i}(t) = 1$$

$$C_{i}^{r}(t) \geq B_{i}(t),$$

$$C_{i}^{r}(t) \geq 0, \quad (i = 1, 2)$$
(6)

where Φ is the total real-time resource of the vehicles considered.

$$\lambda_i(t) = \frac{\beta_{i,1}(t)}{\beta_{i,1}(t) + \beta_{j,1}(t)} \quad (i, j = 1, 2, 3...n)$$
(7)

 $\lambda_i(t)$ denotes the bargaining power of the vehicles. In our case, the vehicles' bargaining power [14] is decided by their willingness probability vector $\beta_i(t)$ as Equation (7). At each allocation step, the vehicle gets its available real-time resource as $C_i^r(t) = B_i(t) + \lambda_i(t) \cdot \sum_{i=1}^2 (C_i^r(t) - B_i(t))$.

After the cooperation, the algorithm updates the parameters of the cooperating vehicles. Part of the spare resources of neighboring vehicle N_j are provided to execute $K(L_K, D_K)$ offloaded from V_i , thus V_j 's risk probability of lacking CPU resources increases. Therefore, the cooperation willingness probability vector $\beta_i(t)$ changes. In addition, the cooperation also changes the participants' bargaining power $\lambda_i(t)$, which will affect their next round of cooperation. We use the updating rule derived from [15], as the Equation (8) - Equation (9).

$$\beta_{i,m}(t) = \beta_{i,m}(t-1) + \alpha \Delta \beta_{i,m}(t),$$

(m = 0, 1), $\alpha \in (0, 1)$ (8)

where, α is the learning rate and the $\Delta \beta_{i,m}(t)$ holds as:

$$\Delta \beta_{i,m}(t) = \frac{\Delta J_i(s, a_m, t)}{\Delta J_i(s, a_m, t) + \Delta J_i(s, a_l, t)},$$

$$\Delta J_i(s, a_m, t) = J_i(s, a_m, t) - J_i(s, a_m, t - 1),$$

$$(m, l = 0, 1 \quad m \neq l) \quad (9)$$

If the estimated execution time $d^g(K)$ is more than the task's maximum tolerable delay $d_{limit,K}$, the task $K(L_K, D_K)$ will be offloaded to ES/remote cloud.

3) Offloading to Edge or remote cloud: When vehicles decide to offload tasks to ES/remote cloud, they communicate with their nearest ES. When the ES is congested, tasks can be offloaded to the remote cloud. The delay $d^e(K)$ of V2I includes communication and computational delay which is determined by the computational capacity of offloading ES, shown in Equation (10).

$$\begin{cases} d^{e}(K) = d^{e}_{c}(K) + d^{e}_{m}(K) \\ d^{e}_{c}(K) = \frac{L_{K}}{C_{E}} \\ d^{e}_{m}(K) = \frac{D^{up}_{K}}{b_{E}} + \frac{D^{down}_{K}}{b_{E}} \end{cases}$$
(10)

where, L_K denotes the task length and D_K^{up}/D_K^{down} represents task upload/download data size. C_E is the CPU resource provided by ES/remote cloud.

In summary, the whole procedure of our proposed algorithm PIRS, as well as AIRS and NCS, are shown in Algorithm 1. The computational complexity of algorithm PIRS and AIRS is mostly affected by the sorting algorithm in Line 13, in which the algorithm gets candidates list N^c by sorting candidates' utility value Equation (2). Our code adopts Python built-in Timesort algorithm [16], and the complexity is O(nlogn). The

computational complexity of NCS is O(1) since it does not have sharing and offload all remaining tasks to MEC.

Algorithm 1 Four-tier offloading system with V2V cooperation algorithm PIRS, AIRS and NCS

1: Initialization: task $K(L_K, D_K)$ generated by vehicle V_i

- 2: if strategy is NCS then
- 3: estimate delay $d^{l}(K)$ Eqn.1
- 4: **if** $d^l(K) < d_{limit,K}$ then
- 5: executes the task locally
- 6: **else**

14:

32:

- 7: the task failed
- 8: if strategy is PIRS or AIRS then
- 9: Offloading strategy:
- 10: V2V cooperate to execute the task
- 11: 1) get geographical neighbor set N
- 12: 2) select candidates list N^c from neighbor set N,by sorting their utility value Eqn.2
- 13: 3) calculate the total resource V_i can get from neighbors:
 - for neighbor N_j in candidate list N^c do if Strategy is PIRS then

15:	if Strategy is PIRS then
16:	N_j gives a part of its spare resource Eqn.6
17:	update willingness probability $\beta_i(t)$, Eqn.8-9
18:	else if Strategy is AIRS then
19:	N_j gives all spare resource
	4) calculate the delay $d^g(K)$, Eqn.5
20:	if $d^g(K) < d_{limit,K}$ then
21:	V2V cooperates to execute the task
22:	else
23:	Offloading to Edge/remote cloud
24:	if Virtual Machine (VM) utilization < utilization
	threshold then
25:	offload to nearest ES
26:	else
27:	offload to remote cloud
28:	calculate the delay $d^e(K)$, Eqn.10
29:	if $d^e(K) < d_{limit,K}$ OR V_i change place then
30:	the task failed
31:	else

2

the task successfully executed

III. EXPERIMENTAL RESULTS

A. Simulation settings

We implement our own Python-based simulator for the V2V part and use an open-source Java-based simulator, Edge-CloudSim [10], for the V2I part, and then integrate them together. In our simulations, the task execution can fail for two reasons. The first reason is the mobility of vehicles. If the vehicle moves out of the wireless network coverage, it is not connected to the previous ES anymore, and it cannot get the response of its previously requested task. The second reason is the delay. If a task execution cannot finish within its maximum tolerable delay, it fails. In our simulation, we adopt

APPLICATION PARAMETERS							
	Augmented Reality	Health App	Compute Intensive	Infotainment App			
Usage percentage(%)	30	20	20	30			
Task arrival poison mean (s)	1	1	10	5			
Maximum tolerable delay (s)	5	8	8	1			
Active/Idle Period (s)	40/5	45/90	60/120	30/45			
Upload/Download	1500/25	1250/20	2500/200	2500/200			
Data size(KB)	1500/25	1250/20	2500/200	2500/200			
Task Length (GI)	9	3	45	45			
VM Utilization on Edge (%)	6	2	30	30			

TABLE I

TABLE II					
CIMIT	ATION DAD AMETERS	c			

SIMULATION PARAMETERS				
Parameter	Value			
Simulation Time	30 minutes			
WAN data rate	1 Gbps			
V2I communication data rate	250 Mbps			
V2V communication data rate	10 Mbps			
CPU capacity per Vehicles/Edge/Remote Cloud	2/160/1600 GIPS			
Maximum number of V2V connection N^n	6			
Number of locations Type 1/2/3	1/1/2			
Average dwell time in Type 1/2/3	30/20/10 seconds			

the parameters of four task applications in paper [8] as our use cases, shown in Table I. The usage percentage of the application is defined as the proportion of the vehicles running this application. The task inter-arrival time means how frequently a given task generates a processing load. This inter-arrival time is exponentially distributed [8]. The maximum tolerable delay is the time limit for the task finishing time. If the task execution time goes beyond it, the task fails. There are also active/idle periods for generating the task. During the active period, applications generate tasks with the aforementioned inter-arrival time, while during the idle period, applications do not generate any processing load. The upload/download data size is the communication data size for the task when it is offloaded to other vehicles or to the edge/remote cloud. The task length represents the task computational quantity and is also an exponentially distributed random variable [8]. The VM utilization denotes the CPU overhead on the VM when it is running on ES. Other parameters of the configuration are listed in Table II. We adopt EdgeCloudSim's built-in nomadic mobility model for our vehicles. In this model, different locations have different values to represent the different average dwell times the vehicles spend at these locations. In our simulation, we set three types of locations with different average dwell times. We use the EdgeCloudSim default value to set the ES layer and remote cloud computational capacity, as well as network communication data rates.

B. Simulation results

We investigate the performance of our PIRS algorithm and compare it to two baselines V2V algorithms: AIRS and NCS. Our results, which include mean and standard deviation, are shown in the following 4 plots. Firstly, we investigate the amount of failed tasks for those three systems. As mentioned before the reasons for failed tasks are the mobility of vehicles and exceeding the tolerable delay. Fig. 2 shows the normalized failed task percentage for the three systems. The systems adopting PIRS and AIRS have lower failed task percentages than the system using NCS. The system with PIRS has the best performance. When the vehicle number is higher, the advantage of PIRS over AIRS is reduced, but the advantage of PIRS over NCS increases. Please note that, in order to better show the performance comparison, we use aggressive parameter settings (i.e., very frequent task inter-arrival time) in order to increase the overall probabilities of failed tasks.



Fig. 2. Failed tasks normalized percentage with the four-tier system.



Fig. 3. Normalized total failed tasks' task length.



Fig. 4. Offloading task percentage.

In Fig. 3, we analyze the total length of failed tasks, and we can see the system with the PIRS leaves the smallest amount of computational task length uncompleted when the vehicle number is less than 80. In other words, this system executed the highest amount of computations successfully. The system with the AIRS has a more uncompleted computational task length than PIRS but less than the system with the NCS. The advantage of PIRS is more obvious with lower density

of vehicles. The reason is that the AIRS algorithm makes the neighbor vehicles N_j provide all of their spare CPU resources at each cooperation, while PIRS takes only part of N_j spare resources. The proposed PIRS algorithm thus provides a more fair distribution in the usage of vehicles' computational resources. This is especially useful for a low number of vehicles, because if a vehicle provides all its computational capacity to another vehicle, it would then have to offload its own task to other vehicles, but there might not be any vehicle nearby. When the number of vehicles becomes higher, there are more options for offloading to other vehicles, thus the performance of PIRS and AIRS show less difference.



Fig. 5. Normalized total offloading task length.

In order to understand how much the V2V resource sharing helps for the whole system performance, we also investigate the first V2V layer performance separately. Fig. 4 shows the percentage of remaining tasks, which need to be offloaded to the MEC layer and remote cloud after the three different algorithms reallocate CPU resources in the V2V layer. Compared to the NCS and AIRS algorithms, PIRS can complete more tasks in the V2V layer, thus offloading fewer tasks to the MEC layer and cloud. The advantage is around 20% to 30% for different scenarios of vehicle densities. Fig. 5 shows the total task length offloaded to ES/remote cloud (this includes the potential failed tasks). We can see that PIRS has the shortest task lengths offloaded to ES/remote cloud when the number of vehicles is less than 80. In the best case, the average number of tasks offloaded by PIRS with 40 vehicles is 10% lower than AIRS, and 28% lower than NCS, respectively. The reason is the same as mentioned above. When the number of vehicles increases over 80, even though a vehicle gives out all of its spare resources to V_i at the previous cooperation, it has a better chance to group with another vehicle, which has adequate spare resources for its future upcoming tasks. Therefore in this scenario, PIRS does not have much advantage compared to AIRS. Finally, both PIRS and AIRS perform better than the non-cooperation case NCS where there is no resource sharing between vehicles.

IV. CONCLUSION

We have proposed a four-tier architecture for vehicular networks, with flexible network connection controlled by SDN in V2V communication. We implement a CPU resource allocation algorithm, dubbed PIRS, based on ANBS in Game Theory, which focuses on allocating idle resources in a proper proportion for each vehicle in every cooperation round. We have carried out simulations to investigate the performance of PIRS and then compared the performance of PIRS with two benchmark algorithms, AIRS and NCS. The results of our simulations show that our proposed approach performs better in all aspects considered: it provides a lower amount of failed tasks, a lower amount of offloading to the edge and remote cloud, and higher success in executed task lengths than AIRS and NCS, especially when the density of the vehicles is lower.

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