Contract-Based Resource Allocation for Low-Latency Vehicular Fog Computing

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Abstract—**Low-latency communication is crucial to satisfy the strict requirements on latency and reliability in 5G communications. In this paper, we firstly consider a contract-based vehicular fog computing resource allocation framework to minimize the intolerable delay caused by the numerous tasks on the base station during peak time. In the vehicular fog computing framework, the users tend to select nearby vehicles to process their heavy tasks to minimize delay, which relies on the participation of vehicles. Thus, it is critical to design an effective incentive mechanism to encourage vehicles to participate in resource allocation. Next, the simulation results demonstrate that the contract-based resource allocation can achieve better performance.**

I. INTRODUCTION

Low-latency communication is crucial for diverse emerging 5G applications such as self driving, collision warning, and environment monitoring [1], [2]. The huge amount of data traffic caused by these applications poses a great challenge on the base station (BS) during peak time, which cannot guarantee the stringent quality of service (QoS) on low-latency and quality of experience (QoE) requirements due to the long distance between user equipments (UEs) and remote data centers.

An alternative choice is to exploit the under-utilized resources of nearby vehicles to alleviate the pressure on the BS and reduce delay. Particularly, future vehicles are more likely to be equipped with powerful onboard computers and large-capacity data storage units for the sake of improving driving safety, convenience, and satisfaction [3]. Hence, the tremendous computation resources provided by vehicles can be utilized to alleviate network congestion during the peak time. Moreover, compared to the BS, vehicles which are more close to pedestrial UEs can provide line-of-sight links to further reduce the transmission delay. This novel idea is known as vehicular fog computing (VFC), which is able to provide more computing resources and less processing delay.

However, despite the above-mentioned advantages, the wide area deployment of VFC still confronts the problem of lack of an effective incentive mechanism for vehicles to share their resources. Most of previous studies assume that vehicles will follow the resource allocation decision and act as fog nodes unconditionally [4]–[7]. This assumption is too optimistic in practical implementation. Due to the cost incurred by resource sharing, self-interested vehicles are reluctant to serve as fog nodes unless they are well compensated.

In [8], Luong *et al.* proposed a comprehensive literature survey of pricing-based incentive mechanisms for resource allocation in cloud-enabled wireless networks. Liu *et al.* provided a Stakckelberg game-based pricing scheme to stimulate edge server owners to participate in computation offloading [9]. As we can observe, most of current works have assumed that the information of the potential fog nodes is perfectly known by the BS. However, the preference of each vehicle towards the total amount of available resources belongs to the vehicle's private information, i.e., the information is only known by the vehicle itself, which is a typical paradigm of information asymmetry [10]. Therefore, it is necessary to design an incentive mechanism, which can improve the utilization of resources and reduce delay under information asymmetry.

In this paper, the BS designs a contract to motivate vehicles to share their resources, which specifies the relationship between the performance and the reward. In the contract, each distinct performance-reward association is defined as a contract item, and a contract generally contains a great variety of contract items. Then, the BS broadcasts the contract, and each vehicle chooses its desired contract item to maximize its payoff.

The remaining chapters of this paper are summarized as follows. The system model is described in section II. Section III introduces the incentive mechanism in VFC and section IV shows the simulation results. The conclusion is given in section V.

II. SYSTEM MODEL

The VFC resource allocation framework is shown in Fig. 1. In each cell, there exists a BS, which takes charge of intra-cell resources coordination, and numerous UEs, which emerge a great number of tasks. During the peak time, the BS can employ a group of vehicles to act as fog nodes and UEs can reduce delay via computation

Fig. 1. The VFC resource allocation framework.

demand offloading. With a proper incentive mechanism designed by the BS, each vehicle can actively adjust the amount of sharing resources according to the reward in order to maximize its individual payoff.

For the sake of simplicity, we adopt a time-slot model [11]. The set of vehicles and the set of UEs within the coverage of the BS remain fixed within each slot, and vary across different slots. During slot t, we assume that there exist M vehicles and N UEs. The set of vehicles and the set of UEs are denoted as $\mathcal{V}_M = \{V_1, \cdots, V_m, \cdots, V_M\}$ and $\mathcal{U}_N = \{U_1, \cdots, U_m, \cdots, U_M\}$, respectively. Denote a triplet $\{D_n, C_n, \tau_n\}$ as the attributes of each UE, where D_n represents the task data size, C_n is the required computation resource for processing the task, and τ_n represents the delay constraint.

III. A CONTRACT-BASED INCENTIVE MECHANISM FOR RESOURCE SHARING

In this section, we propose a contract-based resource allocation strategy for UEs to employ the shared resources to offload their tasks.

A. Vehicle Type Modeling

The preference of a vehicle towards resource sharing is quantified as its vehicle type. Due to the different configuration of each vehicle, the type of vehicles are generally different. A vehicle with a higher type is more willing to share its resources and serve as a fog node compared to a vehicle with a lower type. Thus, it is intuitive for the BS to employ higher-type vehicles. Since the number of vehicles in a cell is usually limited, the set of vehicle types is assumed as a discrete and finite space. Vehicle type is defined as

Definition 1: (Vehicle Type): Considering the set of vehicles $\mathcal{V}_M$, these M vehicles can be sorted in an ascending order based on their preferences and classified into M types. Denote the set of vehicle types as $\Theta = \{\theta_1, \cdots, \theta_m, \cdots, \theta_M\}$, which is given by

$$\theta_1 < \cdots < \theta_m < \cdots < \theta_M, m = 1, \cdots, M. \quad (1)$$

Definition 1 is also applicable when there are multiple vehicles belong to the same type. The computational complexity decreases with the vehicle types, but at the expense of the effectiveness of resource allocation.

In the scenario of information asymmetry, we assume that the BS only knows that there are a total of M types of vehicles and each vehicle $V_m \in \mathcal{V}_M$ belongs to type θ_m with a probability λ_m, i.e., $\sum_{m=1}^{M} \lambda_m = 1$.

B. Contract Formulation

In this paper, the BS can design up to M contract items for vehicles with M types. The contract items describe the employment relationships between the employer, i.e., the BS, who designs a series of incentive contract items, and the employees, i.e., the vehicles, who receive rewards by providing idle resources. For instance, the contract item dedicated for type θ_m vehicle is denoted as (δ_m, π_m), where δ_m denotes the required computation resources, and π_m is the corresponding reward. The whole contract is denoted as $\mathcal{C} = \{(\delta_m, \pi_m), \forall m \in \mathcal{M}\}$, where $\mathcal{M} = \{1, \cdots, m, \cdots, M\}$.

Assuming the total amount of computation tasks that can be processed by the BS during a time interval T is C_{BS}, we have $C_{BS} = \delta_{BS}T$. Here, δ_{BS} is the unit computation capability of the BS per second. With the assistance from vehicles, the computation capability of the BS can be enlarged and the corresponding task processing delay can be reduced. We model the benefit of the BS as a linear function of the reduced delay. By signing the contract item (δ_m, π_m) with type θ_m vehicle, the benefit of the BS is given by

$$R_{BS}(\delta_m) = r_{BS}\left(\frac{C_{BS}}{\delta_{BS}} - \frac{C_{BS}}{\delta_m + \delta_{BS}}\right)$$
$$= r_{BS}T\frac{\delta_m}{\delta_{BS} + \delta_m}. \quad (2)$$

where r_{BS} is the unit benefit brought by the reduced delay.

With the M types of vehicles, the expected utility of the BS is calculated as

$$U_{BS}(\{\delta_m\}, \{\pi_m\}) = \sum_{m=1}^{M} \lambda_m(R_{BS}(\delta_m) - \pi_m). \quad (3)$$

The utility function of type θ_m vehicle which accepts the contract item (δ_m, π_m) is given by

$$U_m^V(\delta_m, \pi_m) = \theta_m \pi_m - \delta_m. \quad (4)$$

The objective of the BS is to optimize its utility under the scenario of asymmetric information via the

adjustment of each contract item. The corresponding optimization problem is formulated as

$$\textbf{P1}: \max_{(\{\delta_m\},\{\pi_m\})} U_{BS}(\{\delta_m\},\{\pi_m\})$$

s.t. $\quad C_1 : \theta_m \pi_m - \delta_m \geq 0, \forall m \in \mathcal{M},$

$\quad C_2 : \theta_m \pi_m - \delta_m \geq \theta_m \pi_{m'} - \delta_{m'}, \forall m, m' \in \mathcal{M},$

$\quad C_3 : 0 \leq \delta_1 < \cdots < \delta_m < \cdots < \delta_M, \forall m \in \mathcal{M},$

$\quad C_4 : \delta_m \leq \theta_m, \forall m \in \mathcal{M}. \hfill (5)$

where C_1, C_2, and C_3 represent the IR, IC, and monotonicity constraints, respectively. C_4 represents the upper bound of δ_m.

Definition 2: The IR, IC, and monotonicity constraints are defined as follows:

- **Individual rationality (IR) constraint:** Type θ_m vehicle, $\forall m \in \mathcal{M}$, will get a nonnegative payoff if it selects the contract item (δ_m, π_m).
- **Incentive compatibility (IC) constraint:** The IC constraint ensures that type θ_m vehicle, $\forall m \in \mathcal{M}$, will get the maximum payoff if and only if it selects the contract item (δ_m, π_m) designed for its own type.
- **Monotonicity constraint:** The reward of type θ_m vehicle, $\forall m \in \mathcal{M}$, should be higher than that of type θ_{m-1} vehicle, and lower than that of type θ_{m+1} vehicle.

Based on the IR, IC, and monotonicity constraints, we conclude that for any $m, m' \in \mathcal{M}$, if $\theta_m > \theta_{m'}$, then $\delta_m > \delta_{m'}$ and $\pi_m > \pi_{m'}$. $\pi_m = \pi_{m'}$ and $\delta_m = \delta_{m'}$ if and only if $\theta_m = \theta_{m'}$.

C. Optimal Contract Design under Information Asymmetry

The corresponding optimization problem **P1** involves M IR constraints and $M(M-1)$ IC constraints. To provide a tractable solution, the following procedures are carried out to simplify the problem.

Step 1: *IR Constraints Elimination*

For type θ_m vehicle, $m \in \mathcal{M}, m \neq 1$, we can derive

$$U_m^V \geq U_{m-1}^V \geq U_1^V \geq 0. \hfill (6)$$

The IR constraints of θ_m vehicle holds automatically as long as the IR constraint of type θ_1 vehicle is guaranteed.

Step 2: *IC Constraints Elimination*

We define the IC constraints between type θ_m and type $\theta_{m'}$, $m' \in \{1, \cdots, m-1\}$, as downward incentive constraints (DICs). Similarly, the IC constraints between type θ_m and type $\theta_{m''}$, $m'' \in \{m+1, \cdots, M\}$, are defined as upward incentive constraints (UICs). In the following, we show that both the DICs and UICs can be reduced.

We consider three adjacent vehicle types, i.e., $\theta_{m-1} < \theta_m < \theta_{m+1}$, which satisfy

$$\theta_{m+1} \pi_{m+1} - \delta_{m+1} \geq \theta_{m+1} \pi_m - \delta_m, \hfill (7)$$
$$\theta_m \pi_m - \delta_m \geq \theta_m \pi_{m-1} - \delta_{m-1}. \hfill (8)$$

where (7) denotes the DIC between type θ_{m+1} and type θ_m, and (8) denotes the DIC between type θ_m and θ_{m-1}.

By combining $\pi_{m+1} \geq \pi_m \geq \pi_{m-1}$, we have

$$\theta_{m+1} \pi_{m+1} - \delta_{m+1} \geq \theta_{m+1} \pi_{m-1} - \delta_{m-1}. \hfill (9)$$

Therefore, if the DIC between type θ_{m+1} and θ_m holds, then the DIC between θ_{m+1} and θ_{m-1} also holds. The DIC constraints can be extended downward from type θ_{m-1} to type θ_1, which are given by

$$\begin{aligned} \theta_{m+1} \pi_{m+1} - \delta_{m+1} &\geq \theta_{m+1} \pi_{m-1} - \delta_{m-1}, \\ &\geq \cdots \\ &\geq \theta_{m+1} \pi_1 - \delta_1. \end{aligned} \hfill (10)$$

Thus, we demonstrate that if the DICs between adjacent types hold, then all the DICs hold automatically. Similarly, we can demonstrate that if the UICs between adjacent types hold, then all the UICs hold automatically.

Based on the above analysis, the M IR constraints and $M(M-1)$ IC constraints can be reduced to 1 and $M-1$, respectively. Furthermore, in order to maximize the utility of the base station, the optimal contract item for type θ_1 vehicle, i.e., (δ_1^*, π_1^*), must enforce

$$U_1^V(\delta_1^*, \pi_1^*) = \theta_1 \pi_1^* - \delta_1^* = 0. \hfill (11)$$

The optimal contract item for any type θ_m vehicle (δ_m^*, π_m^*), $m = 2, \cdots, M$, satisfies the following equality condition:

$$\delta_m^* = \delta_{m-1}^* + \theta_m(\pi_m^* - \pi_{m-1}^*), m = 2, \cdots, M. \hfill (12)$$

Based on the above description, **P1** is rewritten as

$$\textbf{P2}: \max_{(\{\delta_m\},\{\pi_m\})} U_{BS}(\{\delta_m\},\{\pi_m\})$$

s.t. $\quad C_1 : \theta_1 \pi_1 - \delta_1 = 0,$

$\quad C_2 : \delta_m = \delta_{m-1} + \theta_m(\pi_m - \pi_{m-1}), 2 \leq m \leq M,$

$\quad C_3, C_4, \forall m \in \mathcal{M}. \hfill (13)$

We can easily prove that **P2** is a convex programming problem by checking the Hessian matrix, which can be solved by applying Karush-Kuhn-Tucker (KKT) conditions. The Lagrangian associated with **P2** is given by

$$\begin{aligned} &\mathcal{L}(\{\delta_m\},\{\pi_m\},\{\mu_m\},\{\rho_m\},\{\beta_m\}) \\ &= U_{BS}(\{\delta_m\},\{\pi_m\}) + \mu_1(\theta_1 \pi_1 - \delta_1) \\ &+ \sum_{m=2}^M \mu_m \Big(\theta_m(\pi_m - \pi_{m-1}) + \delta_{m-1} - \delta_m \Big) \\ &+ \rho_1 \delta_1 + \sum_{m=2}^M \rho_m(\delta_m - \delta_{m-1}) + \sum_{m=1}^M \beta_m(\delta_m - \theta_m). \end{aligned} \hfill (14)$$

where μ_1 is the Lagrange multiplier corresponding to constraint C_1. $\{\mu_m, m = 2, \cdots, M\}$, $\{\rho_m\}$, and $\{\beta_m\}$ are the vectors of Lagrange multipliers corresponding to

Parameter	Value
Number of vehicles	$5 - 20$
Number of UEs	$15 - 25$
Radius of BS coverage	1000 m
VFC communication radius	200 m
Data size of UE's task	$100 - 200$ Mb
Computing resources of BS	5 GHz
Transmission power of UEs	30 dBm
Noise power	-114 dBm
Bandwidth of UEs	20 MHz
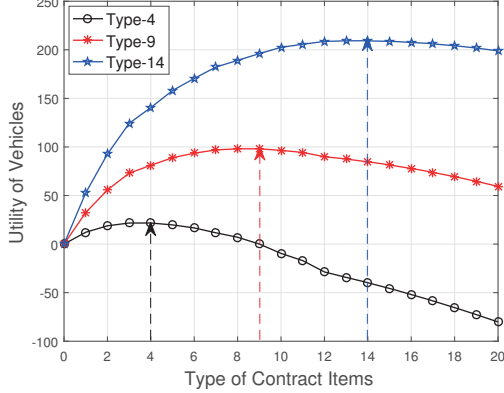
Fig. 2. The utility of vehicle versus the different type of vehicles.

Fig. 3. The utility of BS versus the number of vehicles.

constraints C_2, C_3, and C_4, respectively. KKT conditions are summarized as follows:

- Primal constraints: $0 \leq \delta_1^*$; $\delta_{m-1}^* \leq \delta_m^*, \forall m \in \mathcal{M}, m \neq 1$; $\delta_1^* = \theta_1 \pi_1^*$; $\delta_m^* = \delta_{m-1}^* + \theta_m(\pi_m^* - \pi_{m-1}^*), \forall m \in \mathcal{M}, m \neq 1$; $\delta_m^* \leq \theta_m, \forall m \in \mathcal{M}$;
- Dual constraints: $\mu_m^* \geq 0, \rho_m^* \geq 0$ and $\beta_m^* \geq 0, \forall m \in \mathcal{M}$;
- Complementary slackness: $\rho_1^* \delta_1^* = 0$; $\rho_m^*(\delta_m^* - \delta_{m-1}^*) = 0, \forall m \in \mathcal{M}, m \neq 1$; $\beta_m^*(\delta_m^* - \theta_m) = 0, \forall m \in \mathcal{M}$;
- The first-order conditions of this Lagrangian function is

$$
\begin{cases}
\dfrac{\partial \mathcal{L}}{\partial \delta_m} = \dfrac{\partial R_{BS}(\delta_m)}{\partial \delta_m} - \mu_m + \mu_{m+1} + \rho_m - \rho_{m+1} \\
\qquad + \beta_m = 0, \forall m \in \mathcal{M}, m \neq M, \\
\dfrac{\partial \mathcal{L}}{\partial \delta_M} = \dfrac{\partial R_{BS}(\delta_M)}{\partial \delta_M} - \mu_M + \rho_M + \beta_M = 0, \\
\dfrac{\partial \mathcal{L}}{\partial \pi_m} = -\lambda_m + \mu_m \theta_m - \mu_{m+1}\theta_{m+1} = 0, \\
\qquad \forall m \in \mathcal{M}, m \neq M, \\
\dfrac{\partial \mathcal{L}}{\partial \pi_M} = -\lambda_M + \mu_M \theta_M = 0.
\end{cases}
$$
(15)

IV. SIMULATION
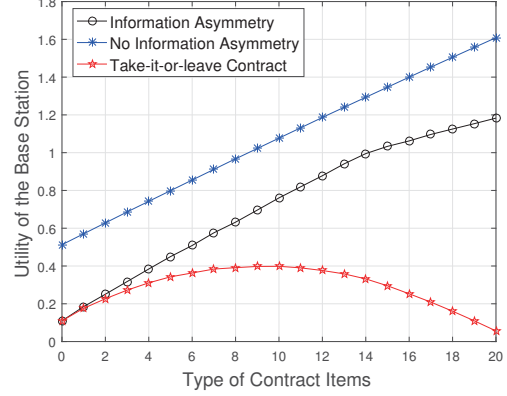
In the paper, we have proposed a contract-based resource allocation strategy in VFC networks for low-latency. To verify whether the proposed algorithm can effectively deal with the resources allocation under information asymmetric and reduce delay, a series of numerical results are conducted in this section. Assuming that the possibility of type θ_m obeys Gaussian distribution, and the simulation parameters are presented in Table I.

Fig. 2 shows the utilities of type-4, type-9 and type-14 vehicles when selecting all the types of contract items provided by the BS, which illustrates that the designed contract is incentive compatible. Each vehicle can achieve the maximum utility if and only if it selects the contract specifically designed for its type. Additionally, it is observed that the vehicles with higher types are able to obtain higher utilities compared to the lower types, that is the BS offers rewards to the vehicles according to their contributions.

Fig. 3 shows the utility of BS versus the vehicle type. It can be observed that the asymmetric information actually protects the vehicles from being overexploited by the base station. With complete information, the base station is able to design a contract such that its utility is much larger compared to the utility achieved under the information asymmetry scenario. The performance gap increases monotonically with the vehicle type.Therefore, information asymmetry is actually beneficial to the vehicles because the base station cannot overexploit a vehicle without knowing the complete information of its type.

V. CONCLUSION

In this paper, the contract-based mechanism is proposed to address the resource allocation problem in the traditional cellular network. To encourage available vehicles to participate in resource allocation, the contract theory is used to determine which vehicles are selected as infrastructures to provide idle resources and how much

of the payoff on them. The simulation results shows that the proposed mechanism can greatly facilitate the participation of vehicles in resource allocation and reduce delay after offloading tasks to appropriate vehicles. In future works, we will study how to combine resource allocation and task assignment in more complicated scenarios.

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