# Computation Resource Allocation and Task Assignment Optimization in Vehicular Fog Computing: A Contract-Matching Approach

Zhenyu Zhou, *Senior Member, IEEE,* Pengju Liu, Junhao Feng, Yan Zhang, *Senior Member, IEEE,* Shahid Mumtaz, *Senior Member, IEEE,* and Jonathan Rodriguez, *Senior Member, IEEE*

***Abstract*—Vehicular fog computing (VFC) has emerged as a promising solution to relieve the overload on the base station and reduce the processing delay during the peak time. The computation tasks can be offloaded from the base station to vehicular fog nodes by leveraging the under-utilized computation resources of nearby vehicles. However, the wide-area deployment of VFC still confronts several critical challenges such as the lack of efficient incentive and task assignment mechanisms. In this paper, we address the above challenges and provide a solution to minimize the network delay from a contract-matching integration perspective. First, we propose an efficient incentive mechanism based on contract theoretical modeling. The contract is tailored for the unique characteristic of each vehicle type to maximize the expected utility of the base station. Next, we transform the task assignment problem into a two-sided matching problem between vehicles and user equipments (UEs). The formulated problem is solved by a pricing-based stable matching algorithm which iteratively carries out the "propose" and "price-rising" procedures to derive a stable matching based on the dynamically updated preference lists. Finally, numerical results demonstrate that significant performance improvement can be achieved by the proposed scheme.**

***Index Terms*—vehicular fog computing, resource allocation, task assignment, contract theory, matching theory.**

## I. Introduction

With the rapid advancement of information and communication technologies, there arises a critical issue that both the data rate and computation demands grow exponentially. For example, emerging 5G applications such as real-time video streaming, augmented reality, interactive gaming, and self driving, require advanced data communication, computation, and storage techniques to handle the complicated data processing and storage operations [1]. This poses a new challenge on the conventional cloud computing paradigm. It is difficult to guarantee the stringent quality of service (QoS) and quality of experience (QoE) requirements due to the long distance between user equipments (UEs) and remote data centers [2]. Edge computing which extends the computation capability to the close proximity of UEs has been proposed as a complementary solution [3], [4]. In [5], Cui *et al.* investigated the energy minimization problem in cache-assisted mobile edge computing (MEC), and proposed a joint caching and offloading mechanism. Guo *et al.* proposed an energy-efficient resource allocation scheme for multi-user MEC to optimally allocate the communication and computation resources [6]. However, in order to cover a large-scale geographic area, a massive number of high-cost energy-inefficient servers have to be deployed and maintained, which inevitably results in significant capital expenditure (CAPEX) and operational expenditure (OPEX). Furthermore, considering the dynamically time-varying demands, the dense deployment of servers will lead to huge resource wastage during the off-peak time. Therefore, how to accommodate the ever-increasing demand in communication and computation with moderate costs via a demand-adaptation approach remains an open problem.

An alternative choice is to exploit the under-utilized resources of nearby vehicles. Particularly, future vehicles will be equipped with more powerful onboard computers, larger-capacity data storage units, and more advanced communication modules for the sake of improving driving safety, convenience, and satisfaction [7], [8]. Hence, the tremendous computation resources provided by a large group of vehicles can be aggregated and utilized to alleviate network congestion during the peak time without deploying additional servers. For example, an array of parked vehicles can serve as fog node and provide real-time computation capability augmentation [9]. Moreover, the computation tasks of UEs can be directly offloaded to vehicles without going through the base station to further reduce the transmission delay. This new computing paradigm is known as vehicular fog computing (VFC) [10], which is a beneficial complement to edge computing and cloud computing.

Manuscript received June 1, 2018; revised November 17, 2018; accepted January 11, 2019. Date of publication January 23, 2019; date of current version April 16, 2019. This work was supported in part by the National Natural Science Foundation of China under Grant 61601181, in part by the Fundamental Research Funds for the Central Universities under Grant 2017MS001, in part by the European Union's Horizon 2020 Research and Innovation Program under Grant 815178, in part by the European Union's Horizon 2020 Research and Innovation Program under the Marie Sklodowska-Curie Grant 824019, and in part by the Sichuan Science and Technology Program under Grant 2019YFH0033. The review of this paper was coordinated by the Guest Editors of the Special Section on Fog/Edge Computing for Autonomous and Connected Cars. (*Corresponding author: Junhao Feng.*)

Z. Zhou, P. Liu and J. Feng are with the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China (E-mal: zhenyu_zhou@ncepu.edu.cn, pengju_liu@ncepu.edu.cn, junhao_feng@ncepu.edu.cn).

Y. Zhang is with the Department of Informatics, University of Oslo, Norway. He is also with Simula Research Laboratory, Norway. (E-mail: yanzhang@ieee.org)

S. Mumtaz is with the Instituto de Telecomunicações, Aveiro, Portugal. (E-mail: smumtaz@av.it.pt).

J. Rodriguez is with the Instituto de Telecomunicações, Aveiro, Portugal, and University of South Wales, Pontypridd, UK (E-mail: jonathan.rodriguez@southwales.ac.uk).

However, despite the above-mentioned advantages, the wide area deployment of VFC still confronts several critical challenges, which are summarized as follows.

First, there lacks an effective incentive mechanism for vehicles to serve as fog nodes. Most of previous studies have assumed that vehicles will share their computation resources unconditionally [11]. This assumption is too optimistic in practical implementation. Due to the cost incurred by task processing, self-interested vehicles are reluctant to serve as fog nodes unless they are well compensated. Furthermore, a vehicle's private information, such as the preference towards resource sharing and the total amount of available resources, is asymmetric, i.e., it is known by the vehicle itself but unavailable for the base station. This is called the scenario of information asymmetry. Therefore, it is of vital importance to develop an incentive mechanism, which can effectively optimize the economic benefit of the network operator or the base station under information asymmetry.

Second, there lacks a low-complexity near-optimal task assignment mechanism. With the existence of multiple vehicles and UEs, a critical challenge is how to assign the computation tasks of UEs to vehicles such that the total network delay can be minimized. Since UEs are owned by independent entities, it is highly possible that they have completely different interests and even prefer conflicting task assignment decisions. Therefore, a computation task can be implemented if and only if all the UEs have reached an agreement on the task assignment decision. Otherwise, some UEs can simply achieve a better performance by ignoring the decision. This is different from conventional VFC task assignment problems where the optimization is performed unilaterally [12], [13].

Accordingly, these challenges motivate us to develop a two-stage computation resource allocation and task assignment approach by combining contract theory and matching theory. In the first stage, in order to motivate vehicles to share their resources, the base station designs a contract, which specifies the relationship between the performance, i.e., the amount of computation resources required from a vehicle, and the reward, i.e., the payment to the vehicle for its contribution. 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 base station broadcasts the contract, and each vehicle chooses its desired contract item to maximize its payoff. In the second stage, the vehicles which have signed the contract with the base station serve as fog nodes. The task assignment problem is modeled as a two-sided matching game, in which the UEs rank the vehicles by considering transmission delay, task execution latency, task size, and matching cost. A stable matching between UEs and vehicles is derived by using the proposed pricing-based matching approach. To the best of the authors' knowledge, this is the first work which investigates the computation resource allocation and task assignment problem in VFC from a contact-matching integration perspective. The main contributions of this work are summarized as follows:

- *Contract-based incentive mechanism design:* We propose an efficient incentive mechanism based on contract theoretical modeling. The contract is tailored for the unique characteristic of each vehicle type to maximize the expected utility of the base station under the constraints of individual rationality (IR), incentive compatibility (IC), and monotonicity. To make the problem tractable, the total number of IR and IC constraints are firstly reduced by exploring the relationships between adjacent vehicle types. Then, the simplified problem is solved by using Karush-Kuhn-Tucker (KKT) conditions. We also consider the scenario without information asymmetry and derive the corresponding optimal contract, which is used as a performance benchmark.
- *Matching-based computation task assignment:* The task assignment problem is intractable due to the combinatorial nature. To reduce the complexity, we transform the task assignment problem into a two-sided matching problem based on the problem structure, which involves a matching between vehicles on one side and UEs on the other side. Then, we propose a pricing-based stable matching algorithm to solve the task assignment problem, which iteratively carries out the *propose* and *price-rising* procedures to derive a stable matching based on the dynamically updated preference lists.
- *Theoretical analysis and performance validation:* We provide a comprehensive theoretical analysis on contract feasibility, matching convergence, matching stability, matching optimality, and computation complexity. The contract feasibility and efficiency as well as the network delay performance are evaluated by conducting a series of simulations under different scenarios. Numerical results demonstrate that the proposed algorithm can approach the optimal performance of the exhaustive searching algorithm, while the computation complexity is several orders of magnitude lower.

The remaining parts of the paper are summarized as follows. A comprehensive review of related works is provided in Section II. The overall system model is introduced in Section III. Section IV presents the contract-based incentive mechanism design. Section V elaborates the matching-based task assignment mechanism. Section VI provides the simulation results. The conclusion is given in Section VII.

## II. Related Works

With the rapid proliferation of vehicles, the studies on VFC have received considerable attentions from both industry and academia. Hou *et al.* investigated the feasibility of VFC and provided a quantitative analysis among capacity, vehicle mobility, and connectivity [10]. Feng *et al.* proposed a novel framework named autonomous vehicular edge (AVE) to increase the computation capabilities of vehicles in a decentralized manner [14]. In [15], Satyanarayanan *et al.* explored how to build a shared real-time information system for vehicles to enable situational awareness based on the convergence of three technology trends. Xiao *et al.* investigated the feasibility of VFC, and developed a cost-effective on-demand VFC architecture by leveraging the mobility of vehicles [16]. In [17], Zhu *et al.* proposed a low-latency quality-enhanced task assignment solution named fog following me (Folo) for VFC.

The task assignment across stationary and mobile fog nodes is formulated as a joint optimization problem, and solved by exploiting mixed integer linear programming. As we can observe, these works rely on a common assumption that all the vehicles are willing to act as fog nodes, and the incentive issues have been neglected.

There exist some works which have already investigated the incentive design problem in cloud/edge/fog computing. In [18], Luong *et al.* proposed a comprehensive literature survey of pricing-based incentive mechanisms for resource allocation in cloud-enabled wireless networks. Liu *et al.* considered the computation offloading problem in MEC, and provided a Stackelberg game-based pricing scheme to stimulate edge server owners while optimizing the utility of the cloud service operator [19]. In [20], Su *et al.* developed a Stackelberg game-based pricing scheme to coordinate the competition and cooperation among moving vehicles, parked vehicles, and road side unit (RSU). In the Stackelberg game, the leaders, i.e., the RSU and parking area, have the perfect knowledge of the moving vehicles and content delivery costs. In addition, they also know each side's optimal strategy. However, most of current works rely on symmetric information, and are not applicable to the scenario of information asymmetry.

Contract theory is regarded as a powerful tool from microeconomics to cope with information asymmetry. A vehicle's private information can be effectively elicited because the contract item is incentive compatible, i.e., the payoff of a vehicle is maximized if and only if it selects the contract item designed for its type. Contract theory has already been widely applied in the optimization of wireless networks. In [21], Du *et al.* proposed a contract-based user association approach for traffic offloading in software-defined heterogeneous networks. Xu *et al.* developed an energy-efficient relay selection scheme by exploiting contract theoretical modeling [22]. Other application scenarios include cognitive radios [23], mobile crowdsourcing [24], and small-cell caching systems [25]. Several previous works have already compared Stackelberg game with contract theory. In [26], Duan *et al.* investigated the incentive mechanism design for smartphone collaboration. The Stackelberg game is used to model the cooperation game for data acquisition, where the shared tasks and the corresponding rewards for collaborators are homogeneous. In comparison, the contract theory is used to motivate cooperation in distributed computing, where computation efficiency and task amount for collaborators heterogeneous. In [24], Liu *et al.* demonstrated that the contract theory provides better profit for the base station than the Stackelberg game due to the fact that the contract is completely designed by the base station, which acts as a monopolist in the market. In the Stackelberg game, since the information is symmetric, the followers also know the action of the leader, and can optimize their payoffs accordingly.

Another critical challenge in VFC is how to assign the computation tasks to vehicular fog nodes. Numerous studies have addressed the task assignment problem with different optimization approaches, e.g., matching theory [1], [27], coalitional game [28], Stackelberg game [29], and multi-player non-cooperative game [30]. Compared to other solutions, matching theory is more suitable to handle the heterogeneous preferences of UEs. Specifically, the task assignment problem can be modeled as a two-sided matching game between UEs and vehicles, and solved in a self-organizing and self-optimizing fashion. Matching theory has already been employed to address various combinatorial problems with mutual preferences in Internet of things (IoT) fog networks [31], device-to-device networks [12], and vehicular content distribution networks [1], etc.

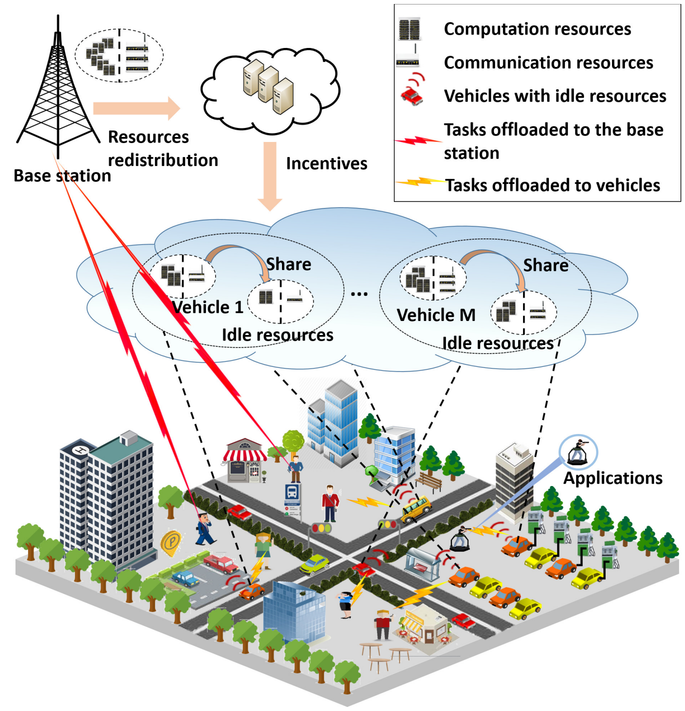


Fig. 1. The VFC framework.

Based on the above literature review, we can conclude that there lacks a uniform framework to address the resource allocation and task assignment optimization problem in VFC from a contract-matching integration perspective. Specifically, how to combine these two powerful tools to minimize the overall network delay requires further investigation.

## III. System Model

The VFC framework is shown in Fig. 1. In each cell, there exists a base station which takes charge of intra-cell communication resource coordination, computation resource allocation and task assignment. During the peak time when the base station is overwhelmed by the incoming computation demands, a group of vehicles are employed to act as fog nodes and relieve the overload problem via task offloading. Any vehicle with idle computation resources is able to act as a fog node by sharing its resources for task processing. With a properly-designed incentive mechanism, each vehicle can actively adjust the amount of resources to be shared in order to maximize its individual payoff. The details for how to design the incentive mechanism will be illustrated in Section IV.

In the same cell, there also exist numerous UEs. Each UE generates a series of computation tasks, each of which can be either processed by the base station or offloaded to a vehicular fog node. The details for how to model the interactions between UEs and vehicles, and how to derive a low-complexity sub-optimal task assignment solution will be illustrated in Section V.

For the sake of simplicity, we adopt a time-slot model in which the time is slotted into discrete intervals [22]. The optimization process is carried out in a slot-by-slot fashion. The set of vehicles and the set of UEs within the coverage of the base station remain fixed within each slot, and vary across different slots, which are denoted as $\mathcal{V}_M = \{V_1, \cdots, V_m, \cdots, V_M\}$ and $\mathcal{U}_N = \{U_1, \cdots, U_n, \cdots, U_N\}$, respectively. During each slot, it is assumed that each UE, e.g., $U_n$, has a computation task to be processed. The key attributes of the task can be described by a triplet $\{D_n, C_n, \tau_n\}$, where $D_n$ represents the task data size, $C_n$ is the required computation resource, i.e., the computation size, and $\tau_n$ represents the delay constraint.

***Remark 1.*** The system model considered in this work can also be extended to the scenario that a UE has multiple computation tasks to be processed per slot. In this case, the multiple tasks can be aggregated and considered as a single task with larger data size and higher computation demand. If UE $U_n$ has no task, we can simply set $D_n = C_n = \tau_n = 0$.

***Remark 2.*** Our model is different from the conventional MEC model where UEs offload their tasks to an edge server. First, the location of the edge server is fixed, while both the fog nodes and UEs considered in our model can be mobile. Second, the incentive issues have been largely neglected in MEC since both the communication and computation infrastructures are deployed and owned by the same network operator. However, in VFC where vehicles are owned by individuals, the incentive issues must be taken into consideration. Third, in the MEC model, UEs within the same cell can only connect to one or at most two base stations. In comparison, due to the high density of vehicles, a UE may be surrounded by multiple vehicles, and the candidate vehicles of different UEs are overlapped with each other. Last but not least, the MEC model is more suitable for the centralized task assignment scenario where the tasks of all the UEs within the same cell are assigned to the same edge server. Our model emphasizes on the decentralized task assignment scenario where the tasks of UEs are assigned to a group of distributed vehicles.

## IV. Contract-based Incentive Mechanism Design

In this section, we propose a contract-based incentive mechanism to motive vehicles to share their computation resources for task offloading. First, we introduce the vehicle type model. Second, the utility functions of the base station and vehicles are introduced, and the resource allocation problem is formulated. Third, we elaborate how to derive the optimal contract under information asymmetry. Finally, the optimal contract design without information asymmetry is provided.

### *A. Vehicle Type Modeling*

The preference of a vehicle towards resource sharing is quantified as its vehicle type. 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 base station to employ higher-type vehicles. Since the number of vehicles in a cell is usually finite, the set of vehicle types belongs to a discrete and finite space. The vehicle type is defined as follows:

**Definition 1. (Vehicle Type):** *The $M$ vehicles in set $\mathcal{V}_M$ can be sorted in an ascending order based on their preferences and classified into $K$ types. Denote the set of vehicle types as $\mathcal{K} = \{1, \cdots, k, \cdots, K\}$, and denote the set of corresponding resource sharing capability as $\Theta = \{\theta_1, \cdots, \theta_k, \cdots, \theta_K\}$, which is given by*

$$\theta_1 < \cdots < \theta_k < \cdots < \theta_K, \quad k \in \mathcal{K} \tag{1}$$

Then, we show how to derive the explicit expression of the vehicle type. For vehicle $V_m$, denote $C_m$ as the computation size of the local task to be processed. Due to resource sharing, the processing delay will be increased, which is given by

$$\Delta\tau_m = \frac{C_m}{\delta_{m,0} - \delta_m} - \frac{C_m}{\delta_{m,0}} \leq \Delta\tau_{m,max}, \tag{2}$$

where $\delta_{m,0}$ and $\delta_m$ represent the total available computation resource and the shared resource, respectively. The inequality specifies that the increased delay should be less than or equal to a threshold $\Delta\tau_{m,max}$ to satisfy QoS or QoE requirements.

Through some manipulations of (2), we can derive the upper bound of $\delta_m$ as

$$\delta_m \leq \frac{\delta_{m,0}^2 \Delta\tau_{m,max}}{\delta_{m,0}\Delta\tau_{m,max} + C_m} = \delta_m^{upper}, \tag{3}$$

where $\delta_m^{upper}$ is the maximum amount of resources that can be shared. We assume that $\delta_m^{upper}$ falls into a continues closed interval $[\delta_{min}, \delta_{max}]$, where $\delta_{min}$ and $\delta_{max}$ represent the minimum and maximum values of $\delta_m^{upper}, \forall m \in \mathcal{M}$, respectively. Then, the interval is divided into $K$ subintervals with the same length, and the lower bound of the $k$-th subinterval is defined as $\theta_k$, which is given by

$$\theta_k = \delta_{min} + \frac{k-1}{K}(\delta_{max} - \delta_{min}). \tag{4}$$

The type of vehicle $V_m$ is said to be $k$ if $\theta_k \leq \delta_m^{upper} < \theta_{k+1}$.

***Remark 3.*** From (4), we can infer that $\theta_k$ increases with $\delta_{m,0}$ and $\Delta\tau_{m,max}$, and decreases with $C_m$. This definition is consistent with practical situations. For example, a vehicle with light local tasks and abundant idle resources can share more resources. As a result, it can gain a higher profit and thus has a higher preference towards resource sharing.

In the scenario of information asymmetry, the base station does not know the precise information of each vehicle's type. Instead, only the statistical knowledge of the vehicle type is available via long term measurements or historical observations. We assume that the base station only knows that there are a total of $K$ types of vehicles and each vehicle $V_m \in \mathcal{V}_M$ belongs to type $k$ with the same probability $\lambda_k$, i.e., $\sum_{k=1}^{K} \lambda_k = 1$.

### B. Contract Formulation

Instead of offering the same contract item to vehicles with different types, the base station can design up to $K$ contract items for $K$ vehicle types, i.e., one contract item per type. For instance, the contract item dedicated for type $k$ vehicle is denoted as $(\delta_k, \pi_k)$, where $\delta_k$ denotes the required computation resources, and $\pi_k$ is the corresponding reward. The whole contract is denoted as $\mathcal{C} = \{(\delta_k, \pi_k), \forall k \in \mathcal{K}\}$.

Assuming the total amount of computation tasks that can be processed by the base station during a time interval $T$ is $C_{BS}$, we have $C_{BS} = \delta_{BS} T$. Here, $\delta_{BS}$ is the computation capability of the base station per second. We assume that the benefit of the base station is positively related to the reduced delay, which is valid since the motivation of exploiting VFC is to reduce the computation delay. For the purpose of simplicity, the linear function is utilized, which has also been employed in numerous works [32], [33]. Nevertheless, the proposed scheme can also be extended to more complicated scenarios with nonlinear functions. By signing the contract item $(\delta_k, \pi_k)$ with type $k$ vehicle, the benefit of the base station is given by

$$\begin{aligned} R_{BS}(\delta_k) &= r_{BS}\left(\frac{C_{BS}}{\delta_{BS}} - \frac{C_{BS}}{\delta_k + \delta_{BS}}\right) \\ &= r_{BS} T \frac{\delta_k}{\delta_{BS} + \delta_k}, \end{aligned} \tag{5}$$

where $r_{BS}$ is the unit benefit brought by the reduced delay. It is noted that although (5) is defined as a linear function of the reduced delay, it is actually a concave function of the variable $\delta_k$, which is nonlinear.

With $K$ types and $M$ vehicles, the expected utility of the base station is calculated as

$$U_{BS}(\{\delta_k\}, \{\pi_k\}) = M \sum_{k=1}^{K} \lambda_k [R_{BS}(\delta_k) - \pi_k]. \tag{6}$$

***Remark 4.*** A contract item $(\delta_k = 0, \pi_k = 0)$ means that type $k$ vehicle has no desire to share its resources. Moreover, the contract item must also guarantee that the utility of the base station is nonnegative, i.e., $R_{BS}(\delta_k) - \pi_k \geq 0$. Otherwise, the base station has no incentive to sign the contract with type $k$ vehicle.

The utility function of type $k$ vehicle which accepts the contract item $(\delta_k, \pi_k)$ is given by

$$U_k^V(\delta_k, \pi_k) = \theta_k \pi_k - \delta_k, \tag{7}$$

where $\theta_k$ characterize the weight of $\pi_k$ to type $k$ vehicle. A higher-type vehicle has a larger weight due to its higher preference towards resource sharing.

The expected social welfare is the total sum utility of the base station and the $M$ vehicles, which is given by

$$U_s(\{\delta_k\}, \{\pi_k\}) = U_{BS}(\{\delta_k\}, \{\pi_k\}) + M \sum_{k=1}^{K} \lambda_k U_k^V(\delta_k, \pi_k). \tag{8}$$

The objective of the base station is to maximize its utility under the scenario of asymmetric information via the optimization of each contract item. The corresponding optimization problem is formulated as

$$\begin{aligned} \mathbf{P1}: & \max_{(\{\delta_k\}, \{\pi_k\})} U_{BS}(\{\delta_k\}, \{\pi_k\}) \\ \text{s.t.} \quad & C_1: \theta_k \pi_k - \delta_k \geq 0, \forall k \in \mathcal{K},\ (IR) \\ & C_2: \theta_k \pi_k - \delta_k > \theta_k \pi_{k'} - \delta_{k'}, \\ & \qquad \forall k, k' \in \mathcal{K}, k \neq k',\ (IC) \\ & C_3: 0 \leq \delta_1 < \cdots < \delta_k < \cdots < \delta_K, \forall k \in \mathcal{K}, \\ & C_4: \delta_k \leq \theta_k, \forall k \in \mathcal{K}, \end{aligned} \tag{9}$$

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

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

- ***Individual rationality (IR) constraint:*** *Type $k$ vehicle, $\forall k \in \mathcal{K}$, will get a nonnegative payoff if it selects the contract item $(\delta_k, \pi_k)$.*
- ***Incentive compatibility (IC) constraint:*** *The IC constraint ensures the* self-revealing *property of the contract. For instance, type $k$ vehicle, $\forall k \in \mathcal{K}$, will get the maximum payoff if and only if it selects the contract item $(\delta_k, \pi_k)$ designed for its own type.*
- ***Monotonicity constraint:*** *The reward of type $k$ vehicle, $\forall k \in \mathcal{K}$, should be higher than that of type $k-1$ vehicle, and lower than that of type $k+1$ vehicle.*

Based on the IR, IC, and monotonicity constraints, we have

**Lemma 1.** *For any $k, k' \in \mathcal{K}$, if $\theta_k > \theta_{k'}$, then $\delta_k > \delta_{k'}$ and $\pi_k > \pi_{k'}$. $\pi_k = \pi_{k'}$ and $\delta_k = \delta_{k'}$ if and only if $\theta_k = \theta_{k'}$.*

**Lemma 2.** *For any $(\delta_k, \pi_k) \in \mathcal{C}$, the following inequalities hold*

$$\begin{aligned} & 0 \leq \pi_1 \leq \cdots \leq \pi_k \leq \cdots \leq \pi_K, \\ & 0 \leq \delta_1 \leq \cdots \leq \delta_k \leq \cdots \leq \delta_K, \\ & 0 \leq U_1^V \leq \cdots \leq U_k^V \leq \cdots \leq U_K^V. \end{aligned} \tag{10}$$

*Proof:* A similar proof of Lemma 1 and Lemma 2 can be found in [34]. The details are omitted here due to space limitation. ∎

Based on Lemma 1 and Lemma 2, we define the sufficient and necessary conditions for contract feasibility.

**Theorem 1.** Contract feasibility: *The contract $\mathcal{C} = \{(\delta_k, \pi_k), \forall k \in \mathcal{K}\}$ is feasible if and only if all the following conditions are satisfied:*

- *$0 \leq \pi_1 \leq \cdots \leq \pi_k \leq \cdots \leq \pi_K$ and $0 \leq \delta_1 \leq \cdots \leq \delta_k \leq \cdots \leq \delta_K$;*
- *$\theta_1 \pi_1 - \delta_1 \geq 0$;*
- *For any $k \in \{2, \cdots, K\}$, $\delta_{k-1} + \theta_{k-1}(\pi_k - \pi_{k-1}) \leq \delta_k \leq \delta_{k-1} + \theta_k(\pi_k - \pi_{k-1})$.*

*Proof:* The detailed proof of Theorem 1 is omitted here due to space limitation. A similar proof can be found in Appendix D of [23]. ∎

### C. Optimal Contract Design under Information Asymmetry

Problem $\mathbf{P1}$ involves $K$ IR constraints and $K(K-1)$ IC constraints. To provide a tractable solution, the following procedures are carried out to simplify the problem.

**Step 1:** *IR Constraints Elimination*

For type $k$ vehicle, $k \in \mathcal{K}, k \neq 1$, we can derive

$$U_k^V \geq U_{k-1}^V \geq U_1^V \geq 0, \tag{11}$$

where the first inequality is due to the IC constraint, the second inequality is based on Lemma 2, and the third inequality is due to the IR constraint. Hence, the IR constraint of type $k$ vehicle holds automatically as long as the IR constraint of type 1 vehicle is guaranteed.

**Step 2:** *IC Constraints Elimination*

We define the IC constraints between type $k$ and type $k'$, $k' \in \{1, \cdots, k-1\}$, as downward incentive constraints (DICs). Similarly, the IC constraints between type $k$ and type $k''$, $k'' \in \{k+1, \cdots, K\}$, 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., $\theta_{k-1} < \theta_k < \theta_{k+1}$, which satisfy

$$\theta_{k+1}\pi_{k+1} - \delta_{k+1} \geq \theta_{k+1}\pi_k - \delta_k, \tag{12}$$

$$\theta_k\pi_k - \delta_k \geq \theta_k\pi_{k-1} - \delta_{k-1}, \tag{13}$$

where (12) denotes the DIC between type $k+1$ and $k$, and (13) denotes the DIC between type $k$ and $k-1$.

By combining $\pi_{k+1} \geq \pi_k \geq \pi_{k-1}$, we have

$$\theta_{k+1}\pi_{k+1} - \delta_{k+1} \geq \theta_{k+1}\pi_{k-1} - \delta_{k-1}. \tag{14}$$

Therefore, if the DIC between type $k+1$ and $k$ holds, then the DIC between type $k+1$ and $k-1$ also holds. The DIC constraints can be extended downward from type $k-1$ to type 1, which are given by

$$\begin{aligned} \theta_{k+1}\pi_{k+1} - \delta_{k+1} &\geq \theta_{k+1}\pi_{k-1} - \delta_{k-1} \\ &\geq \cdots \\ &\geq \theta_{k+1}\pi_1 - \delta_1. \end{aligned} \tag{15}$$

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 $K$ IR constraints and $K(K-1)$ IC constraints can be reduced to 1 and $K-1$, respectively. Furthermore, we have the following properties:

**Proposition 1.** *In order to maximize the utility of the base station, the optimal contract item for type 1 vehicle, i.e., $(\delta_1^*, \pi_1^*)$, must enforce*

$$U_1^V(\delta_1^*, \pi_1^*) = \theta_1\pi_1^* - \delta_1^* = 0. \tag{16}$$

*Proof:* The proof is based on reduction to absurdity. Assuming $\theta_1\pi_1^* - \delta_1^* > 0$, then the base station can improve its own utility by either decreasing $\pi_1^*$ or increasing $\delta_1^*$ until $\theta_1\hat{\pi}_1 - \hat{\delta}_1 = 0$ while simultaneously satisfying the conditions of contract feasibility. Then, we have

$$R_{BS}(\hat{\delta}_1) - \hat{\pi}_1 > R_{BS}(\delta_1^*) - \pi_1^*, \tag{17}$$

which contradicts with the assumption that $(\delta_1^*, \pi_1^*)$ is the optimal contract item. Hence, we must have $\theta_1\pi_1^* - \delta_1^* = 0$. This completes the proof of Proposition 1. ■

**Proposition 2.** *The optimal contract item for any type $k$ vehicle $(\delta_k^*, \pi_k^*)$, $k = 2, \cdots, K$, satisfies the following equality condition:*

$$\delta_k^* = \delta_{k-1}^* + \theta_k(\pi_k^* - \pi_{k-1}^*). \tag{18}$$

*Proof:* From the IC constraint, we have

$$\delta_k^* \leq \delta_{k-1}^* + \theta_k(\pi_k^* - \pi_{k-1}^*), k = 2, \cdots, K \tag{19}$$

Then, the base station can further improve its own utility by either decreasing $\pi_k^*$ or increasing $\delta_k^*$ until the equality holds, which does not violate the conditions of contract feasibility. This completes the proof of Proposition 2. ■

Thus, based on constraint elimination, Proposition 1 and Proposition 2, $\mathbf{P1}$ can be rewritten as

$$\begin{aligned} \mathbf{P2}: &\max_{(\{\delta_k\},\{\pi_k\})} U_{BS}(\{\delta_k\}, \{\pi_k\}), \\ \text{s.t.} \quad & C_1: \theta_1\pi_1 - \delta_1 = 0, (IR) \\ & C_2: \delta_k = \delta_{k-1} + \theta_k(\pi_k - \pi_{k-1}), 2 \leq k \leq K, (IC) \\ & C_3, C_4, \forall k \in \mathcal{K}. \end{aligned} \tag{20}$$

We can easily prove that $\mathbf{P2}$ is a convex programming problem by checking the Hessian matrix. Thus, $\mathbf{P2}$ can be solved by applying KKT conditions. The Lagrangian associated with $\mathbf{P2}$ is given by

$$\begin{aligned} &\mathcal{L}(\{\delta_k\}, \{\pi_k\}, \{\mu_k\}, \{\rho_k\}, \{\beta_k\}) \\ &= U_{BS}(\{\delta_k\}, \{\pi_k\}) + \mu_1(\theta_1\pi_1 - \delta_1) \\ &+ \sum_{k=2}^{K} \mu_k\Big(\theta_k(\pi_k - \pi_{k-1}) + \delta_{k-1} - \delta_k\Big) \\ &+ \rho_1\delta_1 + \sum_{k=2}^{K} \rho_k(\delta_k - \delta_{k-1}) + \sum_{k=1}^{K} \beta_k(\delta_k - \theta_k), \end{aligned} \tag{21}$$

where $\mu_1$ is the Lagrange multiplier corresponding to constraint $C_1$, $\{\mu_k, k = 2, \cdots, K\}$, $\{\rho_k, \forall k \in \mathcal{K}\}$, and $\{\beta_k, \forall k \in \mathcal{K}\}$ are the vectors of Lagrange multipliers corresponding to constraints $C_2$, $C_3$, and $C_4$, respectively. KKT conditions are summarized as follows:

- Primal constraints: $0 \leq \delta_1^*$; $\delta_{k-1}^* \leq \delta_k^*, \delta_k^* = \delta_{k-1}^* + \theta_k(\pi_k^* - \pi_{k-1}^*), \forall k \in \mathcal{K}, k \neq 1$; $\delta_1^* = \theta_1\pi_1^*$; $\delta_k^* \leq \theta_k, \forall k \in \mathcal{K}$;
- Dual constraints: $\mu_k^* \geq 0, \rho_k^* \geq 0$ and $\beta_k^* \geq 0, \forall k \in \mathcal{K}$;
- Complementary slackness: $\rho_1^*\delta_1^* = 0$; $\rho_k^*(\delta_k^* - \delta_{k-1}^*) = 0, \forall k \in \mathcal{K}, k \neq 1$; $\beta_k^*(\delta_k^* - \theta_k) = 0, \forall k \in \mathcal{K}$ ;

- The first-order conditions of the Lagrangian is

$$\begin{cases} \frac{\partial \mathcal{L}}{\partial \delta_k} = \frac{\partial R_{BS}(\delta_k)}{\partial \delta_k} - \mu_k + \mu_{k+1} + \rho_k - \rho_{k+1} \\ \qquad + \beta_k = 0, \forall k \in \mathcal{K}, k \neq K, \\ \frac{\partial \mathcal{L}}{\partial \delta_K} = \frac{\partial R_{BS}(\delta_K)}{\partial \delta_K} - \mu_K + \rho_K + \beta_K = 0, \\ \frac{\partial \mathcal{L}}{\partial \pi_k} = -\lambda_k + \mu_k \theta_k - \mu_{k+1}\theta_{k+1} = 0, \\ \qquad \forall k \in \mathcal{K}, k \neq K, \\ \frac{\partial \mathcal{L}}{\partial \pi_K} = -\lambda_K + \mu_K \theta_K = 0. \end{cases} \tag{22}$$

The contract design and optimization is handled by the centralized base station, and the detailed process is summarized as part of the Algorithm 1.

### D. Optimal Contract Design without Information Asymmetry

If there exists a selfish base station which is perfectly aware of every vehicle's type, it can further increase its profit by exploiting the complete information. The contract has to ensure that the payoff of each vehicle is non-negative. Otherwise, the vehicles have no incentive to accept the contract items. To this end, the contract item also has to meet the IR constraint. Furthermore, the contract item has to satisfy the following property:

**Theorem 2.** *In the contract design without information asymmetry, any optimal contract item $(\delta_k^*, \pi_k^*) \in \mathcal{C}$ should satisfy $\theta_k \pi_k^* = \delta_k^*$. That is, the payoff for any vehicle is zero.*

*Proof:* Theorem 2 can be proved by contradiction. Given an optimal contract item $(\delta_k^*, \pi_k^*)$, if $\theta_k \pi_k^* - \delta_k^* > 0$, then the base station can increase its utility by decreasing $\pi_k^*$ to $\hat{\pi}_k$ which satisfies $\theta_k \hat{\pi}_k - \delta_k^* = 0$. This contradicts with the assumption that $(\delta_k^*, \pi_k^*)$ is optimal. ■

Thus, by enforcing the utility of each vehicle to be zero, $\mathbf{P2}$ can be written as

$$\begin{aligned} \mathbf{P3}: &\max_{(\{\delta_k\},\{\pi_k\})} \; U_{BS}(\{\delta_k\},\{\pi_k\}), \\ \text{s.t.} \quad & \tilde{C}_1: \theta_k \pi_k - \delta_k = 0, \forall k \in \mathcal{K}, \\ & C_3, C_4. \end{aligned} \tag{23}$$

$\mathbf{P3}$ can also be solved by using KKT conditions.

**Theorem 3.** *In the contract design without information asymmetry, for any type $k$ vehicle, $k \in \mathcal{K}$, the optimal reward is $\pi_k^* = 1$ regardless of $\theta_k$.*

*Proof:* From Theorem 2, we have $\theta_k \pi_k^* - \delta_k^* = 0$. Furthermore, from the upper bound of $\delta_k \leq \theta_k$, we can derive $\delta_k^* = \theta_k$ since the base station can always increase $\delta_k$ to increase its utility until the equality holds. Thus, we have $\theta_k \pi_k^* - \theta_k = 0$, and $\pi_k^* = 1$. ■

## V. Matching-based Task Assignment

In this section, we first introduce the task assignment model and the problem formulation. Then, we introduce the proposed pricing-based matching algorithm. Next, we provide a comprehensive theoretical analysis on convergence, stability, optimality, and complexity.

### A. Task Assignment Model

*1) Task Transmission Delay:* After the first-stage resource sharing, the UEs can offload their computation tasks to vehicles which serve as fog nodes. In the offloading mode, data can be directly transmitted from UEs to vehicles to reduce the total number of transmission hops. We assume that each UE is allocated with an orthogonal spectrum resource block such that the co-channel interference among UEs can be ignored. Furthermore, the large-scale fading and the small-scale fading are modeled by using the Rayleigh fading model and the free-space propagation path-loss model, respectively. If the task of UE $U_n$ is offloaded to vehicle $V_m$, the signal to noise ratio (SNR) of the received signal at vehicle $V_m$ is given by

$$\gamma_{m,n} = \frac{p_n d_{n,m}^{-\alpha} h_{n,m}^2}{N_0}, \tag{24}$$

where $p_n$ denotes the transmission power of UE $U_n$. $d_{n,m}$ is the transmission distance between UE $U_n$ and vehicle $V_m$. $\alpha$ is the path-loss exponent. $h_{n,m}$ represents the Rayleigh channel coefficient with a complex Gaussian distribution. $N_0$ denotes the power noise.

Hence, the transmission time required by UE $U_n$ for uploading its task with size $D_n$ can be obtained as

$$T_{n,m}^t = \frac{D_n}{B_{n,m} \log_2(1 + \gamma_{n,m})}, \tag{25}$$

where $B_{n,m}$ refers to the bandwidth of the link between UE $U_n$ and vehicle $V_m$.

We assume that the vehicles travel on a two-lane two-directional road. Due to the fast vehicle mobility, vehicle $V_m$ might move out of the communication range of UE $U_n$ during data transmission, which results in an offloading failure. Denote the dwell time of $V_m$ inside the communication range of $U_n$ as $\tau_{n,m}^o$. An offloading failure occurs if $\tau_{n,m}^o < T_{n,m}^t$. Therefore, $\tau_{n,m}^o$ also represents the delay constraint of data transmission because $U_n$ can only transmit data to $V_m$ when they remain connected. That is, an offloading request is admissible if and only if $T_{n,m}^t < \tau_{n,m}^o$.

To estimate the vehicle dwell time, a simple way is to use the average velocity. Assuming that UE $U_n$ is located along the road side and its communication range is a circle with a diameter $d_n$, $\tau_{n,m}^o$ can be calculated as

$$\tau_{n,m}^o = \hat{d}_{n,m} / \bar{v}_m, \tag{26}$$

where $\hat{d}_{n,m}$ denotes the distance between the location of $V_m$ and the endpoint of the circle's diameter in the vehicle heading direction, and $\bar{v}_m$ denotes the average velocity of $V_m$.

***Remark 5.*** Both $\hat{d}_{n,m}$ and $\bar{v}_m$ can be estimated from the GPS data [35]. For example, if $V_m$ moves in the centrifugal direction to leave the communication area of $V_n$, $\hat{d}_{n,m}$ is calculated as $\hat{d}_{n,m} = \frac{1}{2d_n} - d_{n,m}$. Otherwise, if $V_m$ moves in the centripetal direction, we have $\hat{d}_{n,m} = \frac{1}{2d_n} + d_{n,m}$. We have not put any restriction on the mobility models of vehicles. As long as the vehicle dwell time can be obtained, the proposed matching-based task assignment scheme can be adaptable for different mobility models.

***Remark 6.*** In this work, we assume that the GPS information is known to the base station. This assumption has also been accepted and employed in a number of previous works [8], [14]. Furthermore, even if the GPS information is unavailable to the base station, vehicle positions can still be obtained based on mobility prediction techniques [36]–[39].

*2) Task Execution Delay:* If the type of vehicle $V_m$ is $k$, i.e., the amount of computation resource is $\delta_m = \delta_k^*$, the execution time required to process the task of UE $U_n$ is calculated as

$$T_{n,m}^c = \frac{C_n}{\delta_m} = \frac{C_n}{\delta_k^*}. \tag{27}$$

The transmission latency from $V_m$ to $U_n$ is ignored, due to the fact that the size of computation results is usually negligible compared to that of the input data, e.g., face recognition. If $V_m$ has already moved out of the communication range of $U_n$, the results have to be forwarded firstly from $V_m$ to the base station, and then sent from the base station to $U_n$.

The total delay when the task of UE $U_n$ is assigned to vehicle $V_m$ is given by

$$T_{n,m}^{total} = T_{n,m}^t + T_{n,m}^c. \tag{28}$$

*3) Problem Formulation:* The purpose of this work is to relieve the heavy burden of the base station and reduce the total network delay by leveraging the under-utilized computation resources of vehicles. Hence, we model the objective function as the total delay of the overall network, i.e., the sum delay of all the UEs. We investigate how to assign the tasks of UEs to vehicles such that the objective function is minimized. The task assignment decision is defined as follows:

**Definition 3. (Task Assignment Decision):** *The task assignment decision between $N$ UEs and $M$ vehicles is defined as a $N \times M$ matrix $\mathbf{X}$, where its $(n,m)$-th element , i.e., $x_{n,m}$, is defined as a binary value. $x_{n,m} = 1$ means that the computation task of UE $U_n$ is assigned to vehicle $V_m$. Otherwise, $x_{n,m} = 0$.*

The problem is formulated as follows:

$$\begin{aligned}
\mathbf{P4}: & \min_{\mathbf{X}} \sum_{n=1}^{N} \sum_{m=1}^{M} x_{n,m} T_{n,m}^{total} \\
\text{s.t.} \quad & C_5: \sum_{V_m \in \mathcal{V}_M} x_{n,m} \le 1, \forall U_n \in \mathcal{U}_N, \\
& C_6: \sum_{U_n \in \mathcal{U}_N} x_{n,m} \le 1, \forall V_m \in \mathcal{V}_M, \\
& C_7: T_{n,m}^{total} \le \tau_n, \forall U_n \in \mathcal{U}_N, \forall V_m \in \mathcal{V}_M, \\
& C_8: T_{n,m}^{t} \le \tau_{n,m}^{o}, \forall U_n \in \mathcal{U}_N, \forall V_m \in \mathcal{V}_M.
\end{aligned} \tag{29}$$

Here, $C_5$ and $C_6$ guarantee that there is a one-to-one correspondence among UEs and vehicles. $C_7$ and $C_8$ denote the delay constraints of task assignment and task transmission, respectively.

To provide a tractable solution, the combinatorial problem $\mathbf{P4}$ can be transformed into a two-sided matching problem based on the problem structure. The matching problem can be represented as a triple $(\mathcal{U}_N, \mathcal{V}_M, \mathcal{F})$, where $\mathcal{U}_N$ and $\mathcal{V}_M$ are two distinct and finite sets of matching participants, i.e., UEs and vehicles, respectively. $\mathcal{F}$ represents the set of matching preferences of UEs. Particularly, each UE aims at minimizing its individual delay under the specified constraints. A one-to-one matching $\phi$ is defined as [40]:

**Definition 4. (Matching):** *For the formulated matching problem $(\mathcal{U}_N, \mathcal{V}_M, \mathcal{F})$, the matching $\phi$ is a one-to-one correspondence from set $\mathcal{U}_N \cup \mathcal{M}_K$ onto itself under preference $\mathcal{F}$, i.e., $\phi(U_n) \in \mathcal{V}_M \cup \{U_n\}$, $\forall U_n \in \mathcal{U}_N$. $\phi(U_n) = V_m$ represents that UE $U_n$ is matched with vehicle $V_m$, which is equivalent to $x_{n,m} = 1$. $\phi(U_n) = U_n$ means that $U_n$ has not been matched with any vehicle, and the task of $U_n$ will be handled by the base station.*

### *B. Preference List Construction*

In order to implement the two-sided matching, every UE has to construct its preference list by ranking vehicles from the other side in accordance with the preferences. For UE $U_n$, it can achieve different delay performances when being paired with different vehicles. Therefore, in order to minimize the total delay, we can define that the preference is inversely proportional to the total delay, e.g., $1/T_{n,m}^{total}$. The preference of $U_n$ towards $V_m$ is calculated as

$$G_{n,m}|_{\phi(U_n)=V_m} = \frac{1}{T_{n,m}^{total}} - P_m, \tag{30}$$

where $P_m$ is the price for utilizing the computation resource of $V_m$, the initial value of which is zero. The role of $P_m$ is to resolve the matching conflict, which will be explained later. Here, $1/T^{total}$ is just used as an example. The preference model can be extended to more complicated expressions.

We introduce a complete, reflexive, and transitive binary preference relation [40], i.e., "$\succ$", to compare the preferences towards different vehicles. For instance, $V_m \succ_{U_n} V_{m'}$ represents that $U_n$ prefers $V_m$ to $V_{m'}$, which is given by

$$V_m \succ_{U_n} V_{m'} \Leftrightarrow G_{n,m}|_{\phi(U_n)=V_m} > G_{n,m'}|_{\phi(U_n)=V_{m'}}. \tag{31}$$

Furthermore, $V_m \succeq_{U_n} V_m'$ represents that $U_n$ prefers $V_m$ at least as well as $V_m'$, which is given by

$$V_m \succeq_{U_n} V_{m'} \Leftrightarrow G_{n,m}|_{\phi(U_n)=V_m} \ge G_{n,m'}|_{\phi(U_n)=V_{m'}}. \tag{32}$$

To obtain the entire preference list of $U_n$, we temporarily pair it with every vehicle in order to derive the preference for each combination. We use $F_n$ to denote the preference list of $U_n$ towards all the vehicles. $F_n$ is obtained by sorting all the $M$ vehicles in a descending order according to $G_{n,m}|_{\phi(U_n)=V_m}, \forall V_m \in \mathcal{V}_M$. The total set $\mathcal{F}$ is constructed as $\mathcal{F} = \{F_n, \forall U_n \in \mathcal{U}_N\}$.

### *C. Pricing-based Stable Matching*

After obtaining the preference for all the UEs in $\mathcal{U}_N$, the second-stage task assignment problem can be solved by using a pricing-based stable matching algorithm. The main parts of it are the *propose* and the *price rising* rules, which are defined as follows:

**Definition 5. (Propose Rule):** *For any UE $U_n \in \mathcal{U}_N$, it proposes to its most preferred vehicle which ranks as the first place in its preference list $F_n$, e.g., $V_m$. We have $V_m \succ_{U_n} V_{m'}, \forall V_{m'} \in F_n, V_{m'} \neq V_m$.*

**Definition 6. (Price Rising Rule):** *For any vehicle $V_m \in \mathcal{V}_M$ that has received more than one proposal from UEs, it can raise its price to increase the matching cost, which is given by*

$$P_m = P_m + \Delta P_m. \tag{33}$$

The matching process is implemented in an iterative fashion, and the detailed process is summarized as part of the Algorithm 1. It is noted that the matching-based task assignment can also be managed by the base station. Specifically, each UE uploads its preference list to the base station, and then a stable matching between UEs and vehicles is derived by the base station based on the preference lists of UEs. Eventually, the base station broadcasts the matching result to UEs, which offload their tasks to the corresponding vehicles accordingly. The implementation procedure is explained as follows.

**Phase 1:** Matching Preference Initialization

- Calculate $F_n$ for each UE $U_n \in \mathcal{U}_N$.
- Initialize $\phi$ as an empty set. Define $\Omega$ as the set of vehicles which receive more than one matching proposal. $\Omega = \emptyset$ at the beginning.
- Set $P_m = 0$ for any vehicle $V_m \in \mathcal{V}_M$.

**Phase 2:** Iterative Matching

**Repeat** the following process iteratively.

- If $\exists \phi(U_n) = \emptyset$, preform the propose rule for UEs.
  - Each UE $U_n \in \mathcal{U}_N$ proposes to its most preferred vehicle in its preference list $F_n$.
- If any vehicle $V_m \in \mathcal{V}_M$ receives only one proposal from a UE, then $V_m$ will be directly matched with the UE which has proposed to it. Otherwise, add $V_m$ into set $\Omega$.
- If $\Omega \neq \emptyset$, perform the price rising rule for vehicles which received more than one matching proposal.
  - Each vehicle $V_m \in \Omega$ increases its price by $\Delta P_m$.
  - Every UE which has proposed to $V_m$ updates its preference towards $V_m$ accordingly and renews its proposal.
  - Remove the vehicles which receive only one proposal from $\Omega$.

**Until** Every $U_n$ has been matched with a vehicle, i.e., $\forall \phi(U_n) \neq \emptyset$, or there exists no available vehicle for the unmatched UEs.

**Phase 3:** Task Assignment Implementation

The UEs offload their tasks according to the matching results obtained in **Phase 2**. Assuming $\phi(U_n) = V_m$, UE $U_n$ will send its task to vehicle $V_m$ for processing. For those unmatched UEs in set $\Phi$, their tasks will be processed by the base station. In the next slot, the base station updates the sets $\mathcal{U}_N$ and $\mathcal{V}_M$, and the task assignment process will return to **Phase 1**.

***Remark 7.*** It is noted that any vehicle $V_m \in \mathcal{V}_M$, which cannot satisfy the delay constraint of $U_n$, will be directly removed from $F_n$ despite of the preference.

### *D. Stability, Optimality and Complexity Analysis*

**Definition 7. (Stability):** *A matching $\phi$ is stable if for any $U_n \in \mathcal{U}_N$, there does not exit a $V_m$ such that $V_m \succ_{U_n} \phi(U_n)$.*

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**Algorithm 1** Contract-Matching Algorithm

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**Input:** $M$, $N$, $\{\theta_k\}$, $\{\lambda_k\}$
**Output:** $\mathcal{C}^*$, $\phi$
**Stage I: Contract-based Incentive Mechanism Design**
Sort the types of vehicles based on (4);
Obtain the optimal contract $\mathcal{C}^*$ by solving (20);
**for** $V_m \in \mathcal{V}_M$ **do**
    Calculate the maximum amount of shared resource $\delta_m^{upper}$ based on (3).
    **if** $\theta_k \leq \delta_m^{upper} < \theta_{k+1}$ **then**
        $V_m$ signs the contract item $(\delta_k^*, \pi_k^*)$ with the base station, and shares its idle resource $\delta_k^*$.
    **end if**
**end for**
**Stage II: Matching-based Task Assignment**
**Set** $\phi$=$\emptyset$, $\Omega$=$\emptyset$, $\Delta P_m$=0.1, $P_m$=0 and $\mathcal{U}_{v_m} = \emptyset$ for each $V_m \in \mathcal{V}_M$;
Every UE $U_n \in \mathcal{U}_M$ builds its preference list $F_n$ based on (30) and (31);
**while** $\exists \phi(U_n) = \emptyset$ **do**
    **for** $U_n \in \mathcal{U}_N$ **do**
        UE $U_n$ proposes to its most preferred vehicle in its updated preference list $F_n$;
    **end for**
    **for** $V_m \in \mathcal{V}_M$ **do**
        **if** $V_m$ receives more than one request **then**
            $\Omega = \Omega \cup \{V_m\}$;
            Add UEs which proposed to vehicle $V_m$ to the set $\mathcal{U}_{v_m}$;
        **end if**
    **end for**
    **if** $\Omega = \emptyset$ **then**
        Match vehicles with UEs based on the proposals;
    **else**
        **for** $V_m \in \Omega$ **do**
            Vehicle $V_m$ increases its price $P_m$ by $\Delta P_m$ based on (33);
            Every $U_n \in \mathcal{U}_{v_m}$ updates its preference based on (30), and renews its proposals;
            Remove $U_n$ from $\mathcal{U}_{v_m}$ if it gives up $V_m$;
            Remove $V_m$ from $\Omega$ if it receives only one proposal.
        **end for**
    **end if**
**end while**

---

**Theorem 4.** *The pricing-based matching algorithm produces a stable matching within finite iterations.*

**Theorem 5.** *The obtained stable matching is weak Pareto optimal for UEs.*

*Proof:* A similar proof can be found in our previous works [1], [12]. ■

***Remark 8. (Computational Complexity)*** In the contract-based incentive mechanism design, the formulated optimization problem is a standard convex programming problem with $M$ equality constraints and $2M+1$ inequality constraints. The

TABLE I
PARAMETERS.

| Parameter | Value |
|---|---|
| Number of vehicles | $5-20$ |
| Number of UEs | $6-25$ |
| Data size of UE's task | $100-200$ Mb |
| Computation size of UE's task | $100-400$ Mb |
| Delay constraint | $0.1-2$ s |
| Velocity of vehicles | $2-20$ m/s |
| Cell radius | 1000 m |
| Radius of the UE's communication coverage | 200 m |
| Computing resources of the base station | 5 GHz |
| Transmission power of UEs | 30 dBm |
| Bandwidth of UEs | 20 MHz |
| Noise power | $-114$ dBm |
| Path loss exponent | $-3.4$ |

overall computation complexity is $\mathcal{O}(M)$.

In the process of the pricing-based matching, the complexity for each UE to acquire the preferences of all the vehicles and the complexity for sorting the obtained preferences are $\mathcal{O}(M)$ and $\mathcal{O}(M\log(M))$, respectively. Assuming the number of iterations required for resolving the conflict in the price rising process is $\zeta$, i.e., the conflicting elements are matched within $\zeta$ iterations. Hence, the complexity of the matching process is $\mathcal{O}(N\zeta)(N \geq M)$ or $\mathcal{O}(M\zeta)(M \geq N)$.

The optimal matching result can be obtained by employing the exhaustive searching scheme. The total number of possible combinations is $(M^N N!)$. Thus, the exhaustive searching scheme has to examine every possible combination in order to find out the optimal matching result. The computation complexity is $\mathcal{O}(M^N N!)$.

## VI. SIMULATION RESULTS

In this section, we validate the proposed scheme via simulations.

### A. Contract Feasibility and Efficiency

A series of simulations are conducted to verify the feasibility and the efficiency of the contract-based incentive mechanism. We consider a single cell with one base station, 20 vehicles, and 30 UEs. The number of vehicle types is equal to that of vehicles, and assume the vehicle types are following a Gaussian distribution. Simulation parameters are summarized in Table I. The proposed scheme is compared with the contract without information asymmetry [34] and the take-it-or-leave contract [23]. In the take-it-or-leave contract, the base station offers a uniform contract item which is designed based on a threshold type $k_{th}$. Then, vehicles with higher types, i.e., $k \geq k_{th}, \forall k \in \mathcal{K}$, will accept the contract, while vehicles with lower types, i.e., $k < k_{th}, \forall k \in \mathcal{K}$, will reject the contract.

Fig. 2(a) and Fig. 2(b) show the amount of shared computation resources and the rewards versus different vehicle types, respectively. As we can see, the computation resources that can be shared by vehicles and the corresponding reward increase monotonically with the vehicle type, which have been already demonstrated in Lemma 2. Furthermore, numerical results show that the contract without information asymmetry requires more resources from vehicles compared to that of information asymmetry. The reward provided for each vehicle is exactly 1 regardless of the vehicle type, which is consistent with Theorem 3.

Fig. 2(c) shows the utilities of type 5, type 10, and type 15 vehicles versus the different types of contract items. It is observed that each vehicle can maximize its utility if and only if it selects the specific contract item dedicated for its type. Furthermore, numerical results show that the utilities of vehicles also increase with the vehicle type, which agrees with the analysis summarized in Lemma 2.

Fig. 3(a) and Fig. 3(b) show the utility of the base station and the utility of vehicles versus the vehicle type. Numerical results show 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. Moreover, the contract enforces every vehicle's utility to be zero. The reason behind has been analyzed in the proof of Theorem 2. 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.

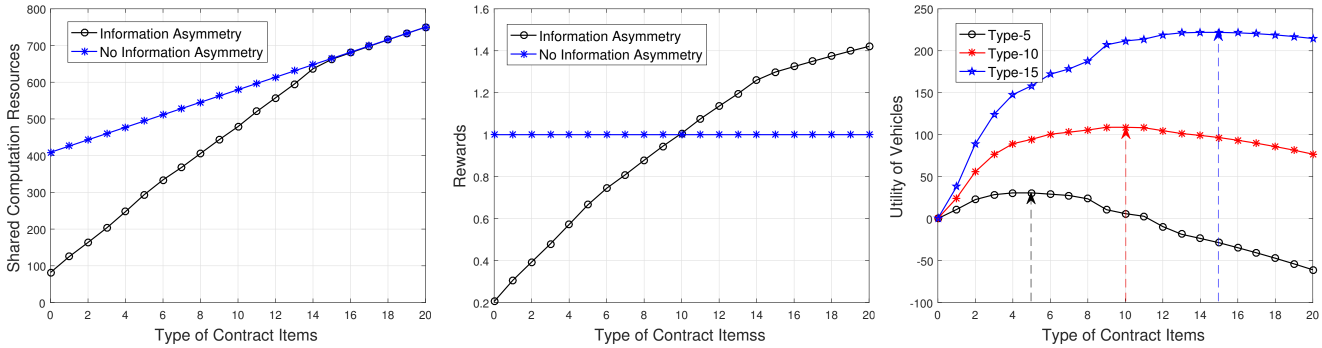
In the take-it-or-leave contract, any vehicle whose type satisfies $k < k_{th}, \forall k \in \mathcal{K}$ will reject the contract due to constraint $C_4$. In this case, either the base station's utility or the vehicle's utility is zero. Only the vehicles with higher types, i.e., $k \geq k_{th}, \forall k \in \mathcal{K}$, can achieve nonzero utilities. However, since the take-it-or-leave contract is designed based on threshold type $k_{th}$, the gap between the utility of type $k$ vehicle and that of the proposed scheme increases along with $k$. The reason is that the take-it-or-leave contract is not incentive compatible.

Fig. 3(c) shows the social welfare versus the vehicle type. Numerical results demonstrate that the social welfare achieved by the proposed contract is close to that of the contract without information asymmetry. The reason is that the utility of the base station obtained by exploiting the complete information leads to enormous utility loss of vehicles. On the other hand, the take-it-or-leave contract achieves the lowest social welfare.

### B. Delay Performance

In simulations, we employ the constant-velocity model [10], [20], and the velocities of vehicles are generated randomly within the range $[2, 20]$ m/s. To provide a relative comparison, the delay performances of different algorithms are normalized and converged to the range of $[0, 1]$ by dividing the largest delay.

Fig. 4 shows the normalized network delay versus the number of matching iterations. Numerical results show that the proposed scheme can converge to a stable matching within a limited number of iterations. It is also observed that both the number of iterations required to reach convergence and the normalized network delay increase with the number of UEs.

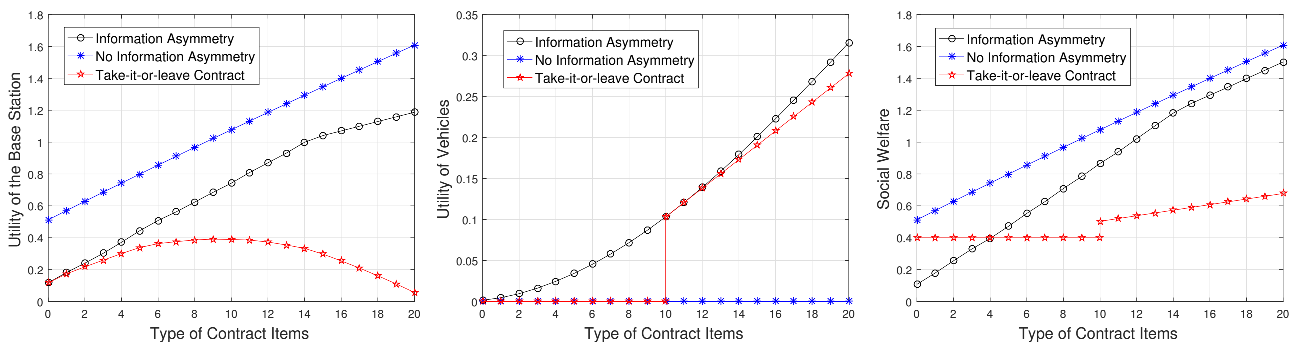



(a) The shared computation resources versus different types of vehicles.

(b) The rewards versus different types of vehicles.

(c) The utility of vehicles versus different types of contract items.

Fig. 2. Contract feasibility: (a) shared computation resources; (b) rewards; (c) utility of vehicles.




(a) The utility of the base station versus different types of vehicles.

(b) The utilities of vehicles versus different types of vehicles.

(c) The social welfare versus different types of vehicles.

Fig. 3. Contract efficiency: (a) utility of the base station; (b) utilities of vehicles; (c) social welfare.

The reason is that the competition among UEs becomes more intense as the number of UEs increases. As a result, additional price-rising iterations are necessary to resolve the competition. Moreover, if the number of UEs is much larger than that of vehicles, a larger amount of tasks have to be processed by the overloaded base station, which significantly increases the network delay.

Fig. 5 shows the normalized network delay versus the number of UEs. Numerical results demonstrate that the network delay is inversely related to the number of vehicles and positively related to the number of UEs, which is consistent with the results of Fig. 4. Furthermore, the proposed scheme is able to achieve a network delay that is close to that of the optimal exhaustive searching algorithm but with a much lower complexity.

Fig. 6 shows the normalized network delay versus the total delay constraint of the computation task. As the total delay constraint increases, the number of eligible vehicles also increases accordingly, and more and more tasks can be offloaded to the vehicles rather than being processed by the overloaded base station with limited computation resources. This will dramatically reduce the network delay since the under-utilized resources of vehicles have been well exploited. Numerical results also demonstrate that the proposed scheme can achieve close-to-optimal performance under all the investigated scenarios.

Fig. 7 shows the normalized network delay versus the vehicle velocity. Numerical results demonstrate that the network delay increases with the vehicle velocity. The reason is that the number of eligible vehicles decreases along with the vehicle velocity due to the stringent constraint of transmission delay. As a result, it is less likely for a UE to be matched with a satisfactory vehicle, and the corresponding task can only be processed by the overloaded base station. Hence, the proposed scheme is more suitable for hot spots where there exist a large number of parked vehicles or the vehicles move slowly due to traffic congestion.

## VII. Conclusion

In this paper, we investigated the computation resource allocation and task assignment problem in VFC from a contract-matching integration perspective. A contract-based incentive mechanism was proposed to motivate vehicles to share their resources, and a pricing-based stable matching algorithm was developed to address the task assignment problem. Numerical results demonstrate that the proposed incentive mechanism achieves a social welfare that is close to the optimal performance without information asymmetry, while the proposed

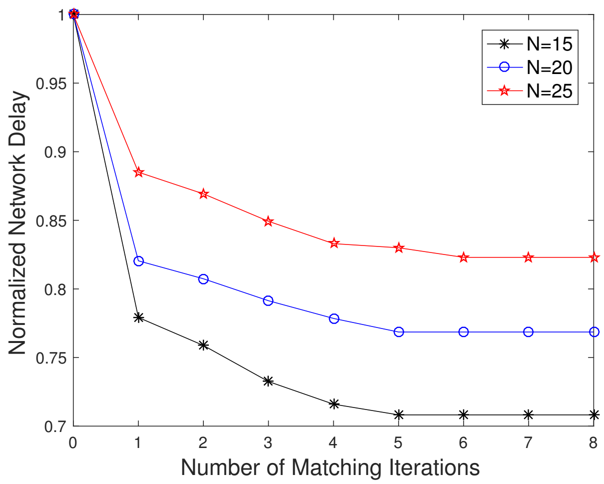



Fig. 4. Normalized delay of UEs vary with the number of iterations.

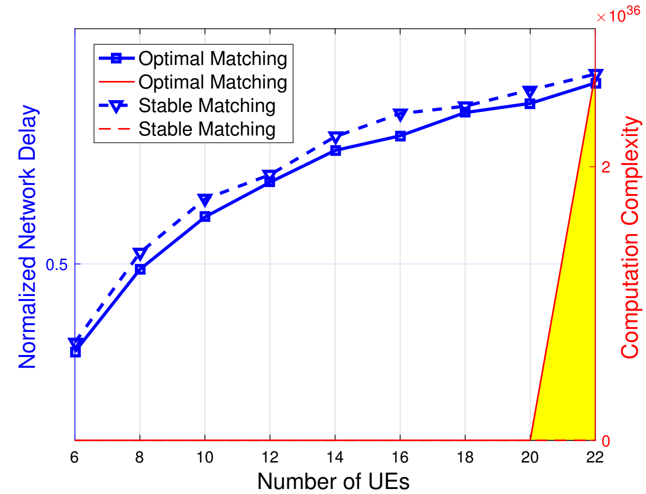



Fig. 5. Normalized delay and computation complexity versus the number of UEs.

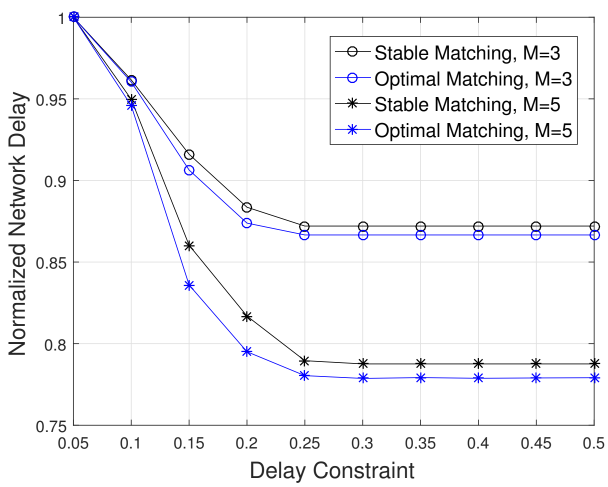



Fig. 6. Normalized delay versus the delay constraint $\tau_n$.

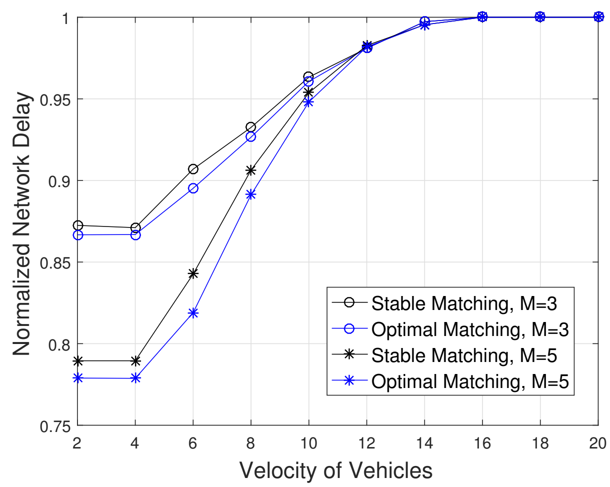



Fig. 7. Normalized delay versus the velocity of vehicles.

task assignment scheme is able to achieve a network delay that is close to that of the optimal exhaustive searching algorithm but with a much lower complexity.

In future works, we will investigate the more complicated scenario where the precise knowledge of channel and vehicle states is unknown, and study how to combine machine learning-based approaches to optimize the long-term delay performance.

Furthermore, the wide-scale deployment of VFC faces numerous security and forensic challenges. Different from cloud computing where the servers are deployed, operated, and maintained by specialized service providers, the fog nodes are generally deployed and maintained by third-party developers or even users. Therefore, to guarantee the reliable operation of VFC, several security mechanisms including confidentiality, integrity, authentication, access control, and forensics, etc., are required [41]. However, some existing security solutions developed for cloud computing may not scale well in VFC [42]. Particularly, the heterogeneous and distributed nature of fog nodes poses new threats on authentication, access control, and resilience [42]. In summary, the research on the security aspect of VFC is still in the infancy stage, which requires further investigation and examination.

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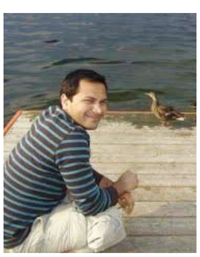
**Zhenyu Zhou** (S06-M11-SM17) received the M.E. and Ph.D. degrees from Waseda University, Tokyo, Japan, in 2008 and 2011, respectively. From April 2012 to March 2013, he was the Chief Researcher with the Department of Technology, KDDI. Since 2013, he has been an Associate Professor with the School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China. He has also been a Visiting Scholar with Tsinghua-Hitachi Joint Lab on Environment-Harmonious ICT, Tsinghua University, since 2014. His research interests include green communications and smart grids.

Dr. Zhou served as an Associate Editor for IEEE Access, a Guest Editor for IEEE Communications Magazine, workshop co-Chair for the 2015 IEEE International Symposium on Autonomous Decentralized Systems, and a TPC member for IEEE VTC, IEEE ICC, IEEE Globecom, IEEE PIRMC, IEEE APCC, IEEE Africon, IEEE CCNC, etc. He received 2017 Premium Award for Best Paper in IET Communications, Young Researcher Encouragement Award from the IEEE Vehicular Technology Society in 2009 and Beijing Outstanding Young Talent from Beijing Government, China.

**Pengju Liu** is currently working towards the Bachelor degree at North China Electric Power University, China. His research interests include resource allocation, energy management in VEC.

**Junhao Feng** is currently working towards the M.S. degree at North China Electric Power University, China. His research interests include resource allocation, interference management, and energy management in D2D communications.

**Yan Zhang (M'05-SM'10)** received the Ph.D. degree from the School of Electrical and Electronics Engineering, Nanyang Technological University, Singapore. He is currently a Full Professor with the Department of Informatics, University of Oslo, Oslo, Norway. His current research interests include next-generation wireless networks leading to 5G, green and secure cyber-physical systems, such as smart grid, healthcare, and transport. He is an IEEE Vehicular Technology Society (VTS) Distinguished Lecturer. He is also a Senior Member of the IEEE ComSoc, the IEEE CS, the IEEE PES, and the IEEE VTS. He is a fellow of the IET. He is an Associate Technical Editor of the IEEE Communications Magazine, an Editor of IEEE Network Magazine, an Editor of the IEEE Transactions on Green Communications and Networking, an Editor of the IEEE Communications Surveys and Tutorials, an Editor of IEEE Internet of Things Journal, and an Associate Editor of the IEEE Access. He serves as the Chair in a number of conferences, including the IEEE GLOBECOM 2017, the IEEE PIMRC 2016, the IEEE CloudCom 2016, the IEEE ICCC 2016, the IEEE CCNC 2016, the WCSP 2016, the IEEE SmartGridComm 2015, and the IEEE CloudCom 2015. He serves as a TPC member for numerous international conferences, including the IEEE INFOCOM, the IEEE ICC, the IEEE GLOBECOM, and the IEEE WCNC.



**Shahid Mumtaz (SM'16)** received the M.Sc. degree from the Blekinge Institute of Technology, Sweden, and the Ph.D. degree from the University of Aveiro, Portugal. He is currently a Senior Research Engineer with the Instituto de Telecomunicações, Aveiro, where he is involved in EU funded projects. His research interests include MIMO techniques, multi-hop relaying communication, cooperative techniques, cognitive radios, game theory, energy efficient framework for 4G, position information-assisted communication, and joint PHY and MAC layer optimization in LTE standard. He has authored several conferences, journals, and books publications.

**Jonathan Rodriguez (M'04-SM'13)** received his Master and Ph.D degree in Electronic and Electrical Engineering from the University of Surrey (UK), in 1998 and 2004 respectively. In 2005, he became a researcher at the Instituto de Telecomunicações and Senior Researcher in the same institution in 2008 where he established the 4TELL Research Group targeting the next generation mobile networks with key interests on energy efficient design, cooperative strategies, security and electronic circuit design. He has served as project coordinator for major international research projects (Eureka LOOP, FP7 C2POWER), whilst acting as the technical manager for FP7 COGEU and FP7 SALUS. He is currently leading the H2020-ETN SECRET project. Since 2009, he has been invited as the Assistant Professor at the Universidade de Aveiro, and granted as the Associate Professor in 2015. His professional affiliations include: Senior Member of the IEEE and Chartered Engineer (CEng) since 2013, and Fellow of the IET (2015).