IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 20, 2019, accepted November 6, 2019, date of publication November 11, 2019, date of current version November 27, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2952664

Stackelberg-Game-Based Mechanism for Opportunistic Data Offloading Using Moving Vehicles

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This work was supported by the Natural Science Foundation of China under Grant 61801409.

ABSTRACT Data offloading through vehicular ad hoc networks (VANETs) is one of the most promising methods for overcoming the overload problem in cellular networks. As data delivery by service providers consumes resources such as bandwidth, storage and power, the incentive scheme with the optimal pricing strategy must be identified. In the literature, most incentive schemes focus on offloading through fixed nodes, such as roadside units (RSUs). It remains very challenging to motivate a moving vehicle to help other users deliver their data due to the high mobility of vehicles. Game theory is a widely adopted method for analyzing pricing issues in wireless networks. Therefore, this paper proposes an optimal pricing strategy that uses the Stackelberg game to model the interaction between a service provider and a service requester. Then, the Stackelberg equilibrium is derived under the corresponding conditions. Next, an algorithm is proposed for selecting the service provider that offers the lowest price based on the results of the Stackelberg equilibrium. Finally, the simulation results demonstrate that the proposed algorithm can effectively reduce the downloading time of a task while maximizing the utilities of both the service provider and the requester.

INDEX TERMS Data offloading, stackelberg game, VANETs, incentive scheme, Internet of Vehicles.

I. INTRODUCTION

With the rapid proliferation of smart mobile devices such as smart phones, tablets and wearable electronics, data-hungry applications such as 4k/8k video streaming, augmented reality/virtual reality (AR/VR), high-precision mapping, and social sharing are popularly used on these devices. The data traffic that is produced by these applications is experiencing explosive growth. According to Cisco's forecast [1], global mobile traffic will increase sevenfold between 2016 and 2021, and video data will account for 78% of mobile traffic by 2021. The continuously increasing data traffic imposes a huge burden on cellular networks, which could cause overload and congestions in cellular networks in the near future. Congestions in backhaul, backbone and access networks may result in severe degradation of the quality of service (QoS), including reduced data rate, packet loss, and packet delay.

For addressing these issues, upgrading cellular networks is the most straightforward approach. The deployment of base stations (BSs) provides additional bandwidth, processing and storage resources to accommodate more traffic. However, upgrading networks is expensive and the continuously increasing demands for bandwidth may soon surpass the capacity of new infrastructures. Opportunistic data offloading, which leverages the opportunistic network that is formed by mobile nodes to offload traffic, has been recently considered as a complementary solution [2]. In opportunistic data offloading, some traffic data can be directly transmitted between mobile nodes without help from the infrastructure. Thus, popular content can be downloaded by only a few mobile nodes and transmitted to other nodes via opportunistic communication.

Numerous vehicles are equipped with sensors, communication, computing, storage and positioning devices. Such vehicles are connected and become moving nodes of vehicular ad hoc networks. VANETs have attracted substantial attention from both academia and industry. Supported by 5G- and IEEE 802.11p-related technologies, VANETs are expected to be realized in the near future [3]. VANETs support various types of applications, including safety-related applications (e.g., collision detection, lane change warning and cooperative merging), smart and green transportation management (e.g., traffic signal control, intelligent traffic scheduling, and fleet management), location-dependent services (e.g., point of interest and route optimization), and entertainment applications (e.g., online games, videos, Wechat, and

The associate editor coordinating the review of this manuscript and approving it for publication was Muhammad Khalil Afzal.

Facebook) [4]. Content requests from drivers and passengers are substantially increased, thereby resulting in a huge burden on cellular networks. Moreover, VANETs have unique features such as high vehicle mobility, frequent link breakages and high topological dynamicity. These features render it more difficult for cellular networks to satisfy the QoS requirements of all applications. Hence, to reduce the load of cellular networks, it is necessary to offload traffic to opportunistic networks that are formed by moving vehicles.

VANETs include two communication modes: vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V). Based on the data offloading paths, current offloading schemes can be classified into two categories [3]: V2I-based and V2V-based data offloading. For V2I-based data offloading, roadside units serve as ‘‘bridges’’ between cellular networks and vehicles, which can download and store popular data and transmit them to passing vehicles. However, the deployment of RSUs is expensive, and it is almost impossible to provide seamless coverage. Compared to V2I mode, V2V mode is more flexible and can be used in ad hoc mode. Therefore, V2V-based offloading is a low-cost method. In this paper, we focus on V2V-based data offloading. By establishing a one-hop or multi-hop path between two vehicles, data can be transmitted directly between them. Vehicles are selected for downloading and storing popular content from the Internet and transmitting them to other vehicles via one-hop or multi-hop V2V communications. However, it requires extra resources such as bandwidth, storage and power for service providers to download, store and deliver this content. It is challenging to encourage vehicles to share their resources and to facilitate the transmission of other vehicles' packets. The main technical and commercial issues for service providers and requesters are as follows:

1) How can an appropriate service provider be selected?
2) How can the amount of data that should be offloaded to the service provider be selected?
3) What is the optimal pricing strategy for both the service provider and the requester?

Game theory is an effective method for analyzing the interactions between offloading service providers and requesters. Game-theory-based approaches have been widely used in incentive schemes for data offloading [27]–[36]. A classical game typically has three components: a set of players (or participants), available strategies for each player and a utility function for each player [5]. In a data offloading game through VANETs, service providers and requesters are players and they take actions to maximize their own utilities. At the end, if no player has an incentive to unilaterally deviate from its current strategy, the state is named the Nash equilibrium (NE). Therefore, we can find the optimal pricing and offloading strategy by seeking the NE state of an offloading game. Out of all games, the Stackelberg game has been extensively used to address the pricing problem in data offloading. The basic strategy of the Stackelberg game is that one player, who is referred to as the leader, has the right to take the first action. Then, the other player, who is referred to as the follower, observes the leader's action and make his own decision accordingly. The main advantages of exploiting the Stackelberg game are as follows: first, it is played in sequential steps, which describes the interaction between a service provider and a service requester very accurately; second, the difference between the leader and the follower accords with the unequal positions of a service provider and a service requester; and third, it can offer an optimal price and a percentage of the offloaded data for both a service provider and a requester if the Stackelberg equilibrium exists [5]–[6].

Therefore, in this paper, we propose a Stackelberg-game-based pricing scheme for data offloading in software-defined-network (SDN)-based VANETs, which obtains the optimal price and offloading percentage to facilitate data delivery from service providers to service requesters. In contrast to the available approaches, this scheme uses moving vehicles as service providers and considers the special features of moving vehicles, such as the mobility of vehicles, the V2V contact duration, the bandwidths among BSs, the service provider and the service request, and the popularity of the content. If a moving vehicle needs to obtain content, one of its neighboring vehicles that offers the lowest price is selected as the service provider so that the vehicle can obtain a part of the content from the BS and the remaining content from the service provider. The Stackelberg game is used to model the interaction between a service provider and a service requester. Based on the derived Stackelberg equilibrium, an algorithm is proposed for selecting the optimal service provider. The main contributions of this paper are threefold:

- First, we formulate the interaction between a service provider and a requester as a Stackelberg game, which considers the movements of vehicles, the V2V contact durations, the bandwidths among BSs, the service provider and the requester, and the popularity of the content.
- Second, we derive the Nash equilibrium and the corresponding existence conditions. On the basis of these conditions, a selection algorithm is proposed for a service requester to select the service provider that offers the lowest unit price.
- Third, extensive simulations are conducted to evaluate the performance of the proposed algorithm. The experimental results demonstrate that the proposed algorithm can effectively reduce the downloading time of a task while maximizing the utilities of both the service provider and the requester.

The remainder of this paper is organized as follows: Section II reviews related work on data offloading. Section III describes the problem and system models. Section IV presents the Stackelberg-game-based scheme for data offloading in VANETs, followed by the simulation results and performance analysis of the proposed scheme in Section V. Section VI summarizes this paper.

II. RELATED WORKS

A. DATA OFFLOADING THROUGH WIFI APS OR MOBILE NODES

Data offloading has recently attracted extensive research attention. Many schemes have been proposed in the literature. In [7]–[9], WiFi access points (APs) are used to offload data from cellular networks. Lee *et al.* [7] studied human mobility patterns and found that approximately 65% of the traffic of cellular networks can be offloaded to WiFi and 55% of the battery power can be saved. However, they did not discuss how to offload data to APs. Balasubramanian *et al.* [8] designed a system, namely, *Wiffler,* that augments the capacity of cellular networks by leveraging delay tolerance and fast switching. Simulation results demonstrate that 45% of the traffic can be offloaded to WiFi, while the delay tolerance is 60 seconds. Nevertheless, this method is not suitable for real-time applications. Higgins *et al.* [9] proposed a mechanism, namely, *Intentional Networking*, for using network diversity to improve the aggregate bandwidth. This mechanism can substantially reduce the system latency by offloading data to WiFi networks. However, the amount of data that should be offloaded to WiFi networks is unknown. In the above schemes, APs serve as the offloading nodes. Furthermore, mobile nodes are selected as the offloading nodes in [10]–[13]. Barbera *et al.* [10], [11] discussed a social-attribute-based method for selecting the offloading nodes and the considered social attributes, such as betweenness, closeness, degree, closeness centrality and pagerank. However, neither the mobility of nodes nor the link quality is considered in this method. In contrast to [10]–[11], Wang *et al.* [12] leveraged social network services such as online impact spreading and offline mobility patterns to build a social graph. However, the link quality was not considered. Barua *et al.* [13] reported a link-quality-based algorithm, namely, *select best (SB)*, for selecting the offloading nodes with the highest link quality. However, the selection procedure introduces an additional delay.

B. DATA OFFLOADING THROUGH VANETS

Data offloading through VANETs is one of the most challenging and active topics. Current strategies in the literature can be classified into two categories: V2I- and V2V-based data offloading.

To overcome the challenge of fleeting connection times between vehicles and RSUs, Chen *et al.* [14] used a two-phase resource allocation process, which consisted of link scheduling and bandwidth allocation, to engineer the utilization patterns of wireless and backhaul links. Zhioua *et al.* [15] considered the offloading procedure as an optimization problem of maximizing a set of flows to offload cellular data through RSUs. However, the mobility of vehicles is not considered in the above two schemes. To overcome this problem, Malandrino *et al.* [16], [17] introduced a fog-of-war model for expressing the prediction accuracy of vehicle mobility and exploited mobility prediction to decide which data RSUs should fetch from cellular networks and deliver to vehicles. However, capacity of the links and the load balance of RSUs are not considered. Therefore, Sun *et al.* [18] used a cooperative downloading scheme to offload data of online videos from cellular networks through RSUs. Based on predicting vehicle mobility and throughput, the cooperative scheme uses a storage-time aggregated graph to plan the transmission times of data. However, the performance of this scheme strongly depends on the accuracy of the adopted model of vehicle movement. Thus, this scheme may not perform well in complex scenarios such as urban roads. To increase the resource utilization efficiency, Si *et al.* [19] explored a new architecture, namely, *DaVe,* for offloading delay-tolerant data to VANETs. Nevertheless, the offloaded data may suffer from long delays.

While the aforementioned schemes use RSUs to offload data, moving vehicles can also be used as offloading nodes [20]–[26]. Zhioua *et al.* [20] used a model, namely, *VOPP*, to determine the potential for offloading data from cellular networks through VANETs. The objective is to select the maximum number of data flows that can be routed to the downloaders. Li *et al.* [21] formulated the offloading problem as a utilization maximization problem under linear constraints and proposed an algorithm for determining when erasure coding can be used to improve the system performance and how to allocate network resources. However, in the above two schemes, the authors considered only a snapshot of the VANETs and modeled the offloading problem as a maximization problem. The mobility of vehicles was not considered. To select the most suitable offloading nodes, a selection scheme that considers users' interests and near-future contact predictions is proposed in [22]. However, the selected offloading nodes may become the bottleneck of the system. Huang *et al.* [23] designed a control scheme for offloading data from cellular to V2V paths under the SDN inside the mobile edge computing (MEC) architecture. The SDN controller calculates whether a V2V path exists between two vehicles and decides whether to switch to the V2V path. However, the centralized management mechanism and the procedure for path discovery may result in a huge overhead. Kolios *et al.* [24] established a flexible network flow model for capturing the movement patterns of vehicles. Based on the flow model, they used an optimal forwarding decision strategy for V2V-assisted offloading. However, it is difficult to predict the movements of vehicles. Thus, the performance of the proposed scheme will degrade if the prediction is not accurate. Huang *et al.* [25] investigated a credit-based clustering (CBC) scheme for point of interest (POI) geo data sharing in vehicular social networks. In each cluster, a vehicle is selected as the cluster head to download POI geo data from the cellular network and share them with its cluster members. Thus, it is highly important to select a proper head cluster, and the stability of a cluster head strongly influences the performance of the strategy. Feng *et al.* [26] presented a vehicle-assisted offloading (VAO) scheme that uses the vehicle queue that is waiting for a red light to transfer data traffic from cells of busy street intersections to its idle adjacent cells. However, motivating the vehicles to participate in offloading remains challenging.

C. INCENTIVE SCHEMES FOR DATA OFFLOADING

All the above works focus on the technical perspective of data offloading without considering economic incentives. Economic incentives are important for offloading through opportunistic networks that are formed by vehicles, as data offloading consumes bandwidth, storage and power resources of service vehicles. Game theory is an effective approach for addressing the above issues and provides service providers and requesters with the optimal price and task allocation schemes. However, most of the available incentive schemes are designed for data offloading through APs or mobile nodes. Few approaches are designed for data offloading through VANETs.

Kang and Sun [27] investigated the interactions between WiFi APs and mobile network operators (MNO) and proposed an incentive mechanism that uses both salary and bonus to attract WiFi APs to participate in data offloading. Wang *et al.* [28] developed a distributed market framework for pricing the offloading service and characterized the interaction between service providers and requesters as a multi-leader multi-follower Stackelberg game. However, in [27] and [28], the authors did not distinguish data according to priorities and APs according to capacity, and only considered the size of the offloaded data and the unit price. Furthermore, Shah-Mansouri *et al.* [29] divided access point owners (APOs) into two types: price-setting and price-taking APOs. Then, a three-stage Stackelberg game is used to study the MNO's profit maximization problem. However, features of the data are still not considered in [29]. Similarly, Zhang *et al.* [30] divided the data into two types, namely, delay-tolerant and delay-sensitive, and utility functions were designed for the two types of data. However, the mobility of nodes is not considered.

In vehicular environments, Cheng *et al.* [31] proposed an approach for predicting the WiFi offloading potential and access cost, based on which they introduced two offloading mechanisms: auction-game-based offloading (AGO) and congestion-game-based offloading (CGO). However, the prediction approach does not consider the locations of vehicular users or the features of the application sessions. Su *et al.* [32] encouraged parked vehicles to facilitate content delivery in VANETs so that moving vehicles could obtain content from both RSUs and parked vehicles. Moreover, a price model is developed so that three parties, namely, moving vehicles, RSUs and parked vehicles, can attain their maximum utilities. However, both RSUs and parked vehicles are stationary. Based on the architecture of SDN, Aujla *et al.* [33] designed a Stackelberg-game-based intelligent network selection scheme for data offloading in vehicular networks. However, the centralized offloading management mechanism introduces additional overhead. Therefore, Liu *et al.* [34] reported two decentralized data offloading mechanisms: multi-item auction (MIA)-based and congestion game (COG)-based. Xu *et al.* [35] proposed a fast cloud-based network selection scheme for vehicular networks. Vehicles select the optimal access networks via a coalition formation game approach. However, in [34] and [35], the mobility of vehicles is not considered. In contrast to the above incentive schemes, Dua *et al.* [36] developed a game-theory-based algorithm for selecting the optimal vehicle onto which to offload data from RSUs that considers the connectivity, density of vehicles, distance, speed and angle of movement. However, features of the data are still not considered. TABLE 1 compares the available approaches.

In contrast to the available incentive schemes for data offloading in VANETs, this paper uses moving vehicles as offloading nodes. The proposed scheme considers the special features of moving vehicles, which include the mobility of vehicles, the V2V contact duration, the bandwidths among BSs, the client vehicles and helper vehicles, and the popularity of contents.

III. PROBLEM OVERVIEW AND SYSTEM MODELS

This section describes the participants in the Stackelberg game. Then, the scenario and basic assumptions are presented in detail. Finally, the traffic model, mobility model, communication model and interest model are presented.

A. PARTICIPANTS IN THE STACKELBERG GAME

Client: A client is a vehicle user who has a downloading task that needs to be offloaded. A client can be denoted as a 5-tuple, namely, $c = \{\lambda, D_C, r_{BC}, v_C, p_C\}$, where λ is defined as the offloading rate, namely, the proportion of the downloading data size that the client decides to offload; D_C is the total data size of the downloading task (bit); r_{BC} represents the downloading data rate (bit/s) between the base station (BS) and the client; v_C is the velocity (m/s) of the client; and p_C denotes the instantaneous position of the client.

Helper: A helper is a vehicle user who has idle bandwidths that can be used to help download and deliver other users' data. A helper can be represented by a 7-tuple, namely, $h = \{\eta, \varepsilon_{BH}, \varepsilon_{HC}, r_{BH}, r_{HC}, v_H, p_H\}$, where η denotes the unit price (\$/bit) the helper charges for helping download and deliver the offloaded data; ε_{BH} and ε_{HC} represent the unit costs (\$/bit) for downloading the offloaded data from the BS and delivering it to the client, respectively; r_{BH} and r_{HC} denote the data rates (bit/s) between the BS and the helper and between the helper and its client, respectively; and v_H and p_H denote the velocity (m/s) and the instantaneous position, respectively, of the helper.

B. SCENARIO AND ASSUMPTIONS

As illustrated in FIGURE 1, we consider the multi-lane highway scenario of VANETs, where base stations of cellular networks are deployed alongside the road to provide seamless coverage and are connected to the content servers in the Internet through wire-line links. All vehicles are equipped with two wireless interfaces: a cellular network interface and an

TABLE 1. Comparison of available approaches.

Ref.	Game theory	Scenario	Offloading node	Main shortcoming
[7]	No	heterogeneous	APs	Lack of a method for offloading data
[8]	No	heterogeneous	APs	Additional delay
[9]	No	heterogeneous	APs	The amount of data to be offloaded to WiFi APs must be specified
[10-11]	No	heterogeneous	Mobile nodes	Lack of consideration of mobility of nodes and link quality
[12]	No	heterogeneous	Mobile nodes	Lack of consideration of link quality
[13]	No	heterogeneous	Mobile nodes	Additional delay
[14]	No	VANET	RSUs	Lack of consideration of the mobility of vehicles
[15]	No	VANET	RSUs	Lack of consideration of the mobility of vehicles
[16-17]	No	VANET	RSUs	Lack of consideration of link capacity and load balance
[18]	No	VANET	RSUs	Difficulty predicting the movements of vehicles
[19]	No	VANET	RSUs	Additional delay
[20]	No	VANET	Vehicles	Lack of consideration of the mobility of vehicles
[21]	No	VANET	Vehicles	Lack of consideration of the mobility of vehicles
[22]	No	VANET	Vehicles	Lack of capacity of offloading nodes
[23]	No	VANET	Vehicles	Additional overhead
[24]	No	VANET	Vehicles	Difficultly predicting the movements of vehicles
[25]	No	VANET	Vehicles	Lack of consideration of the stability of a cluster head
[26]	No	VANET	Vehicles	Lack of an incentive scheme
[27]	Yes	heterogeneous	APs	Lack of consideration of the features of the data
[28]	Yes	heterogeneous	APs	Lack of consideration of the features of the data
[29]	Yes	heterogeneous	APs	Lack of consideration of the features of the data
[30]	Yes	heterogeneous	APs	Lack of consideration of the mobility of vehicles
[31]	Yes	VANET	APs	Lack of locations of vehicles and features of data
[32]	Yes	VANET	Parked vehicles, RSUs	Offloading nodes are stationary
[33]	Yes	VANET	RSUs, APs	Additional overhead
[34]	Yes	VANET	APs	Lack of consideration of the mobility of vehicles
[35]	Yes	VANET	APs	Lack of consideration of the mobility of vehicles
[36]	Yes	VANET	Vehicles	Lack of consideration of the features of the data

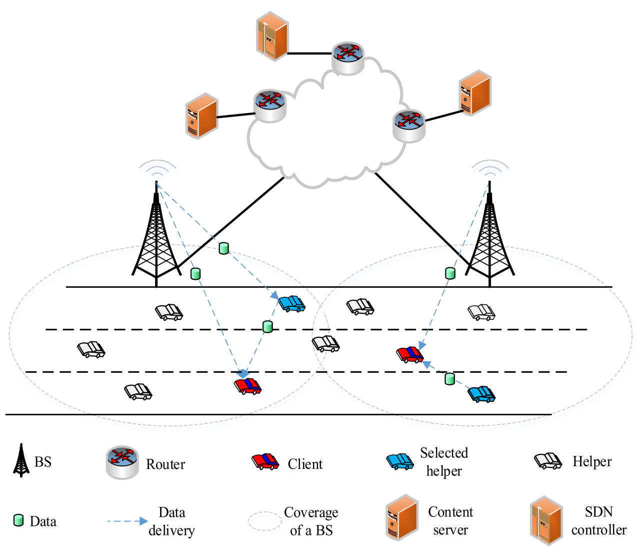


FIGURE 1. Network scenario.

IEEE 802.11p network interface. Therefore, they can connect to the cellular network using the 2G/3G/4G protocol, and they can also communicate with each other using the IEEE 802.11p protocol. In the following, we do not distinguish between the term "user" and the term "vehicle". The SDN controller is deployed to manage the data offloading and delivery, and it can communicate with the cellular network, vehicle users and content servers. The SDN controller acts as the intermediary between users and content servers. If a client wants to download content, it sends a request to the SDN controller via the cellular network. Then, the SDN controller sends back the set of helpers and the information on the requested content, which depend on where the requested content is stored. If a neighboring vehicles of the client have replicas of the requested content, the helpers are these vehicles; otherwise, the helpers are all neighboring vehicles of the client. Meanwhile, the SDN controller sends a message to all helpers that asks them to participate in the competition. Next, helpers send their own information to the client. Finally, the client selects the best helper from the set of helpers according to the knockdown price. The helper with the lowest knockdown price is selected to help download and deliver part of the data to the client. If the knockdown prices that are offered by all helpers are too high, the client will download from the BS directly. A vehicle in the system can be either a client or a helper, depending on the link quality and the content it already has. However, during the time period that we consider, the identity of a vehicle user is stable and absolute. In the system, there are $C + H$ vehicle users, which are labelled as $i \in \{1, 2, \cdots, C + H\}$, where C is the number of clients that have downloading tasks and H is the number of helpers that have sufficient resources for helping download and deliver a portion of the data. The basic assumptions are as follows:

- The velocity and direction of each vehicle remain unchanged during the period of offloading that we consider.
- Data offloading only occurs between two vehicles when they have a one-hop V2V communication link to protect the reliability of data transmission, namely, the data of a client can only be offloaded to its one-hop neighbors.
- Each client can only offload its downloading task to one helper; however, each helper can provide services to multiple clients.

C. SYSTEM MODELS

1) TRAFFIC AND MOBILITY MODELS

Let C and H denote the set of clients and the set of helpers, respectively, where $C = \{c_i \,|\, i \in \{1, 2, \cdots, C\}\}$, $|C| = C$ and $\mathrm{H} = \{h_i|i \in \{1, 2, \cdots, H\}\}$, $|\mathrm{H}| = H$. According to [32] and [37], the velocity of each vehicle in sets C and H can be divided into Ydiscrete levels: $v_i \in \{v_0, v_1, \cdots, v_y, \cdots, v_{Y-1}\}$. The arrival rates of vehicles that enter the coverage of a BS or the coverage of a client with velocity v_y are defined as ρ_y^{BS} and ρ_y^C, respectively. Then, the occurrence probability z_y^{BS} of each velocity level for a BS and the occurrence probability z_y^C of each velocity for a client are obtained by

$$z_y^{BS} = \frac{\rho_y^{BS}}{\sum_{y=0}^{Y-1} \rho_y^{BS}}, \tag{1}$$

and

$$z_y^{C} = \frac{\rho_y^{C}}{\sum_{y=0}^{Y-1} \rho_y^{C}}. \tag{2}$$

According to [38] and [39], the velocity of each vehicle in the coverage of a BS or a client can remain stable. Then, the time that a vehicle with velocity v_y is in the coverage of a BS or a client can be calculated as

$$\tau_y = \frac{2R_{BS}}{v_y}, \tag{3}$$

and

$$\tau_y = \frac{2R_V}{v_y}, \tag{4}$$

where R_{BS} and R_V are the transmission ranges of the BS and the vehicle, respectively.

2) COMMUNICATION MODEL

Since every BS has the same coverage radius R_{BS}, a vehicle $i$can communicate with a BS only if it moves into the coverage of the BS, namely, if $\| p_i - p_{BS} \| \leq R_{BS}$, where p_i and p_{BS} are the instantaneous positions of vehicle i and the BS, respectively. Similarly, two moving vehicles i and j can opportunistically communicate with each other only if they move into each other's transmission ranges, namely, if $\| p_i - p_j \| \leq R_V$. For simplicity, the data rate r_{BS-i} from the BS to vehicle i and the data rate r_{i-j} between two vehicles i and j are considered fixed during the offloading period that we consider [40].

3) INTEREST MODEL

In a system with multiple data items, some data items are popular and many users want to download them, while other data items are not popular and only a few users are interested in them. In this work, we model the popularity of data items by users' interest distributions on keywords [41]–[42]. Suppose the system has K keywords, which are denoted by the set K. D denotes the set of all data items. Any data item d, where $d \in D$, is described by a subset K_d of keywords, $K_d \subseteq K$. To indicate the importance of a keyword k, $k \in K$, where w_k is used to represent the weight of$k$. Without loss of generality, we assume $\sum_{k \in K} w_k = 1$. To model users' interests in various keywords, we define I_u^k as the degree of user u's interest in keyword k. Without loss of generality, we assume $\sum_{k\in K} I_u^k = 1$. Thus, the interest probability $P_u^d$of user$u$ in data item d is defined as

$$P_u^d = \sum\nolimits_{k \in K_d} w_k I_u^k. \tag{5}$$

The variables and notations that are used in this paper are listed in TABLE 2.

IV. GAME ANALYSIS

This section analyzes the interaction between a client and a helper as a Stackelberg game. First, the utility function of each participant is introduced. Second, we model the interaction between the client and the helper as a Stackelberg game. Third, the optimal strategy of each participant is determined by deriving the Nash equilibrium. Fourth, an algorithm is proposed for selecting the helper with the lowest knockdown unit price based on the results of the Nash equilibrium.

A. UTILITY FUNCTIONS

1) UTILITY FUNCTION OF A CLIENT

The utility function of a client can be defined as the difference between the time that is saved by offloading and the cost of obtaining the data. The utility function of a client is defined as

$$U_C = F(T, T') - H(\eta), \tag{6}$$

where $F(T, T')$ is the user satisfaction function on the time difference, $T$is the time it needs to download the data without a helper, T' is the time it needs to download the data with a helper, and $H(\eta)$ denotes the payment to the helper.

If a client downloads the data from a BS all by itself, the time it needs is calculated as

$$T = \frac{D_C}{r_{BC}}. \tag{7}$$

If a client downloadsλD_C bits from the helper and $(1-\lambda) D_C$ bits from the BS, the time it needs is calculated

TABLE 2. Variables and notations.

Notation	Description
$\mathcal{C}$ and C	Set and number of clients
$\mathcal{H}$ and H	Set and number of helpers
$\mathcal{K}$ and K	Set and number of keywords
$\mathcal{D}$ and D	Set and number of data items
$\mathcal{U}$ and U	Set and number of users in a region
λ	Offloading rate
η	Unit price that a helper charges
ε_{BH} and ε_{HC}	Unit costs for a helper to download and relay the data, respectively
D_C	Data size of the downloading task
r_{BC}, r_{BH} and r_{HC}	Data rates from the BS to the client, from the BS to the helper, and from the helper to the client
v_C and v_H	Velocities of the client and the helper
p_C and p_H	Positions of the client and the helper
R_{BS} and R_V	Transmission ranges of a BS and a vehicle
ρ_y^{BS} and ρ_y^{C}	Arrival rates of vehicles that enter the coverage of the BS and the client
I_u^k	Degree of interest of user u in keyword k
P_u^d	Interest probability of user u in data item d
U_C and U_H	Utilities of the client and the helper

as

$$T' = max\left[\frac{(1-\lambda)\,D_C}{r_{BC}}, \gamma\frac{\lambda D_C}{r_{BH}} + \frac{\lambda D_C}{r_{HC}}\right], \gamma \in \{0,1\}, \quad (8)$$

whereγ represents whether the helper already has the required data in its storage before the client sends a request. If yes, $\gamma = 0$; otherwise, $\gamma = 1$. Here, we assume that the cellular network interface and the IEEE 802.11p network interface that are equipped on each vehicle can operate simultaneously. If the helper already has the required data, it will transmit the data to the client directly; in this case, $\gamma = 0$. Then, (8) can be simplified to

$$T' = max\left[\frac{(1-\lambda)\,D_C}{r_{BC}}, \frac{\lambda D_C}{r_{HC}}\right]. \quad (9)$$

Otherwise, the helper will download the data from the BS and transmit the data to the client; in this case, $\gamma = 1$.

Therefore, from (7) and (8), the time that is saved by offloading is

$$T' - T = \frac{D_C}{r_{BC}} - max\left[\frac{(1-\lambda)\,D_C}{r_{BC}}, \gamma\frac{\lambda D_C}{r_{BH}} + \frac{\lambda D_C}{r_{HC}}\right], \times\gamma \in \{0,1\}. \quad (10)$$

$F(T, T')$ is defined as

$$F\left(T, T'\right) = \ln\left(1 + \frac{D_C}{r_{BC}} - max\left[\frac{(1-\lambda)\,D_C}{r_{BC}}, \gamma\frac{\lambda D_C}{r_{BH}} + \frac{\lambda D_C}{r_{HC}}\right]\right), \times\gamma \in \{0,1\}, \quad (11)$$

For a client, the cost is mainly the total payment to the helper. Thus, the cost function $H(\eta)$ is defined as

$$H(\eta) = \eta\lambda D_C. \quad (12)$$

From (11) and (12), the utility function of a client is

$$U_C(\lambda) = \alpha_1 \ln\left(1 + \frac{D_C}{r_{BC}} - max\left[\frac{(1-\lambda)\,D_C}{r_{BC}}, \gamma\frac{\lambda D_C}{r_{BH}} + \frac{\lambda D_C}{r_{HC}}\right]\right) - \alpha_2\eta\lambda D_C, \gamma \in \{0,1\}, \quad (13)$$

where α_1 and α_2 are willingness factors that represent the preference of the client for the task, which satisfy $\alpha_1+\alpha_2 = 1$, $0 \le \alpha_1 \le 1$, and $0 \le \alpha_2 \le 1$.

As the client and the helper are both moving vehicles, the total transmission time of the offloaded data should be less than the inter-contact duration between the client and helper:

$$\gamma\frac{\lambda D_C}{r_{BH}} + \frac{\lambda D_C}{r_{HC}} \le \frac{\| p_C - p_H \|}{\Delta v}, \gamma \in \{0,1\} \quad (14)$$

where Δv denotes the velocity difference between the client and the helper, namely, $\Delta v = v_C - v_H$.

2) UTILITY FUNCTION OF A HELPER

The strategy of a helper is to maximize the revenue by determining the price. The revenue includes the direct revenue, which is the profit that is earned by relaying the data to the client, and the indirect revenue, which is the profit that is earned by delivering the downloaded data to other users that are interested in the data. As bandwidth, storage and power resources are required for downloading and relaying the data, the cost should be considered. Thus, the utility function of the helper can be defined as

$$U_H = H(\eta) + H'(\lambda) - L(\lambda), \quad (15)$$

where $H(\eta)$ is the direct profit, $H'(\lambda)$ is the indirect profit, and $L(\lambda)$ is the cost of delivering the data.

The more popular a data item is, the higher the profit it may bring to the helper, as the helper can deliver it to other users, in addition to the client. Thus, $H'(\lambda)$ is defined as

$$H'(\lambda) = \lambda \sum\nolimits_{u\in U} \sum\nolimits_{k\in K_d} w_k I_u^k, \quad (16)$$

where U is the set of users in a region and U denotes the number of users in set U.

The cost of a helper is defined as

$$L(\lambda) = \left(\gamma\varepsilon_{BH} + \varepsilon_{HC}\right)\lambda D_C, \gamma \in \{0,1\}. \quad (17)$$

From (12), (16), and (17), the utility function of a helper is

$$U_H(\eta) = \beta_1\left(\eta - \gamma\varepsilon_{BH} - \varepsilon_{HC}\right)\lambda D_C \beta_2 \gamma\lambda \times \sum\nolimits_{u\in U} \sum\nolimits_{k\in K_d} w_k I_u^k, \gamma \in \{0,1\}, \quad (18)$$

where β_1 and β_2 are the weights of the direct and indirect profits, respectively, which satisfy $\beta_1 + \beta_2 = 1, 0 \le \beta_1 \le 1$, and$0 \le \beta_2 \le 1$. If the helper already has the required data, $\gamma = 0$, and both the cost for downloading the data from the BS and the indirect revenue will be 0. Then, the utility function of the helper can be simplified to

$$U_H(\eta) = (\eta - \varepsilon_{HC})\lambda D_C. \quad (19)$$

Otherwise, $\gamma = 1$.

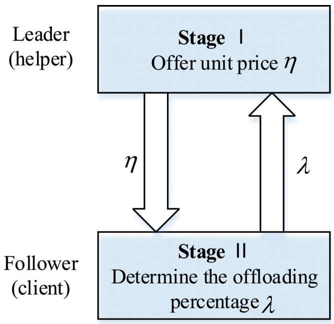


FIGURE 2. A two-stage non-cooperative Stackelberg game.

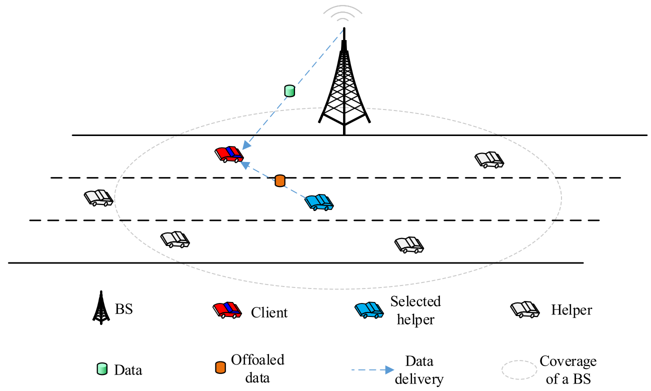


FIGURE 3. Scenario (1): the helper has the required data.

B. STACKELBERG GAME

We model the data request of a client and the pricing of a helper as a non-cooperative Stackelberg game, in which the helper is the leader of the game and the client is the follower of the game. As illustrated in FIGURE 2, the Stackelberg game consists of two stages: In stage I, each potential helper offers its unit price η. In stage II, the client determines the percentage λ of data to obtain from each helper according to the price η. Finally, the client chooses the helper with the lowest η. In the game, each party is selfish and individual, and pursues its maximum utility. Therefore, the problem can be formulated as follows:

Problem 1:

$$\begin{aligned}
&\max\ U_C(\lambda)\\
&\quad=\alpha_1\ln\left(1+\frac{D_C}{r_{BC}}-max\left[\frac{(1-\lambda)D_C}{r_{BC}},\gamma\frac{\lambda D_C}{r_{BH}}+\frac{\lambda D_C}{r_{HC}}\right]\right)\\
&\quad-\alpha_2\eta\lambda D_C,\ \gamma\in\{0,1\},\\
&\text{such that}\ \begin{cases}0\le\lambda\le 1\\ \gamma\frac{\lambda D_C}{r_{BH}}+\frac{\lambda D_C}{r_{HC}}\le\frac{\|p_C-p_H\|}{\Delta v}\end{cases}
\end{aligned}\tag{20}$$

Problem 2:

$$\begin{aligned}
&\max\ U_H(\eta)\\
&\quad=\beta_1\left(\eta-\gamma\varepsilon_{BH}-\varepsilon_{HC}\right)\lambda D_C+\beta_2\gamma\lambda\sum\nolimits_{u\in U}\sum\nolimits_{k\in K_d}w_k I_u^k,\\
&\quad\gamma\in\{0,1\}.\\
&\text{such that}\ \gamma\varepsilon_{BH}+\varepsilon_{HC}\le\eta\le\eta_{max},
\end{aligned}\tag{21}$$

where η_{max} denotes the maximum unit price that a helper can offer.

C. STACKELBERG EQUILIBRIUM SOLUTION

According to whether the helper has the required data before the client sends a request, the discussion of the Stackelberg equilibrium can be further divided into two situations. In each situation, we adopt the backward induction method [32] to solve the Stackelberg game, which means we derive the optimal offloading rate λ^* for the client in stage II firstly, given that the helper's strategy is fixed, and then we obtain the optimal unit price η^* for the helper in stage I.

1) THE HELPER HAS THE REQUIRED DATA

When the helper already has the required data before the client sends a request, the helper delivers the data to the client directly, as illustrated in FIGURE 3. Then, the problem can be simplified as

$$\begin{cases}\max U_C(\lambda)=\alpha_1\ln\left(1+\frac{D_C}{r_{BC}}-max\left[\frac{(1-\lambda)D_C}{r_{BC}},\frac{\lambda D_C}{r_{HC}}\right]\right)\\ -\alpha_2\eta\lambda D_C\\ \text{s.t.}0\le\lambda\le\min(1,\frac{r_{HC}\Delta\tau}{D_C}),\ \Delta\tau=\frac{\|p_C-p_H\|}{\Delta v}\end{cases},\tag{22}$$

$$\begin{cases}\max U_H(\eta)=(\eta-\varepsilon_{HC})\lambda D_C\\ \text{s.t.}\varepsilon_{HC}\le\eta\le\eta_{max}\end{cases}\tag{23}$$

Stage II: When the helper has determined its price, the client must decide the percentage λ of data to obtain from the helper to maximize its utility function. Let λ^0 denote the value of λ that satisfies $\frac{(1-\lambda)D_C}{r_{BC}}=\frac{\lambda D_C}{r_{HC}}$. Then, we obtain $\lambda^0=\frac{r_{HC}}{r_{HC}+r_{BC}}$. According to the relationship among 1, $\frac{r_{HC}\Delta\tau}{D_C}$, and λ^0, $U_C(\lambda)$ can be further divided into three cases.

Case 1: $\frac{r_{HC}\Delta\tau}{D_C}\le\lambda^0\le 1$

$$U_C(\lambda)=\alpha_1\ln\left(1+\frac{\lambda D_C}{r_{BC}}\right)-\alpha_2\eta\lambda D_C,\ 0\le\lambda\le\frac{r_{HC}\Delta\tau}{D_C}.\tag{24}$$

We calculate the first derivative of $U_C(\lambda)$ with respect to λ and obtain

$$\frac{\partial U_C}{\partial\lambda}=\frac{\alpha_1}{\frac{r_{BC}}{D_C}+\lambda}-\alpha_2\eta D_C.\tag{25}$$

Then, we calculate the second derivative of $U_C(\lambda)$ with respect to λ and obtain

$$\frac{\partial^2 U_C}{\partial\lambda}=-\frac{\alpha_1}{\left(\frac{r_{BC}}{D_C}+\lambda\right)^2}<0.\tag{26}$$

It is easy to prove that the function $U_C(\lambda)$ is a strictly concave function. Therefore, we can determine the optimal strategy by solving $\frac{\partial U_C}{\partial\lambda}=0$. $\lambda^\#$ denotes the value of λ that satisfies $\frac{\partial U_C}{\partial \lambda} = 0$, namely, $\lambda^{\#} = \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right)$. Then, the optimal strategy $\lambda^*$of the client is expressed as

$$\lambda^* = \begin{cases} 0, \eta \geq \dfrac{\alpha_1}{\alpha_2 r_{BC}} \\ \dfrac{1}{D_C}\left(\dfrac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right), \dfrac{\alpha_1}{\alpha_2\left(r_{BC} + r_{HC}\Delta\tau\right)} \\ \qquad < \eta < \dfrac{\alpha_1}{\alpha_2 r_{BC}} \\ \dfrac{r_{HC}\Delta\tau}{D_C}, \eta \leq \dfrac{\alpha_1}{\alpha_2\left(r_{BC} + r_{HC}\Delta\tau\right)} \end{cases} \tag{27}$$

Case 2: $\lambda^0 < \frac{r_{HC}\Delta\tau}{D_C} \leq 1$

$$U_C(\lambda) = \begin{cases} \alpha_1 \ln\left(1 + \dfrac{\lambda D_C}{r_{BC}}\right) - \alpha_2 \eta \lambda D_C, 0 \leq \lambda < \lambda^0 \\ \alpha_1 \ln\left(1 + \dfrac{D_C}{r_{BC}} - \dfrac{\lambda D_C}{r_{HC}}\right) - \alpha_2 \eta \lambda D_C, \\ \qquad \lambda^0 \leq \lambda \leq \dfrac{r_{HC}\Delta\tau}{D_C} \end{cases} \tag{28}$$

If $\lambda^0 \leq \lambda \leq \frac{r_{HC}\Delta\tau}{D_C}$, $\frac{\partial U_C}{\partial \lambda} = \frac{-\alpha_1 \frac{D_C}{r_{HC}}}{1+\frac{D_C}{r_{BC}}-\frac{\lambda D_C}{r_{HC}}} - \alpha_2 \eta D_C < 0$. Thus, if $\lambda = \lambda^0$, $U_C(\lambda)$ is maximal. The optimal strategy λ^* of the client is expressed as

$$\lambda^* = \begin{cases} 0, \eta \geq \dfrac{\alpha_1}{\alpha_2 r_{BC}} \\ \dfrac{1}{D_C}\left(\dfrac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right), \dfrac{\alpha_1(r_{HC} + r_{BC})}{\alpha_2(r_{BC}^2 + r_{HC}r_{BC} + r_{HC}D_C)} \\ \qquad < \eta < \dfrac{\alpha_1}{\alpha_2 r_{BC}} \\ \dfrac{r_{HC}}{r_{HC} + r_{BC}}, \eta \leq \dfrac{\alpha_1(r_{HC} + r_{BC})}{\alpha_2(r_{BC}^2 + r_{HC}r_{BC} + r_{HC}D_C)} \end{cases} \tag{29}$$

Case 3: $\lambda^0 \leq 1 < \frac{r_{HC}\Delta\tau}{D_C}$

$$U_C(\lambda) = \begin{cases} \alpha_1 \ln\left(1 + \dfrac{\lambda D_C}{r_{BC}}\right) - \alpha_2 \eta \lambda D_C, 0 \leq \lambda < \lambda^0 \\ \alpha_1 \ln\left(1 + \dfrac{D_C}{r_{BC}} - \dfrac{\lambda D_C}{r_{HC}}\right) - \alpha_2 \eta \lambda D_C, \\ \qquad \lambda^0 \leq \lambda \leq 1 \end{cases} \tag{30}$$

Equation (30) is very similar to (28). The optimal strategy of the client in *case 3* is the same as the strategy that is expressed in (29).

Stage I: The helper determines the unit price in this stage. In the complete information game, the helper knows the strategy and utility function of the client. From (27) and (29), it follows that $\lambda^* \in \left\{0, \frac{r_{HC}\Delta\tau}{D_C}, \frac{r_{HC}}{r_{HC}+r_{BC}}, \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2\eta} - r_{BC}\right)\right\}$.

Case 1: $\lambda^* = 0$. No offloading occurs and the client downloads the data on its own.

Case 2: $\lambda^* = \frac{r_{HC}\Delta\tau}{D_C}or\frac{r_{HC}}{r_{HC}+r_{BC}}$. We calculate the first derivative of $U_H(\eta)$ with respect to η and obtain $\frac{\partial U_H}{\partial \eta} = \lambda D_C > 0$. Thus, the optimal strategy of the helper is $\eta^* = \eta_{max}$.

Case 3: $\lambda^* = \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2\eta} - r_{BC}\right)$. Then, $U_H(\eta)$ is

$$U_H(\eta) = (\eta - \varepsilon_{HC})\left(\frac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right). \tag{31}$$

We calculate the first derivative of $U_H(\eta)$ with respect to η and obtain

$$\frac{\partial U_H}{\partial \eta} = \frac{\alpha_1 \varepsilon_{HC}}{\alpha_2 \eta^2} - r_{BC}. \tag{32}$$

Then, we calculate the second derivative of $U_H(\eta)$ with respect to η and obtain

$$\frac{\partial^2 U_H}{\partial \eta} = -\frac{2\alpha_1 \varepsilon_{HC}}{\alpha_2 \eta^3} - r_{BC} < 0. \tag{33}$$

Similarly, it is easy to prove the $U_H(\eta)$ is a concave function. Therefore, we can obtain the optimal strategy by solving $\frac{\partial U_H}{\partial \eta} = 0$. $\eta^{\#}$ denotes the value of η that satisfies $\frac{\partial U_H}{\partial \eta} = 0$, namely, $\eta^{\#} = \sqrt{\frac{\alpha_1 \varepsilon_{HC}}{\alpha_2 r_{BC}}}$. Then, the optimal strategy of the helper is expressed as follows:

Case 1: $\frac{r_{HC}\Delta\tau}{D_C} \leq \lambda^0 \leq 1$

$$\eta^* = \begin{cases} \max\left(\dfrac{\alpha_1}{\alpha_2\left(r_{BC} + r_{HC}\Delta\tau\right)}, \varepsilon_{HC}\right), \\ \qquad \eta^{\#} \leq \max\left(\dfrac{\alpha_1}{\alpha_2\left(r_{BC} + r_{HC}\Delta\tau\right)}, \varepsilon_{HC}\right) \\ \sqrt{\dfrac{\alpha_1 \varepsilon_{HC}}{\alpha_2 r_{BC}}}, \max\left(\dfrac{\alpha_1}{\alpha_2\left(r_{BC} + r_{HC}\Delta\tau\right)}, \varepsilon_{HC}\right) \\ \qquad < \eta^{\#} < \min\left(\dfrac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}\right). \\ \min\left(\dfrac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}\right), \eta^{\#} \geq \min(\dfrac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}) \end{cases} \tag{34}$$

Case 2: $\lambda^0 < \frac{r_{HC}\Delta\tau}{D_C} \leq 1$ or $\lambda^0 \leq 1 < \frac{r_{HC}\Delta\tau}{D_C}$

$$\eta^* = \begin{cases} \max\left(\dfrac{\alpha_1(r_{HC} + r_{BC})}{\alpha_2(r_{BC}^2 + r_{HC}r_{BC} + r_{HC}D_C)}, \varepsilon_{HC}\right), \\ \qquad \eta^{\#} \leq \max\left(\dfrac{\alpha_1(r_{HC} + r_{BC})}{\alpha_2(r_{BC}^2 + r_{HC}r_{BC} + r_{HC}D_C)}, \varepsilon_{HC}\right) \\ \sqrt{\dfrac{\alpha_1 \varepsilon_{HC}}{\alpha_2 r_{BC}}}, \max\left(\dfrac{\alpha_1(r_{HC} + r_{BC})}{\alpha_2(r_{BC}^2 + r_{HC}r_{BC} + r_{HC}D_C)}, \varepsilon_{HC}\right) \\ \qquad < \eta^{\#} < \min(\dfrac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}) \\ \min\left(\dfrac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}\right), \eta^{\#} \geq \min(\dfrac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}) \end{cases} \tag{35}$$

2) THE HELPER DOES NOT HAVE THE REQUIRED DATA

If the helper does not have the required data, the helper must download the data from the BS and deliver it to the client, as illustrated in FIGURE 4. The problem is formulated as

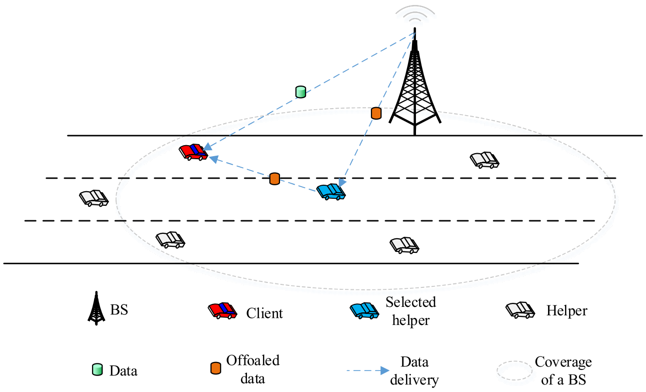


FIGURE 4. Scenario (2): the helper does not have the required data.

follows:

$$\begin{cases} \max U_C(\lambda) = \alpha_1 \ln\left(1 + \frac{D_C}{r_{BC}} - max\left[\frac{(1-\lambda) D_C}{r_{BC}}, \frac{\lambda D_C}{r_{BH}} + \frac{\lambda D_C}{r_{HC}}\right]\right) - \alpha_2 \eta \lambda D_C \\ \text{s.t.} 0 \le \lambda \le \min\left(1, \frac{r_{BH} r_{HC} \Delta\tau}{(r_{BH} + r_{HC}) D_C}\right), \end{cases} \tag{36}$$

$$\begin{cases} \max U_H(\eta) = \beta_1(\eta - \varepsilon_{BH} - \varepsilon_{HC})\lambda D_C \\ \quad + \beta_2 \lambda \sum_{u \in U} \sum_{k \in K_d} w_k I_u^k \\ \text{s.t.} \varepsilon_{BH} + \varepsilon_{HC} \le \eta \le \eta_{max} \end{cases} \tag{37}$$

Stage II: From $\frac{(1-\lambda)D_C}{r_{BC}} = \frac{\lambda D_C}{r_{BH}} + \frac{\lambda D_C}{r_{HC}}$, we obtain $\lambda^0 = \frac{r_{BH} r_{HC}}{r_{BC} r_{HC} + r_{BC} r_{BH} + r_{BH} r_{HC}}$. Similar to Scenario 1), $U_C(\lambda)$ can also be divided into three cases according to the relationship among 1, $\frac{r_{BH} r_{HC} \Delta\tau}{(r_{BH} + r_{HC}) D_C}$ and λ^0.

Case1: $\frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})} \le \lambda^0 < 1$

$$U_C(\lambda) = \alpha_1 \ln\left(1 + \frac{\lambda D_C}{r_{BC}}\right) - \alpha_2 \eta \lambda D_C, \quad 0 \le \lambda \le \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})}. \tag{38}$$

As in Scenario 1), $U_C(\lambda)$ is a strictly concave function. Let $\frac{\partial U_C}{\partial \lambda} = 0$. Then, $\lambda^\# = \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right)$. The optimal strategy of the client is

$$\lambda^* = \begin{cases} 0, \eta \ge \frac{\alpha_1}{\alpha_2 r_{BC}} \\ \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_{2\eta}} - r_{BC}\right), \quad \frac{\alpha_1(r_{BH} + r_{HC})}{\alpha_2(\Delta\tau r_{BH} r_{HC} + r_{BC} r_{HC} + r_{BC} r_{BH})} < \eta < \frac{\alpha_1}{\alpha_2 r_{BC}} \\ \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})}, \quad \eta \le \frac{\alpha_1(r_{BH} + r_{HC})}{\alpha_2(\Delta\tau r_{BH} r_{HC} + r_{BC} r_{HC} + r_{BC} r_{BH})}. \end{cases} \tag{39}$$

Case 2: $\lambda^0 \le \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})} \le 1$

$$U_C(\lambda) = \begin{cases} \alpha_1 \ln\left(1 + \frac{\lambda D_C}{r_{BC}}\right) - \alpha_2 \eta \lambda D_C, 0 \le \lambda < \lambda^0 \\ \alpha_1 \ln\left(1 + \frac{D_C}{r_{BC}} - \frac{\lambda D_C}{r_{BH}} - \frac{\lambda D_C}{r_{HC}}\right) - \alpha_2 \eta \lambda D_C, \\ \quad \lambda^0 < \lambda \le \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})}. \end{cases} \tag{40}$$

The optimal strategy of the client is

$$\lambda^* = \begin{cases} 0, \eta \ge \frac{\alpha_1}{\alpha_2 r_{BC}} \\ \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right), \quad \frac{\alpha_1 A}{\alpha_2 r_{BC}(D_C r_{BH} + A)} < \eta < \frac{\alpha_1}{\alpha_2 r_{BC}} \\ \frac{r_{BH} r_{HC}}{r_{BC} r_{HC} + r_{BC} r_{BH} + r_{BH} r_{HC}}, \quad \eta \le \frac{\alpha_1 A}{\alpha_2 r_{BC}(D_C r_{BH} + A)} \end{cases} \tag{41}$$

where $A = r_{BH} r_{HC} + r_{BC} r_{HC} + r_{BC} r_{BH}$.

Case 3: $\lambda^0 < 1 \le \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})}$

$$U_C(\lambda) = \begin{cases} \alpha_1 \ln\left(1 + \frac{\lambda D_C}{r_{BC}}\right) - \alpha_2 \eta \lambda D_C, 0 \le \lambda \le \lambda^0 \\ \alpha_1 \ln\left(1 + \frac{D_C}{r_{BC}} - \frac{\lambda D_C}{r_{BH}} - \frac{\lambda D_C}{r_{HC}}\right) - \alpha_2 \eta \lambda D_C, \\ \quad \lambda^0 \le \lambda \le 1. \end{cases} \tag{42}$$

The optimal strategy of the client is the same as (41).

Stage I: From (39) and (41), it follows that $\lambda^* \in \{0, \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})}, \lambda^0, \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right)$.

Case 1: $\lambda^* = 0$. No offloading occurs and the client downloads the data by itself.

Case 2: $\lambda^* = \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})} or \frac{r_{BH} r_{HC}}{r_{BC} r_{HC} + r_{BC} r_{BH} + r_{BH} r_{HC}}$. The optimal strategy of the helper is $\eta^* = \eta_{max}$.

Case 3: $\lambda^* = \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2 \eta} - r_{BC}\right)$. U_H is

$$U_H(\eta) = \beta_1(\eta - \varepsilon_{BH} - \varepsilon_{HC})\lambda D_C + \beta_2 \lambda \sum_{u \in U} \sum_{k \in K_d} w_k I_u^k. \tag{43}$$

Similar to Scenario 1), it can be proved that $U_H(\eta)$ is a strictly concave function. Therefore, we can obtain the optimal strategy by solving $\frac{\partial U_H}{\partial \eta} = 0$. From $\frac{\partial U_H}{\partial \eta} = 0$, we obtain $\eta^\# = \sqrt{\frac{\alpha_1}{\alpha_2 r_{BC}}(\varepsilon_{BH} + \varepsilon_{HC} - \frac{\beta_2 B}{\beta_1 D_C})}$, where $B = \sum_{u \in U} \sum_{k \in K_d} w_k I_u^k$. Then, the optimal strategy of the client is as follows:

Case 1: $\frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})} \le \lambda^0 < 1$

The optimal strategy of the client is expressed in (44), as shown at the bottom of the next page.

Case 2: $\lambda^0 \le \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})} \le 1$ or $\lambda^0 < 1 \le \frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH} + r_{HC})}$

The optimal strategy of the client is expressed in (45), as shown at the bottom of the next page.

D. STACKELBERG-GAME-BASED ALGORITHM FOR IDENTIFYING THE BEST HELPER

This section presents a Stackelberg-game-based algorithm for selecting the helper with the lowest price from set H_D or H_I, where H_D and H_I denote the set of helpers that have the required data and the set of helpers that do not have the required data, respectively. A vehicle user who has a downloading task checks if there are vehicle users who already have the data. If yes, it runs algorithm 1 to select the best helper from set H_D; if no, it runs algorithm 1 to select the best helper from set H_I.The time complexity of algorithm 1 is $O(n)$. Thus, its complexity is low and it is suitable for running on a vehicle. In addition, to run algorithm 1, a client must input the instantaneous information on itself, the helpers and the required data item. The instantaneous information of the client includes (D_C, r_{BC}, v_C, p_C); the instantaneous information of all helpers includes set H_D or H_I and $(\varepsilon_{BH}, \varepsilon_{HC}, r_{BH}, r_{HC}, v_H, p_H)$ of each helper; the information of the data item includes the set U and the interest probability P_u^d. As algorithm 1 runs on the client vehicle, it has the information on itself. The information on the helpers and the required data item can be obtained from the helpers and the SDN controller. According to the procedure for offloading that is presented in Section III-B, the SDN controller returns the information regarding the data items to the client. Then, each helper sends the information about itself to the client. Therefore, it is feasible to implement algorithm 1 on moving vehicles.

Algorithm 1 A Stackelberg-Game-Based Algorithm for Identifying the Best Helper from set H_D or H_I

Initialization: Given $\mathrm{H}_D(\mathrm{or}\mathrm{H}_I)$, $\eta_{best} = \eta_{max}, \lambda_{best} = 0$.
Repeat
$\forall h \in \mathrm{H}_D(\mathrm{or}\mathrm{H}_I)$
If $\frac{r_{HC}\Delta\tau}{D_C} \leq \lambda^0 \leq 1(\mathrm{or}\frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH}+r_{HC})} \leq \lambda^0 < 1)$
If $\eta_{min} > \frac{\alpha_1}{\alpha_2 r_{BC}}$
$\lambda^* = 0, \eta^* = 0$
Else if $\eta_{max} < \frac{\alpha_1}{\alpha_2(r_{BC}+r_{HC}\Delta\tau)}$ $(\mathrm{or}\,\eta_{max} < \frac{\alpha_1(r_{BH}+r_{HC})}{\alpha_2(\Delta\tau r_{BH} r_{HC}+r_{BC} r_{HC}+r_{BC} r_{BH})})$
$\lambda^* = \frac{r_{HC}\Delta\tau}{D_C}(or\frac{\Delta\tau r_{BH} r_{HC}}{D_C(r_{BH}+r_{HC})}), \eta^* = \eta_{max}$
Else
$\lambda^* = \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2\eta^*} - r_{BC}\right)$, η^* is obtained via (34) (or (44))
End if
Else
If $\eta_{min} > \frac{\alpha_1}{\alpha_2 r_{BC}}$
$\lambda^* = 0, \eta^* = 0$
Else if $\eta_{max} < \frac{\alpha_1(r_{HC}+r_{BC})}{\alpha_2(r_{BC}^2+r_{HC} r_{BC}+r_{HC} D_C)}$ (or $\eta_{max} < \frac{\alpha_1 A}{\alpha_2 r_{BC}(D_C r_{BH}+A)}$)
$\lambda^* = \frac{r_{HC}}{r_{HC}+r_{BC}}(\mathrm{or}\frac{r_{BH} r_{HC}}{r_{BC} r_{HC}+r_{BC} r_{BH}+r_{BH} r_{HC}}), \eta^* = \eta_{max}$
Else
$\lambda^* = \frac{1}{D_C}\left(\frac{\alpha_1}{\alpha_2\eta^*} - r_{BC}\right)$, η^* is obtained via (35) (or (45))
End if
End if
If $\eta^* < \eta_{best}$
$\eta_{best} = \eta^*, \lambda_{best} = \lambda^*$
End if
Pop h from H_D (or H_I)
Until $\mathrm{H}_D(\mathrm{or}\mathrm{H}_I) = \emptyset$

V. PERFORMANCE EVALUATION

This section evaluates the performance of the proposed scheme via Monte Carlo simulation on MATLAB 2018b. We present the settings of the simulation parameters and conduct the performance evaluation and discussion.

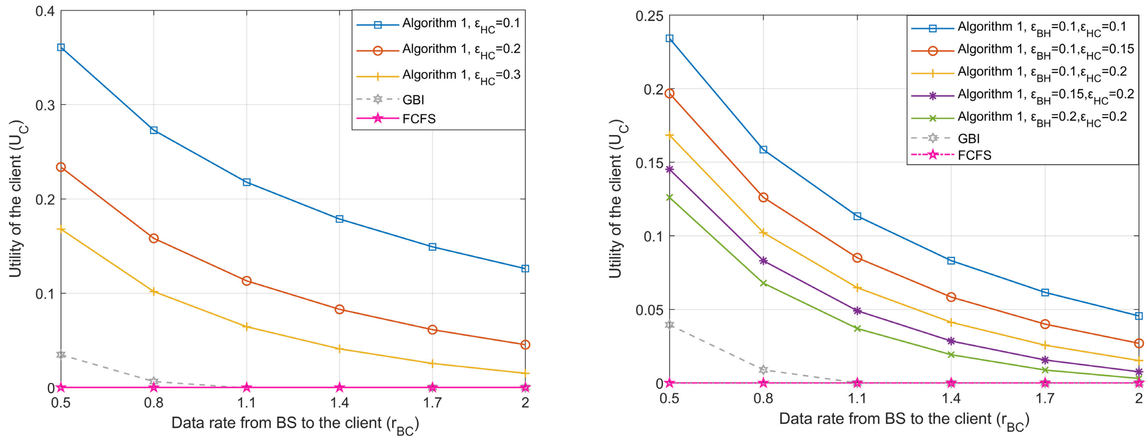
A. PARAMETER SETTINGS

We consider a straight highway with 2 lanes and vehicles move on the highway at speeds that are between 20 m/s to 40 m/s. BSs are deployed alongside the road to provide seamless coverage. The coverage radius of each BS is 500 m. To generalize the simulation results, each result is obtained from 1000 simulations. The parameter settings of the simulation are listed in TABLE 3 [32], [43]. The proposed algorithm is compared with two methods [32], [43] that were recently proposed in the literature:

- Gradient-based iteration (GBI): This algorithm is used to obtain a three-party Stackelberg game equilibrium, where the three parties are parked vehicles, RSUs and moving vehicles [32].

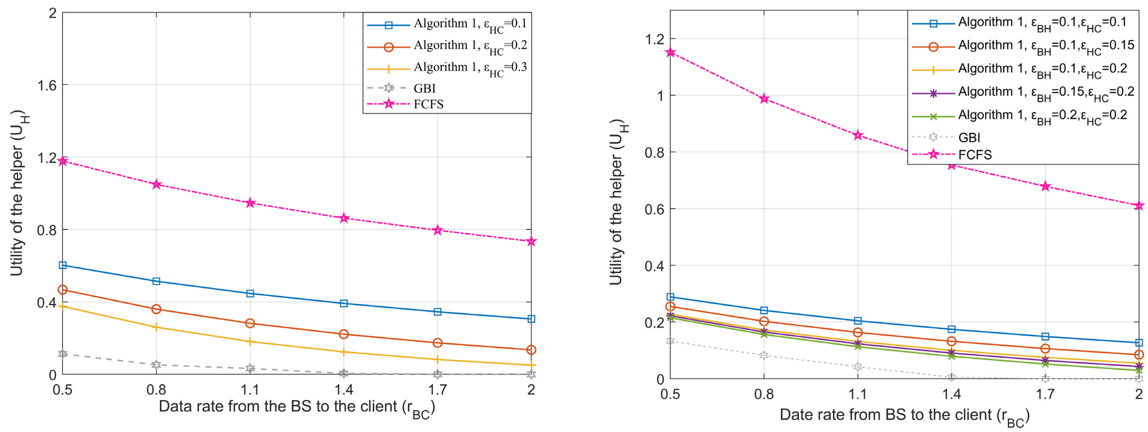
$$\eta^* = \begin{cases} \max\left(\frac{\alpha_1(r_{BH}+r_{HC})}{\alpha_2(\Delta\tau r_{BH} r_{HC}+r_{BC} r_{HC}+r_{BC} r_{BH})}, \varepsilon_{BH}+\varepsilon_{HC}\right), \eta^\# \leq \max\left(\frac{\alpha_1(r_{BH}+r_{HC})}{\alpha_2(\Delta\tau r_{BH} r_{HC}+r_{BC} r_{HC}+r_{BC} r_{BH})}, \varepsilon_{BH}+\varepsilon_{HC}\right) \\ \eta^\#, \max\left(\frac{\alpha_1(r_{BH}+r_{HC})}{\alpha_2(\Delta\tau r_{BH} r_{HC}+r_{BC} r_{HC}+r_{BC} r_{BH})}, \varepsilon_{BH}+\varepsilon_{HC}\right) < \eta^\# < \min(\frac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}) \\ \min\left(\frac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}\right), \eta^\# \geq \min(\frac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}), \end{cases} \tag{44}$$

$$\eta^* = \begin{cases} \max\left(\frac{\alpha_1 A}{\alpha_2 r_{BC}(D_C r_{BH}+A)}, \varepsilon_{BH}+\varepsilon_{HC}\right), \eta^\# \leq \max\left(\frac{\alpha_1 A}{\alpha_2 r_{BC}(D_C r_{BH}+A)}, \varepsilon_{BH}+\varepsilon_{HC}\right) \\ \eta^\#, \max\left(\frac{\alpha_1 A}{\alpha_2 r_{BC}(D_C r_{BH}+A)}, \varepsilon_{BH}+\varepsilon_{HC}\right) < \eta^\# < \min(\frac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}) \\ \min\left(\frac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}\right), \eta^\# \geq \min(\frac{\alpha_1}{\alpha_2 r_{BC}}, \eta_{max}). \end{cases} \tag{45}$$



(a) (b)

FIGURE 5. Utility of the client versus $\mathbf{r_{BC}}$: (a) the helper has the required data and (b) the helper does not have the required data.



(a) (b)

FIGURE 6. Utility of the helper versus $\mathbf{r_{BC}}$: (a) the helper has the required data and (b) the helper does not have the required data.

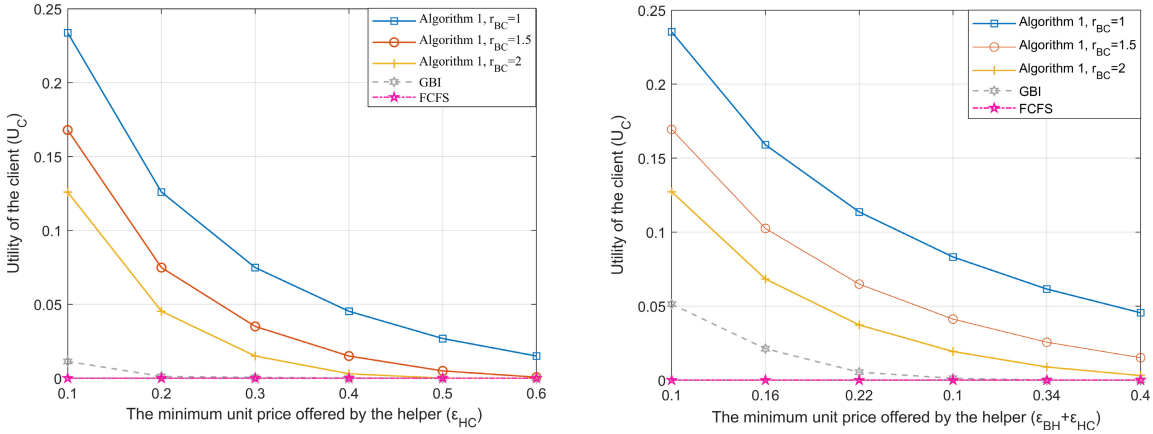
TABLE 3. Simulation parameters.

Parameter	Value
D_C	300 mb
r_{BC}	[1,4] mb/s
r_{BH}	[1,4] mb/s
r_{HC}	[1,10] mb/s
R_{BS}	500 m
R_V	300 m
Speed of vehicles	[20, 40] m/s
Density of vehicles	0.05 vehicles/m
Length of road	4000 m
ε_{BH}	[0.1, 0.3]
ε_{HC}	[0.1, 0.6]
η	[0.1, 10]
α_1	0.5
α_2	0.5
β_1	0.5
β_2	0.5

- First come first serve (FCFS): A client vehicle chooses the first accessing helper vehicle and selects λ^0 and η_{max} as the offloading rate and the knockdown unit price. This algorithm is used for comparison in [43].

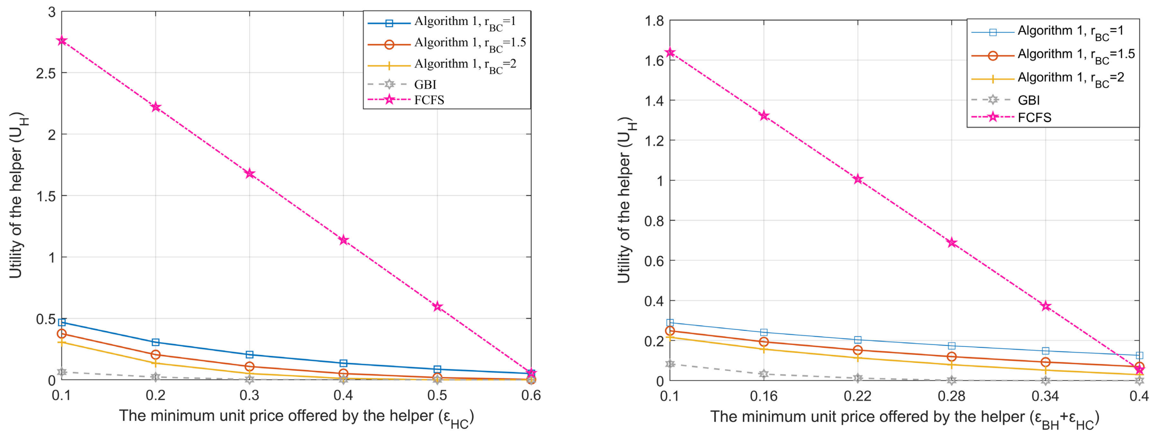
B. SIMULATION RESULTS

FIGURE 5 and FIGURE 6 plot the utilities of the client and the helper when the data rate from the BS to the client changes. According to FIGURE 5 (a) and (b), the utility of the client for algorithm 1 is greater than those for the GBI and FCFS algorithms. This is because the utility function of algorithm 1 differs from those of the GBI and FCFS algorithms. The utility function is set to be always greater than or equal to 0. Therefore, for the FCFS algorithm, the utility of the client is always zero in both scenarios, which means FCFS cannot optimize the utility of the client. According to FIGURE 5 (a) and (b), the utility of the client for algorithm 1 gradually decreases as the data rate from the BS to the client increases in both scenarios; this is because when the value of r_{BC} is small, it takes a long time to download the task data from the BS without a helper. With the increase of r_{BC}, the time that it takes to download the task data from the BS without a helper becomes small; hence, the total revenue that can be obtained from offloading also becomes small. The utility of a helper for algorithm 1 also decreases as the data rate from the BS to the client increases



(a) (b)

FIGURE 7. **Utility of the client versus the minimum unit price that is offered by the helper: (a) the helper has the required data and (b) the helper does not have the required data.**



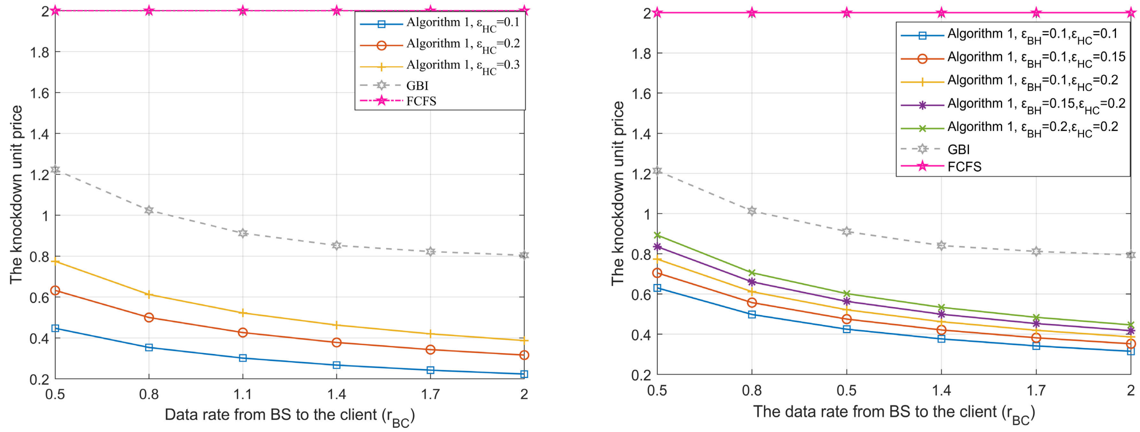
(a) (b)

FIGURE 8. **Utility of the helper versus the minimum unit price that is offered by the helper: (a) the helper has the required data and (b) the helper does not have the required data.**

in both scenarios. This is because the knockdown unit price decreases with the increase of r_{BC}. As a result, the total income that can be obtained is also decreased. In addition, according to FIGURE 5 and FIGURE 6, the utility of the client for the FCFS algorithm is 0 and the utility of the helper is greater than that for algorithm 1; hence, FCFS cannot optimize two utility functions simultaneously.

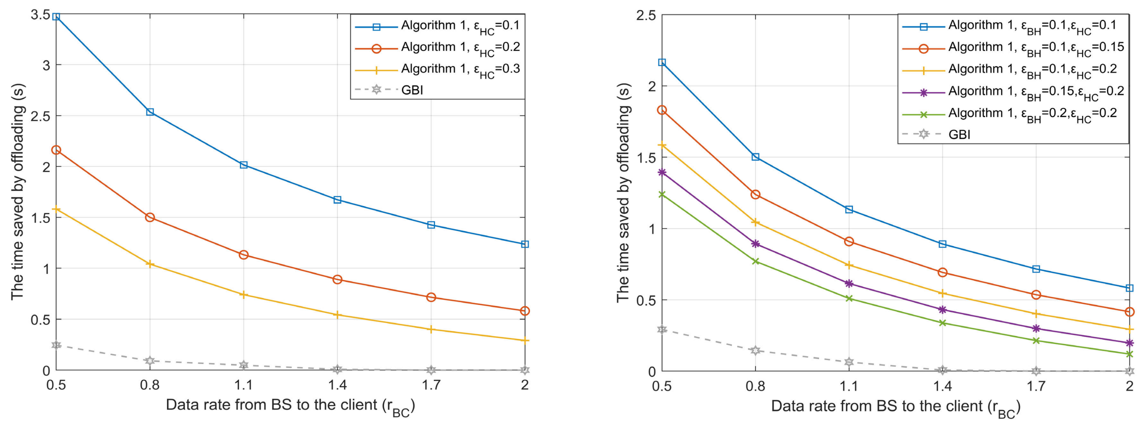
FIGURE 7 and FIGURE 8 plot the utilities of the client and the helper when the minimum unit price that can be offered by the helper changes. The minimum unit price equals ε_{HC} in FIGURE 7 (a) and FIGURE 8 (a), while it equals $\varepsilon_{BH}+\varepsilon_{HC}$ in FIGURE 7 (b) and FIGURE 8 (b). In addition, the utility of the client for algorithm 1 is gradually decreased as the minimum unit price that can be offered by the helper increases. This is because the knockdown unit price increases with the increase of the minimum unit price; hence, the money that the client pays to the helper increases. In FIGURE 8 (a) and (b), the utility of the helper for algorithm 1 decreases as the minimum unit price that can be offered by the helper increases. The decreased utility of the helper for algorithm 1 results from the percentage of the data that are offloaded to the helper decreasing with the increase of the minimum unit price. Similarly, the utility of the client for Algorithm 1 is greater than those for GBI and FCFS algorithms, as shown in FIGURE 7 (a) and (b). In addition, the utility of the client for FCFS is also 0, and the utility of the helper for FCFS is greater than that of Algorithm 1.

FIGURE 9 analyzes the variation tendency of the knockdown unit price with the increase of r_{BC}. According to FIGURE 9 (a) and (b), the knockdown unit price for algorithm 1 decreases as the value of r_{BC} increases. This is because as r_{BC} increases, the time that is needed to download the data from the BS without a helper decreases, thereby increasing the bargaining performance. As a result, the knockdown unit price decreases. In addition, algorithm 1 can achieve a lower knockdown unit price than GBI and FCFS algorithms. Note that the price is set to η_{max} during the simulations. FIGURE 10 analyzes the relationship between the time that



(a) (b)

FIGURE 9. Knockdown unit price versus r_{BC}: (a) the helper has the required data and (b) the helper does not have the required data.



(a) (b)

FIGURE 10. Time saved via offloading versus r_{BC}: (a) the helper has the required data and (b) the helper does not have the required data.

is saved via offloading and the data rate from the BS to the client. According to FIGURE 10, the time that is saved via offloading for algorithm 1 gradually decreases with the increase of r_{BC}. This is because the original time that is required for downloading the data decreases with the increase of r_{BC}. In addition, the time that is saved by algorithm 1 is greater than that by GBI. This is because algorithm 1 can yield a better optimization result than GBI.

VI. CONCLUSION

This paper proposes a Stackelberg-game-based incentive scheme for opportunistic data offloading in SDN-based vehicular networks, which considers the mobility of vehicles, the popularity of contents and the content storage of vehicles. The Stackelberg-game-based model accurately describes the interaction between a client and a helper. Based on the results of the Stackelberg equilibrium, an algorithm is proposed for selecting the helper that offers the lowest price to the client. The simulation results demonstrate that the proposed scheme can effectively reduce the downloading time of a task while satisfying both the client and the helper.

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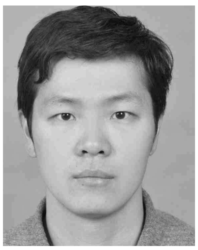

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