RAIM: A Reverse Auction-Based Incentive Mechanism for Mobile Data Offloading Through Opportunistic Mobile Networks

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***Abstract*—Offloading cellular traffic through Opportunistic Mobile Networks (OMNs) has been an effective method to ease the traffic burden of cellular networks. However, providing data offloading services consumes a lot of resources. Since nodes in OMNs are rational and selfish, they will not be willing to provide data offloading services if they are not properly rewarded. Therefore, it is important to exploit incentive mechanisms to motivate nodes to provide data offloading services. This paper proposes a Reverse Auction-based Incentive Mechanism, named RAIM. In RAIM, reverse auction is used as the incentive mechanism, and the incentive-driven data offloading process is modeled as Non-Linear Integer Programming (NLIP) from the business point of view, aiming to minimize the cost of the Content Service Provider (CSP). Then, a heuristic method named Decay-based Helper Selection Method (DBHSM) is proposed to resolve the problem. Moreover, a payment rule based on the standard Vickrey-Clarke-Groves scheme is proposed to ensure the individual rationality and truthfulness properties of DBHSM. Finally, real mobility trace-driven simulation results show that DBHSM outperforms other baseline methods in terms of the CSP's cost and the offloading rate under different scenarios.**

***Index Terms*—Reverse Auction, Mobile Data Offloading, Opportunistic Mobile Networks, Real Mobility Trace.**

I. Introduction

WITH the rising popularity of smart devices and wireless services, the mobile traffic in mobile network is growing explosively. The large demands for a variety of contents have put forward urgent needs for the Content Service Provider (CSP) to meet the users' service quality/experience requirements towards 5 G mobile networks [1]–[3]. According to Cisco's recent reports, global mobile traffic was 11.5 exabytes per month at the end of 2017, but by 2022, global mobile traffic will reach 77 exabytes per month [4]. Therefore, there is an imminent requirement for the CSP to provide quick and hopeful ways to ease the traffic load of cellular networks.

Mobile data offloading, which uses complementary network technologies to offload mobile traffic planned to transmit via cellular networks originally, is an effective method to solve the traffic congestion in cellular networks [5]–[8]. It can be implemented through Small Base Stations (SBSs), Wi-Fi networks, Opportunistic Mobile Networks, or heterogeneous networks. Data offloading through SBSs, Wi-Fi networks and heterogeneous networks have become a mature technology, but they all depend on infrastructures, which has the disadvantages of limited coverage, high installation and maintenance costs [9].

Another effective method to offload cellular traffic is to use Opportunistic Mobile Networks (OMNs) [10]–[12]. OMNs allow users with intermittent connections to communicate using their smart devices equipped with wireless interfaces (such as Bluetooth, Wi-Fi, D2D) within the range of mutual communication [13], [14]. Therefore, instead of transmitting the content to each requesting user via the cellular network, OMN-based offloading or opportunistic offloading can first transmit the content to only a small set of selected users. Then, these users can further help transmit the content to other requested users via opportunistic forwarding. A large portion of the mobile services provided by the CSP, such as multimedia newspapers, weather forecasts, or advertisement, are not strictly real-time requirements, and need to be transmitted to a large number of users. Thanks to these non-real-time applications, the CSP can transmit the content to only a small set of selected users, named helpers in this paper, so as to reduce cellular traffic and thus the operation cost.

Researchers have found that opportunistic offloading can offload about 70% cellular traffic in their simulations [15]. However, users may not be willing to provide data offloading services without receiving proper financial incentives [16]–[18]. This is because offloading data for the CSP will cause additional resource consumptions inevitably, e.g., energy consumption, capacity consumption, etc [19]. In addition, when providing data offloading services for the CSP, nodes may have to sacrifice their own benefit, e.g., transmission rate,

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quality of service, etc [20]. Therefore, it is important to exploit an effective incentive mechanism to stimulate users in OMNs to provide data offloading services [21].

In this paper, a Reverse Auction-based Incentive Mechanism, named RAIM, is proposed to motivate nodes in OMNs to provide data offloading services. In RAIM, the reverse auction is employed as the incentive mechanism, where the CSP acts as the auctioneer, and mobile nodes act as the bidders. Then, the incentive-driven data offloading process is modeled as Non-Linear Integer Programming (NLIP), aiming to minimize the cost of the CSP. As the optimization problem is NP-complete, a Decay-based Helper Selection Method (DBHSM) is proposed to solve the problem, which adds a decay factor to update the offloading potential of each node, and selects far apart nodes with higher offloading potential and less payment as helpers.

The contributions of this paper are summarized as:

1) A Reverse Auction-based Incentive Mechanism, named RAIM, is proposed to motivate nodes in OMNs to provide data offloading services. From the business point of view, the incentive-driven data offloading process is formulated as NLIP, which aims to minimize the cost of the CSP.
2) A heuristic Decay-based Helper Selection Method (DBHSM) is proposed to resolve the problem.
3) A payment rule based on the standard Vickrey-Clarke-Groves (VCG) scheme is proposed to ensure the individual rationality and truthfulness properties of DBHSM.
4) Real mobility trace-driven simulation results demonstrate that the proposed DBHSM outperforms other baseline methods in terms of the CSP's cost and the offloading rate under different scenarios.

The reminder of this paper is organized as follows. Section II reviews the related work, and Section III introduces the system model involved in this paper. After introducing the optimization problem in Section IV, Section V introduces a heuristic method: DBHSM, and the payment rule. Section VI introduces the performance evaluation. Finally, the paper is concluded in Section VII.

II. Related Work

Many researchers have exploited opportunistic offloading from different perspectives. For the first time, Han *et al.* in [15] exploited opportunistic offloading to relieve the traffic load of cellular networks. They focus on selecting k initial seeds to minimize the traffic through cellular networks, and propose a greedy algorithm based on the contact graph to resolve this problem. Similarly, authors in [22] investigated the social contact graph for load allocation, and selected initial seeds according to users' social importance. Authors in [23] investigated the problem of load allocation when subscribers download multiple contents from the server. Lu *et al.* [24] proposed a probability framework to estimate the data transmission probability through OMNs and then, based on that, they maximally improved the probability of data transmission from a user to infrastructure through OMNs. Gao *et al.* in [25] investigated how to offload deadline-sensitive data through opportunistic offloading and minimize the expected total data transmission cost. In [26], Wang *et al.* proposed the TOSS framework to alleviate the load of cellular networks via OMNs, which takes into account many practical ingredients, e.g., content size, deadline, and buffer size of users. Wu *et al.* in [27] investigated the cooperative traffic offloading via D2D communications, and considered the joint optimization of the transmission rate for content offloading and MD's relay duration. To solve the optimization problem, they proposed an efficient algorithm HOTRD to find the optimal solution. In [28], Park *et al.* proposed a cooperative base station caching and X2 link traffic offloading system based on Software Defined Network (SDN) for 5 G network to provide video streaming services. Sun *et al.* in [29] studied the cooperative computing offloading problem of MEC in 6 G mobile networks and built a MEC architecture supporting collaborative edge computing. They formulated the cooperative computation offloading problem as a MDP, and proposed two intelligent computation offloading algorithms according to Soft Actor Critic to improve the QoS of MDs. Our former work in [30] defined a freshness-aware seed selection optimization problem with considering both the freshness of the content and the cellular transmission cost, which aims to maximize the total content utility. However, these studies assume that users in OMNs are cooperative, and they do not consider the case that users in OMNs are selfish or rational.

Some economic theory-based incentive mechanisms, e.g., social relationship [33], game theory [32], contract theory [33], and auction theory, have been proposed to stimulate nodes to provide data offloading services [31]. In [40], Hou *et al.* proposed a social relationship based auction to achieve efficient data offloading through WiFi APs. Authors in [32] proposed an incentive framework for D2D offloading to maximize the network economic efficiency, which encourages users to disseminate popular contents to other requested users by formulating the data offloading process as a two-stage Stackelberg game. In [33], Chen *et al.* proposed a contract-based incentive mechanism for D2D offloading, which aims to maximize the expected revenue of operators under the premise of ensuring the quality of service. Authors in [34] proposed a contract-based model to solve the problem of motivating users to provide data offloading services through D2D communications, which overcomes the information asymmetry in OMNs. In [35], Wu *et al.* investigated the incentive mechanism for mobile video offloading through crowdsourcing, and proposed a market-driven Quality of Video oriented incentive method, named Vbargain, which treats the packet forwarding and exchange process as a bargain.

Some researches also have put forward different incentive mechanisms based on the auction theory. In [36], Zhuo *et al.* proposed a reverse auction-based incentive mechanism, named Win-Coupon, which can motivate nodes with high tolerant delay and large offloading potential to offload traffic to OMNs. In [37], Song *et al.* proposed a reverse auction-based incentive mechanism, which takes the cost constraint into consideration and can stimulate mobile users to participate in content distribution through OMNs. In [38], Zhang *et al.* stimulated mobile nodes to store and disseminate popular contents for mobile network operators by using the reverse auction theory. In [39], Paris *et al.* proposed a combinatorial reverse auction-based incentive mechanism to select the cheapest third-party WiFi access devices and offload the maximum amount of data traffic from the mobile network operators. In [41], Zhu *et al.* proposed a randomized combinatorial reverse auction-based incentive mechanism, named Rado, to stimulate users to take part in content sharing through D2D communications, and proved that Rado does its best effort to ensure truthfulness while guaranteeing social welfare. In [42], Hajiesmaili *et al.* employed a reverse action mechanism to stimulate devices to provide data offloading services through D2D communications, which aims to minimize the CSP's social cost. Furthermore, they also proposed an online and an approximation method to resolve the problem in polynomial time. In [43], Xu *et al.* designed truthful incentive mechanisms and two bid models for multiple cooperative tasks to minimize the social cost. In [44], Jiang *et al.* proposed a truth discovery algorithm as a component of the incentive mechanism for the crowdsourcing with copiers, and then designed a reverse auction based mechanism to maximize the social welfare.

Similar to the above previous studies, this paper also proposes a reverse auction-based incentive mechanism for offloading data through OMNs. However, this paper models the incentive-driven data offloading problem in OMNs as NLIP from the business point of view, which aims to minimize the CSP's cost. Furthermore, to improve the performance of data offloading, a Decay-based Helper Selection Method is proposed to select far apart nodes with higher offloading potential and less payment as helpers.

III. System Model

This section gives an introduction of the system model related to our proposed method.

A. Mobile Data Offloading Model

Similar to the data offloading model in [15], some contents need to be distributed from a Content Service Provider (CSP) to all requested users (using nodes instead below) before a given deadline. Here, we consider the data offloading process of a certain content with a given deadline T, and we do not consider the storage of nodes (i.e., we assume that all nodes have enough capacities to store contents). Without loss of generality, each node's preference for the content is equal to the popularity of the content with a probability e. Fig. 1 shows the opportunistic offloading scenario considered in this paper, which is composed of a Base Station (BS), a CSP, and a set of mobile nodes in a single cell. Here, the BS is deployed by the CSP. Besides, all nodes are within the service coverage of the BS, and the set of nodes is $\mathcal{N}$. Each node can download its interesting contents from the BS, and the BS is responsible for transmitting the content to all requested nodes. Due to the limited backhaul and radio access capacity of BS, the CSP may select some nodes as helpers to help offload traffic to other nodes who request the content, so as to maximize the network throughput and reduce the cost of the CSP, particularly when the network is congested.

However, generally speaking, nodes in the network are selfish and rational, so they will not be willing to offload the content without any revenue. In order to stimulate nodes to provide data offloading services, the CSP needs to pay helpers to compensate for their resource consumptions. The data offloading process can be described as follows. First, at time 0, the CSP injects the content to a small subset of nodes, named helpers, via cellular networks. Then, the helpers will be responsible for transmitting the content to other requested nodes via opportunistic communications, such as Wi-Fi, Bluetooth, or Device-to-Device (D2D). At last, if the request is not served within the maximum tolerant delay, the content will be transmitted directly by the BS.

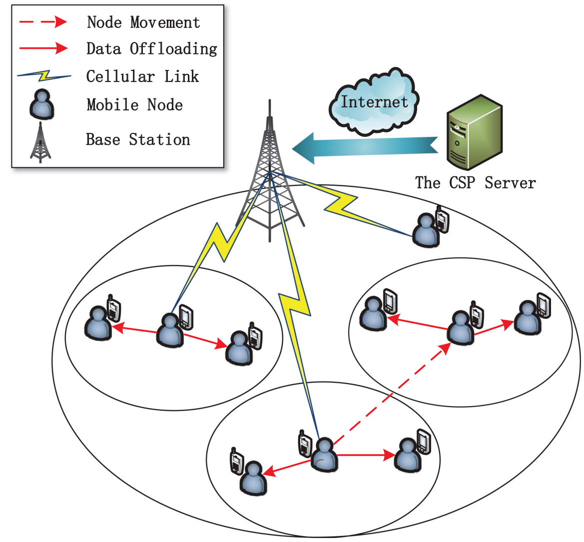


Fig. 1. Opportunistic offloading scenario.

Similar to the studies in [10], [45], for simplicity we assume that once two nodes are in contact, the content can be delivered successfully. Each pair of nodes (i, j), $i, j \in \mathcal{N}$ meets other pairs of nodes at an exponentially distributed time interval with rate β_{ij} independently. The assumption of exponential inter-contact time in real mobility traces is the norm for the analysis of OMNs, and the calculation of the contact rate β_{ij} between nodes i and j is shown as [45]:

$$\beta_{ij} = \frac{\eta_{ij}}{\sum_{m=1}^{\eta_{ij}} ICO_{ij}^{m}}, \tag{1}$$

where η_{ij} represents the number of contacts between nodes i and j, and ICO_{ij} is the inter-contact time samples between them. Since e_j is a constant which denotes the probability that node j is interested in the content, thus, the probability distribution function of the inter-contact time between nodes i and j can be expressed as: $f(y) = e_j\beta_{ij}e^{-e_j\beta_{ij}y}$.

Then, we can derive the offloading probability that node j who requests the content can be served by node i within the maximum tolerant delay T as:

$$\begin{aligned} P_{ij}(T) &= \int_0^T f(y)dy \\ &= \int_0^T e_j\beta_{ij}e^{-e_j\beta_{ij}y}dy, \end{aligned} \tag{2}$$

where e_j is the probability that node j is interested in the content.

B. The CSP's Cost Model

We define that the unit cost of traffic through cellular networks is α, and the size of the content is s. $\mathcal{T}_1$ denotes the total cellular traffic that should be transmitted by the CSP before selecting helpers. If the CSP selects some nodes as helpers to help offload cellular traffic, the amount of cellular traffic that can be offloaded by helpers is $\mathcal{T}_2$. It is worth noticing that not all helpers are interested in the content; if a helper does not request the content, the CSP needs to transmit extra cellular traffic to the helper. Considering this situation, we use $\mathcal{T}_3$ to denote the extra cellular traffic. If the payment to helpers is not considered, the CSP's transmission cost function via cellular networks can be formulated as follows:

$$U(\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3) = (\mathcal{T}_1 - \mathcal{T}_2 + \mathcal{T}_3)\alpha. \tag{3}$$

Here, $U(\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3)$ represents the CSP's transmission cost function via cellular networks.

C. The Mobile Nodes' Bidding Model

Assuming that N mobile nodes exist in the network, represented by $\mathcal{N} = \{1, 2, \ldots, N\}$, and several nodes are requesting the same content at the same time, each node $i \in \mathcal{N}$ has the following properties:

- True value of the unit cost in opportunistic communication v_i: It is the true value of cost led by helping the CSP to serve the data offloading process. It is noted that v_i, which is the private information of node i, cannot be captured by any other nodes, even the CSP.
- The node i's expected unit price in opportunistic communication b_i: It is the expected reward that node i wants to obtain from the CSP to compensate for its consumption led by providing the data offloading service. It should be also noted that the bid b_i may be not equal to the real private value v_i, which is only known to node i.

D. Reverse Auction Model

We use the reverse auction to motivate nodes to participate in data offloading. The CSP initiates an auction and collects the nodes' bids at the beginning, then calculates each node pair's contact rate according to their historical contact records and evaluates each node's offloading potential. The CSP will select proper helpers according to the offloading potential and bids. Helpers will receive the corresponding compensation according to the traffic they offloaded. In specific, the CSP acts as an auctioneer to purchase helpers' storage and offloading capabilities to deliver the content through opportunistic communications, while at the same time, helpers act as sellers and submit their expected prices to the CSP. The process of the reverse auction can be summarized as follows:

- The nodes within the coverage of the BS submit their expected prices b_i to the CSP.
- Each node reports its preference of the content to the CSP. Then, the CSP selects some nodes as helpers to offload the content through opportunistic communications according to the information received.
- The CSP calculates and pays the actual payment for each helper.

For ease of reference, we have listed the notations used in this paper and provided corresponding explanations in TABLE I.

TABLE I
NOTATIONS AND SYMBOLS

Notation	Explanation
β_{ij}	The contact rate between nodes i and j
η_{ij}	The number of contacts between nodes i and j
ICO_{ij}	The inter-contact time samples between nodes i and j
e_j	The probability that node j is interested in the content
$P_{ij}(T)$	The offloading probability that node j who requests the content can be served by node i within the tolerant delay T
$\mathcal{T}_1$	The total traffic that the CSP needs to transmit before selecting helpers
$\mathcal{T}_2$	The amount of traffic that can be offloaded by helpers
$\mathcal{T}_3$	The extra cellular traffic transmitted to helpers who are not interested in the content
α	The CSP's unit traffic price
$\mathcal{N}$	The set of all nodes within the coverage of the BS
v_i	True value of the unit cost in opportunistic communication of node i
b_i	The expected unit traffic price of helper i
x_i	Binary variable indicates if node i is selected as a helper
a_i	Binary variable indicates if node i is requesting the content
s	The content data size
B_i	The node i's expected compensation for the cost consumed in the data offloading process
S_i	The offloading potential of node i
Δ_i	The cost that CSP can save by offloading the content through node i
$C_{\mathcal{H}}$	The CSP's cost after selecting helpers
$\mathcal{H}$	The set of helpers that are selected by the CSP
T	The maximum tolerant delay
$J_{\mathcal{H}}$	The benefit of the CSP after selecting helpers
M_i	The marginal contribution of helper i
$\mathcal{L}_i$	Node i's one hop neighbors in the contact graph
p_i	The real payment of helper i
u_i	The utility of helper i
ψ_i	The sum of the real cost consumed by helper i in the data offloading process

IV. Problem Formulation

This section introduces the objective function of the CSP, and models the incentive-driven data offloading problem as an optimization problem, aiming to minimize the cost of the CSP.

$x_i \in \{0, 1\}$ is used to denote whether node i is selected as the helper, and $a_i \in \{0, 1\}$ is used to indicate whether node i requests the content. If node i is selected as the helper, $x_i = 1$, otherwise $x_i = 0$. Similarly, if node i requests the content, $a_i = 1$, otherwise $a_i = 0$. We define the set $\mathcal{X}$ that contains all the selecting variables as $\mathcal{X} = \{x_i | i \in \mathcal{N}\}$ and define the set $\mathcal{A}$ that contains all the content requesting variables as $\mathcal{A} = \{a_i | i \in \mathcal{N}\}$. Then, the CSP's cost function can be given as:

$$\begin{aligned} C_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) &= U(\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3) + \sum_{i \in \mathcal{N}} x_i B_i \\ &= U\left(\sum_{i \in \mathcal{N}} a_i s, \sum_{i \in \mathcal{N}} (1 - x_i) a_i s, \sum_{i \in \mathcal{N}} x_i (1 - a_i) s\right) \\ &\quad + \sum_{i \in \mathcal{N}} x_i B_i, \end{aligned} \tag{4}$$

which represents the sum of the CSP's transmission cost via cellular networks and the compensation for helpers. $U(\cdot)$ is the CSP's cost function without considering the payments to helpers which is shown in (3). According to the definition of $\mathcal{T}_1$, it is obvious that $\sum_{i\in\mathcal{N}} a_i s$ can be used to calculate $\mathcal{T}_1$; according to the definition of $\mathcal{T}_2$, we should consider the sum amount of traffic that is requested by nodes except the helpers, so we can set $x_i = 0$, $a_i = 1$, and use $\sum_{i\in\mathcal{N}}(1 - x_i)a_i s$ to calculate $\mathcal{T}_2$; according to the definition of $\mathcal{T}_3$, we should consider the sum amount of traffic that is sent from the CSP to the helpers not interested in the content, so we can set $x_i = 1$, $a_i = 0$, and use $\sum_{i\in\mathcal{N}} x_i(1 - a_i)s$ to calculate $\mathcal{T}_3$. $\mathcal{H}$ is the set of helpers, B_i is node i's expected compensation for the cost consumed in the data offloading process, which can be calculated as:

$$B_i = S_i b_i, \tag{5}$$

where S_i is the offloading potential which denotes the amount of cellular traffic that can be offloaded by node i. We will give the detail about how to calculate S_i later.

The CSP aims to minimize its cost, so the optimization objective is formalized as follows:

$$\min \quad C_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) \tag{6}$$

$$\text{s.t.} \quad \sum_{i\in\mathcal{N}} x_i \le \sum_{i\in\mathcal{N}} a_i, \quad \forall i \in \mathcal{N}, \tag{7}$$

$$x_i b_i \le \alpha, \quad \forall i \in \mathcal{N}, \tag{8}$$

$$x_i, a_i \in \{0, 1\}, \quad \forall i \in \mathcal{N}, \tag{9}$$

where constraint (7) guarantees that the sum traffic transmitted by the BS after selecting helpers is smaller than that without helpers, constraint (8) indicates that the reward expected by the helpers cannot be higher than the unit traffic cost of the CSP, and constraint (9) guarantees the integer nature of binary variables.

Since B_i in Eq. (4) is a function of x_i ($i \in \mathcal{X}$), Eq. (4) is a quadratic equation and is nonlinear. According to constraint (9), the independent variable x_i is an integer, so the above optimization problem belongs to Non-Linear Integer Programming (NLIP). As we all know, the knapsack problem is a NP-complete problem with combinatorial optimization. Meanwhile, it is obvious that the proposed optimization problem is more complicated than the knapsack problem, thus it is NP-complete, and has no accurate and fast algorithm to solve it in polynomial time. Therefore, a heuristic method is introduced in this paper to reduce the time complexity and get the approximate optimal solution.

V. Problem Solving

This section introduces the proposed Decay-based Helper selection Method, called $DBHSM$ to resolve the above problem. The CSP will select the winning nodes as helpers to provide data offloading services, and pay them according to their contributions. The proposed helper selection method is given, and then the CSP's payment determination to the helpers is introduced.

A. Decay-Based Helper Selection Method

This part proposes a Decay-based Helper Selection Method, named DBHSM to get the approximate optimal solution. We first introduce several definitions.

Definition 1: (The offloading potential of node i) The offloading potential of node i is defined as the amount of cellular traffic that can be offloaded when node i is selected as a helper, the formula is given as:

$$S_i = s \sum_{j\in\mathcal{N}\setminus\{i\}} (1 - x_j)P_{ij}(T), \tag{10}$$

where $P_{ij}(T)$ denotes the probability that node j can obtain the content from node i via opportunistic communication within the tolerant delay T, which has been given in Eq. (2).

Δ_i is used to represent the cost that the CSP can save by offloading the content through node i, and the formula is given as:

$$\Delta_i = \alpha[S_i - (1 - a_i)s]. \tag{11}$$

Therefore, $\Delta_i - B_i$ denotes the actual saving cost after selecting node i as the helper.

Definition 2: (The benefit of the CSP) The CSP aims to minimize its cost, thus the benefit of the CSP can be defined as the reduction of the CSP's cost after selecting helpers, which is given as:

$$J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) = s\alpha \sum_{i\in\mathcal{N}} a_i - C_{\mathcal{H}}(\mathcal{X}, \mathcal{A}), \tag{12}$$

where the first part indicates the total cost of the traffic that should be transferred by the BS before selecting helpers, the second part indicates the actual cost of the CSP after selecting helpers.

Definition 3: (The Marginal Contribution of helper i) The marginal contribution of helper i can be defined as the increment of the CSP's benefit after selecting node i as the helper, which is given as:

$$M_i = J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}), \tag{13}$$

where $J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A})$ denotes the optimal solution without considering the participation of node i.

The traditional way to solve NP complete problem is to use the Greedy algorithm. CSP greedily select the MD who has the maximum offloading potential as the helper for each round. However, the Greedy algorithm is very simple and has poor performance. To further improve the performance of data offloading, a Decay-based Helper Selection Method, named DBHSM is proposed in this part. In fact, when a certain node i is selected as the helper, the offloading potential increases slightly if another node near i is selected as the helper again as node i can offload the content to these nodes. Therefore, it is better to select far apart nodes as they can offload the content to more nodes in the network. In other words, when a node is selected as the helper, the selection probability of its neighbors and neighbors' neighbors should be reduced. Under this mechanism, the selected helpers are far apart and can offload more traffic in the local structure.

To realize this idea, a decay factor is added to update the offloading potential of each node. In DBHSM, the CSP needs to calculate the contact rate $\beta_{ij},\ i, j \in \mathcal{N}$. Based on β_{ij}, maximum tolerant delay T and its interest in the content, the CSP can obtain the offloading probability $P_{ij}(T),\ j \in \mathcal{N} \setminus \{i\}$ that node j can be served by node i within the maximum tolerant delay T according to (2). Then, the CSP can obtain node i's offloading potential $S_i, i \in \mathcal{N}$ according to (10). For the 1st round, the CSP will select node i as the helper if it has the maximum value of the cost that can be saved by offloading the content minus the total bid prices, i.e., $\Delta_i - B_i$. Furthermore, node i will be checked if it could increase CSP's benefit or not in each while-loop, i.e., if the Marginal Contribution of node i is positive (Lines 10-11 in Algorithm 1). A node can be selected as a helper eventually only if it can bring benefits to the CSP.

If node i is selected as the first helper, and node i's one-hop neighbors in the contact graph is denoted as $\mathcal{L}_i$. We first update the offloading potentials of node i's neighbors, and then update offloading potentials of its neighbors' neighbors. For node i's neighbors, we update the offloading probability $P_{ij}(T)$ that node j who requests the content can be served by node i within the maximum tolerant delay T as:

$$P_{ij}(T) = 0, \quad j \in \mathcal{L}_i. \tag{14}$$

For its neighbors' neighbors, we update the offloading probability $P_{jk}(T)$ that node k who requests the content can be served by node j within the maximum tolerant delay T as:

$$P_{jk}(T) = P_{jk}(T) - d, \quad j \in \mathcal{L}_i, k \in \mathcal{L}_j \setminus \{i\}, \tag{15}$$

where d is a decay factor being between 0 and 1, and $P_{jk}(T) = 0$ if $P_{jk}(T)$ is negative.

Then, we can update the offloading potential of the remaining nodes except node i as:

$$S_j = s \sum_{k \in \mathcal{N} \setminus \{j\}} (1 - x_k) P_{jk}(T), \tag{16}$$

where $j \in \mathcal{N} \setminus \{i\}$ denotes the remaining nodes except node i, and the previous process is repeated to select helpers for the next while-loop. The details of DBHSM are shown in Algorithm 1.

For an intuitive explanation, we adopt DBHSM to select two helpers on a small toy network with 7 nodes. For simplicity, let's assume that all nodes are interested in the content, and all nodes' expected prices are the same. Since helpers are selected in the descending order of $\Delta_i - B_i$, then according to Eq. (10), the selection of helpers depends on the sum of the offloading probability $P_{ij}(T)$. As shown in Fig. 2, in the 1st round, similar to the selection process in the Greedy algorithm, node 1 is selected as the helper, because $P12(T) + P13(T) + P14(T) = 0.75 + 0.68 + 0.86 = 2.29$ is the maximum. In the 2nd round, node 1 will not take part in the subsequent selection, and node 1's neighbors and its neighbors' neighbors will update their offloading potentials. Here, we set the decay factor d as 0.1. Then, $P_{12}(T), P_{21}(T), P_{13}(T), P_{31}(T), P_{14}(T),\ P_{41}(T)$ are updated as 0, $P_{25}(T) = 0.65 - 0.1 = 0.55$, and so on. Therefore, we select node 5 as the helper in the 2nd round, because $P_{52}(T) + P_{54}(T) + P_{56}(T) + P_{57}(T) = 0.51 + 0.38 + 0.37 + 0.62 = 1.88$ is the maximum. The above process is repeated until a selected helper cannot bring benefits to the CSP.

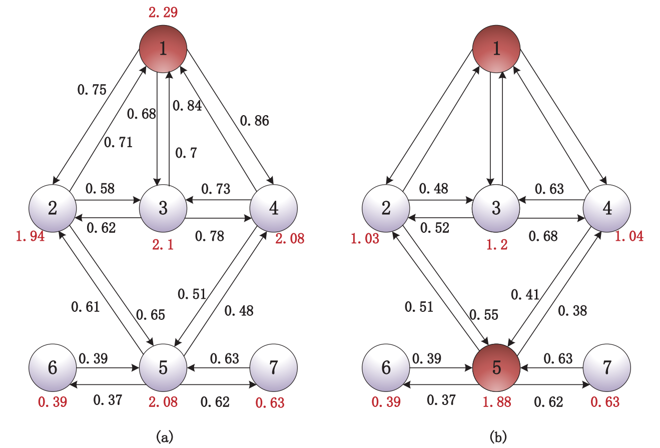


Fig. 2. An illustration of the DBHSM. ((a) the 1st round, (b) the 2nd round.).

Algorithm 1. Helper Selection in DBHSM

Require: $\mathcal{N}$, T, b_i, s, α, $\mathcal{X}$, $\mathcal{A}$, d, $\mathcal{L}_i$
Ensure: $\mathcal{H}$
1: *Initialization*: $\mathcal{H} \leftarrow \emptyset$;
2: **for** $i \in \mathcal{N}$ **do**
3:   **for** $j \in \mathcal{N}, i \neq j$ **do**
4:     Calculate β_{ij} according to (1);
5:     Calculate $P_{ij}(T)$ according to (2);
6:   **end for**
7: **end for**
8: Calculate S_i according to (10);
9: $i \leftarrow \arg\max_{n \in \mathcal{N}} (\Delta_n - B_n)$;
10: **while** the Marginal contribution $M_i > 0$ **do**
11:   $\mathcal{H} \leftarrow \mathcal{H} \cup \{i\}$;
12:   Update $P_{ij}(T) = 0, j \in \mathcal{L}_i$;
13:   Update $P_{jk}(T)$ to $P_{jk}(T) - d$ and set the value as 0 if $P_{jk}(T) - d$ is negative, $j \in \mathcal{L}_i$, $k \in \mathcal{L}_j$, $k \neq j$;
14:   Update the offloading potentials of the remaining nodes according to (16);
15:   $i \leftarrow \arg\max_{n \in \mathcal{N} \setminus \mathcal{H}} (\Delta_n - B_n)$;
16: **end while**
17: **return** $\mathcal{H}$

B. Payment Determination of DBHSM

After offloading the content, the CSP needs to determine the payment to compensate for helpers' cost. When selecting helpers, the CSP has already known their expected prices, but owing to the nature of rationality and selfishness, each helper wants a higher reward which is not equal to the actual value they provided. Based on this, it is necessary to formulate a uniform rule to guarantee the rationality of payment. This part introduces a payment rule based on the standard VCG scheme to stimulate nodes to provide data offloading services in OMNs, and ensures the individual rationality and truthfulness properties of the proposed DBHSM.

Algorithm 2. Payment Determination of DBHSM

Require: $\mathcal{N}, \mathcal{H}, b_i, \mathcal{X}, \mathcal{A}$
Ensure: p_i

```
for i ∈ N do
    p_i = 0;
end for
for i ∈ H do
    J_H^{-i}(X, A) = J_H(X, A) − (Δ_i − B_i);
    N ← N\{i};
    Repeat Algorithm 2 to Update H;
    Calculate p_i according to (18);
end for
return p_i
```

In the standard VCG scheme, the bidder submits a quotation and reports its valuation of the project without knowing the bids of other bidders. According to Definition 1, $\Delta_i - B_i$ denotes the actual saving cost after selecting node i as the helper, then $J_{\mathcal{H}}^{-i}(\mathcal{X}, \mathcal{A})$ is defined as the optimal solution without considering the contribution of node i, which is calculated as:

$$J_{\mathcal{H}}^{-i}(\mathcal{X}, \mathcal{A}) = J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - (\Delta_i - B_i). \tag{17}$$

Moreover, $J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A})$ is used to represent the optimal solution without considering the participation of node i. Then, the payment paid to helper i is given as:

$$p_i = \Delta_i - (J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) - J_{\mathcal{H}}^{-i}(\mathcal{X}, \mathcal{A})). \tag{18}$$

Let $\psi_i = v_i S_i$ represent the sum of the real cost consumed by helper i in data offloading. Accordingly, the utility of each helper $i \in \mathcal{H}$ is calculated as:

$$u_i = p_i - \psi_i. \tag{19}$$

The payments and utilities of those nodes who are not selected as helpers are 0. Algorithm 2 shows the details of the proposed payment determination of DBHSM.

VI. Theoretic Analysis

This section aims to prove that the proposed DBHSM satisfies three important properties: individual rationality, truthfulness and computational efficiency. The individual rationality property ensures that each helper can get a non-negative reward, which is the main motivation for nodes to provide data offloading services. The truthfulness property prevents helpers obtaining higher compensation from untruthful bids. Computational efficiency property guarantees that the algorithm can be completed in the polynomial time.

Theorem 1: (Individual Rationality). The payment rule defined in (18) satisfies the individual rationality property, e.g., $\forall i \in \mathcal{H}, u_i \geq 0$.

Proof: According to the payment rule in (18), we obtain:

$$\begin{aligned} p_i =& \Delta_i - (J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) - J_{\mathcal{H}}^{-i}(\mathcal{X}, \mathcal{A})) \\ =& \Delta_i - J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) + J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - (\Delta_i - B_i) \\ =& J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) + B_i. \end{aligned}$$

We assume that if each helper $i \in \mathcal{H}$ bids truthfully, i.e., $B_i = \psi_i$, we get:

$$\begin{aligned} u_i &= p_i - \psi_i \\ &= J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) \\ &\geq 0. \end{aligned}$$

Therefore, through the analysis above, the individual rationality property is satisfied. ■

Theorem 2: (Truthfulness). The payment rule defined in (18) ensures the truthfulness property. It is proved that it is a weakly dominant strategy for each node who is selected as the helper to set the bid $b_i = v_i$.

Proof: If a certain helper i submits the bid b_i' untruthfully, i.e., $b_i' \neq v_i$. Based on (19), the helper i's utility is formalized as:

$$\begin{aligned} u_i' &= p_i' - \psi_i \\ &= \Delta_i' - (J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) - J_{\mathcal{H}}^{-i}(\mathcal{X}', \mathcal{A})) - \psi_i \\ &= J_{\mathcal{H}}(\mathcal{X}', \mathcal{A}) - J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) + B_i - \psi_i. \end{aligned}$$

Therefore, the difference of each helper's utility in set $\mathcal{H}$ after submitting the untruthful bid and the truthful bid can be calculated as follows:

$$\begin{aligned} \Delta u_i &= u_i' - u_i \\ &= J_{\mathcal{H}}(\mathcal{X}', \mathcal{A}) - J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) + B_i' - \psi_i \\ &\quad - [J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - J_{\mathcal{H}\setminus\{i\}}(\mathcal{X}, \mathcal{A}) + B_i - \psi_i] \\ &= J_{\mathcal{H}}(\mathcal{X}', \mathcal{A}) + B_i' - J_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - B_i \\ &= C_{\mathcal{H}}(\mathcal{X}, \mathcal{A}) - B_i - C_{\mathcal{H}}(\mathcal{X}', \mathcal{A}) + B_i' \\ &= U\left(\sum_{i\in\mathcal{N}} a_i s, \sum_{i\in\mathcal{N}} (1-x_i) a_i s, \sum_{i\in\mathcal{N}} x_i (1-a_i) s\right) + \sum_{i\in\mathcal{N}} x_i B_i \\ &\quad - B_i - U\left(\sum_{i\in\mathcal{N}} a_i s, \sum_{i\in\mathcal{N}} (1-x_i') a_i s, \sum_{i\in\mathcal{N}} x_i' (1-a_i) s\right) \\ &\quad - \sum_{i\in\mathcal{N}} x_i' B_i' + B_i' \\ &= U\left(\sum_{i\in\mathcal{N}} a_i s, \sum_{i\in\mathcal{N}} (1-x_i) a_i s, \sum_{i\in\mathcal{N}} x_i (1-a_i) s\right) + \sum_{k\in\mathcal{N}\setminus\{i\}} x_k B_k \\ &\quad - U\left(\sum_{i\in\mathcal{N}} a_i s, \sum_{i\in\mathcal{N}} (1-x_i') a_i s, \sum_{i\in\mathcal{N}} x_i' (1-a_i) s\right) \\ &\quad - \sum_{k\in\mathcal{N}\setminus\{i\}} x_k' B_k' \end{aligned}$$

Since $(x_i, a_i)(i \in \mathcal{H})$ is the solution that minimizes the cost function (4), we can get:

$$U\left(\sum_{i\in\mathcal{N}} a_i s, \sum_{i\in\mathcal{N}}(1-x_i)a_i s, \sum_{i\in\mathcal{N}} x_i(1-a_i)s\right) + \sum_{k\in\mathcal{N}\setminus\{i\}} x_k B_k$$
$$\leq U\left(\sum_{i\in\mathcal{N}} a_i s, \sum_{i\in\mathcal{N}}(1-x_i')a_i s, \sum_{i\in\mathcal{N}} x_i'(1-a_i)s\right) + \sum_{k\in\mathcal{N}\setminus\{i\}} x_k' B_k'.$$

Therefore, $\Delta u_i \leq 0$. In other words, helpers cannot increase their utility from untruthful bids. ∎

Theorem 3: (Computational Efficiency). The proposed DBHSM is computationally efficient.

Proof: The computational complexity of DBHSM is related to the number of mobile nodes and helpers. We assume that the number of nodes is N, then the computational complexity of calculating offloading potential (Lines 2-9 in Algorithm 1) does not exceed $O(2\ N^2)$. Furthermore, we assume that the number of nodes that will be selected as helpers is H and the number of helper's neighbors is L, thus the while-loop (Lines 10-16 in Algorithm 1) executes $H+1$ times. In each loop, finding a helper with the largest value of $\alpha S_i - B_i$ (Lines 10-17 in Algorithm 2) does not exceed $O(N^2)$ time. As a result, the computational complexity of DBHSM is $O((H+3)N^2+(H+1)L)$. Then, we can get the computational complexity of Algorithm 2 as $O((H^2+3H)N^2+(H^2+H)L)$, which is completed in the polynomial time. ∎

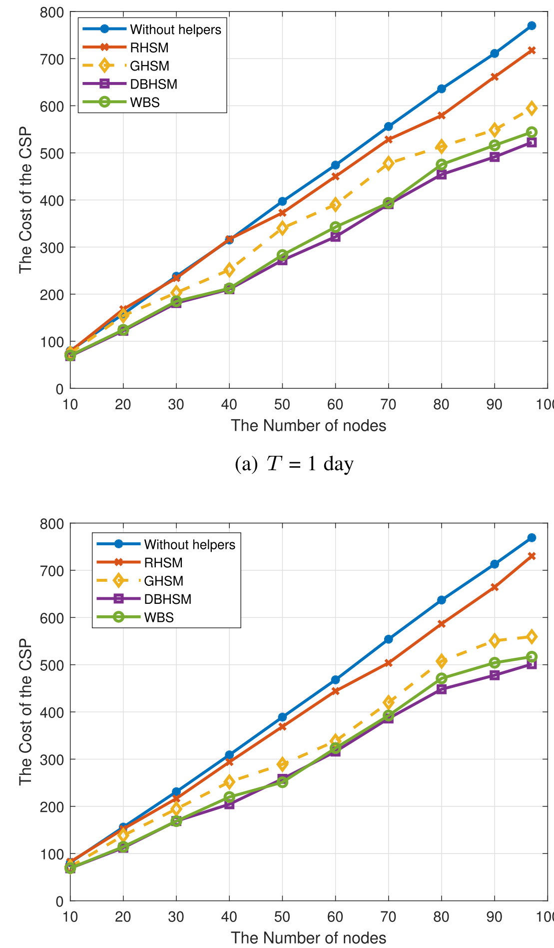
VII. Performance Evaluation

This section evaluates the performance of the proposed method, and exploits the impact of different parameters.

A. Simulation Settings

The experiments are conducted using two real mobility traces: the MIT Reality trace [46] and the Infocom 06 trace [47]. The MIT Reality trace contains a record of 299 days of contacts with 97 nodes carrying Nokia 6600 in the MIT university, and the Infocom 06 trace records the contact history of 76 nodes with iMote participating in the IEEE Infocom 2006 conference; the details of the two real mobility traces are presented in TABLE II. In the experiments, we consider one specific content which has been requested by different nodes at the same time, and the size of the content is 50 MB We assume that all nodes in the two real mobility traces are within the coverage of the BS, and the popularity of the content is $e = 0.8$ which equals the probability of each node requesting the content. The CSP's unit cost of traffic through cellular networks is 0.2 monetary units (e.g., US dollars, or RMB)/(MB). Each node's expected price is uniformly distributed over [0.01, 0.05]. The value of factor decay is set as $d = 0.5$ in both of the traces.

To evaluate the performance, DBHSM is compared with the Greedy Helper Selection Method which selects helpers greedily based on the Greedy algorithm, the Random Helper Selection Method which selects helpers randomly, the method without helpers and the Winning Bid Selection method [48], in which the helper selection process is divided into three phases. In the first phase, the CSP calculates the offloading potential of each nodes according to the historical records. In the second phase, an n-to-one directed weighted graph is constructed based on the offloading probability of each node pair, then the CSP selects suitable node with the maximum offloading potential as the helper, and the selected node is removed in the graph. Finally, updating the offloading potential of the remaining nodes and repeating the phases 1 and 2 until no suitable node can be selected. Here, GHSM is used to represent the Greedy Helper Selection Method, RHSM is used to represent the Random Helper Selection Method, Without helpers is used to represent the method without helpers, and WBS is used to represent the Winning Bid Selection method. For fairness, the number of selected helpers in RHSM is the same as that in the proposed DBHSM, and the payment rules of the above four methods are the same as that in DBHSM, which has been shown in algorithm 2. As shown in (4), the optimization objective of this paper is to minimize the CSP's cost, so the CSP's cost is used as the performance metric. In addition, this part also compares the offloading rate of different methods, and verifies the individual rationality and truthfulness of the proposed DBHSM. The offloading rate denotes the ratio of cellular traffic offloaded via opportunistic communications,



(a) T = 1 day

(b) T = 2 days

Fig. 3. Performance comparison in terms of the CSP's cost in the MIT Reality trace (d = 0.5, e=0.8).

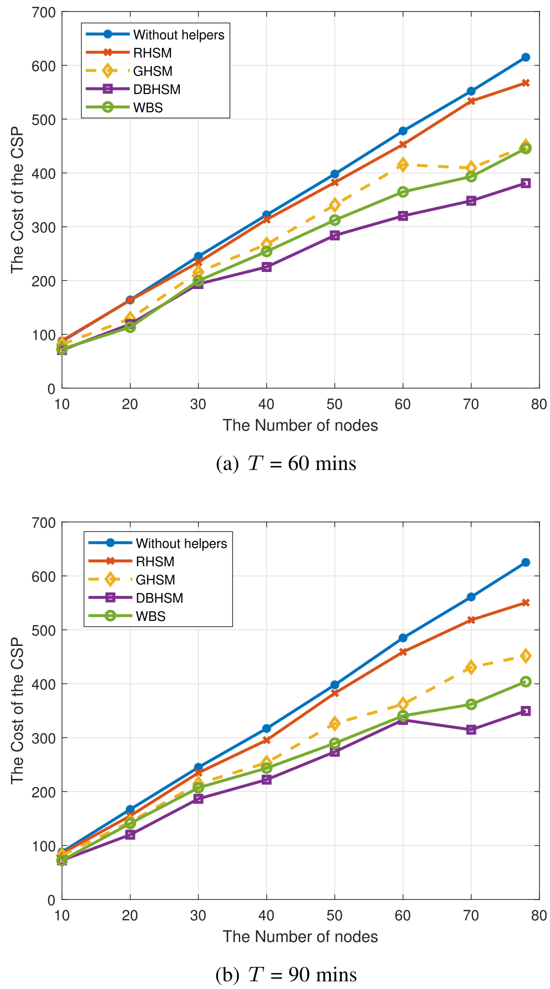


Fig. 4. Performance comparison in terms of the CSP's cost in the Infocom 06 trace (d = 0.5, e=0.8).

which can be calculated as $\mathcal{T}_2/\mathcal{T}_1$, where $\mathcal{T}_1$ and $\mathcal{T}_2$ are the total cellular traffic that should be transmitted by the CSP before selecting helpers, and the amount of traffic transmitted via opportunistic communications, respectively.

B. Performance Comparison

This part shows the performance comparison of DBHSM with GHSM, RHSM, WBS, and the method without helpers in terms of the CSP's cost under different scenarios.

Fig. 3 and Fig. 4 show the comparison of the CSP's cost in the MIT Reality and Infocom 06 traces, respectively. Due to the fact that the contact frequency in the MIT Reality trace is very low, the maximum tolerant delay of nodes in it is much longer than that in the Infocom 06 trace. We set the maximum tolerant delay as $T = 1(day)$ and $T = 2(days)$ in the MIT Reality trace, respectively. Moreover, we set the maximum tolerant delay as $T = 60(minutes)$ and $T = 90(minutes)$ in the Infocom 06 trace, respectively.

Fig. 3 shows the performance comparison in terms of CSP's cost in the MIT Reality trace, when T is 1 d and 2 days, respectively. It is shown that as the number of nodes increases, the CSP's cost increases continually. This is obvious because

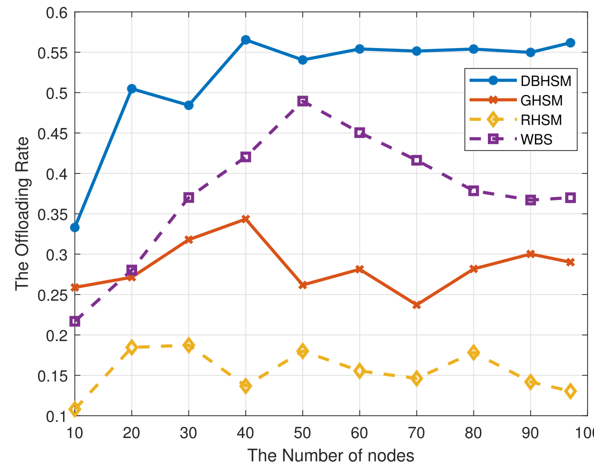


Fig. 5. Performance comparison in terms of the offloading rate in the MIT Reality trace.

more nodes will request the content, as the number of nodes increases. The proposed DBHSM outperforms other methods in the MIT Reality trace, especially when the number of nodes is larger. The main reason is that as the number of nodes increases, more requests may be served by different helpers, and the DBHSM can resolve the problem to get the approximate optimal helper set. In comparison, the performance of WBS is slightly better than GHSM and RHSM. The main reason is that GHSM selects helpers greedily, and ignores the helpers' overlapping offloading potentials, so the selected helper set is not optimal. Although WBS considers the possibility of the overlapping offloading potential, this is not enough because only eliminating the offloading probability with the helpers has little impact on the offloading potential. For the RHSM, since it selects helpers randomly, its performance is poor. As expected, the CSP's cost is the largest in the method without helpers, which indicates that the method without helpers performs worst.

Fig. 4 shows the performance comparison in terms of CSP's cost in the Infocom 06 trace when T is 60 minutes and 90 minutes, respectively. It can be found that DBHSM also outperforms other methods with the increase of the number of nodes in the Infocom 06 trace. Compared with the results in the MIT Reality trace, the WBS also outperforms GHSM and RHSM in the Infocom 06 trace especially when the tolerant delay is larger. Furthermore, the method without helpers still performs worst. Therefore, in the following, we do not compare it with other mothods.

Fig. 5 and Fig. 6 show the performance comparison in terms of the offloading rate in the MIT Reality trace and Infocom 06 trace with different number of nodes, respectively. If the offloading rate is higher, which means that more traffic can be offloaded via opportunistic communications, then the CSP's cost will be reduced. In Fig. 5, the tolerant delay is set as $T = 1$ day. Similar to the results in Fig. 3 and 4, it can be seen that the offloading rate of the proposed DBHSM is much higher than the other three baseline methods, especially when the number of nodes increases. This is because DBHSM also considers the possibility of the overlapping offloading potential,

TABLE II
PARAMETERS OF REAL MOBILITY TRACES

Trace	MIT Reality	Infocom 06
Device	Nokia 6600	iMote
Duration (days)	299	4
Network type	Bluetooth	Bluetooth
The number of nodes	97	76
Granularity (seconds)	300	120

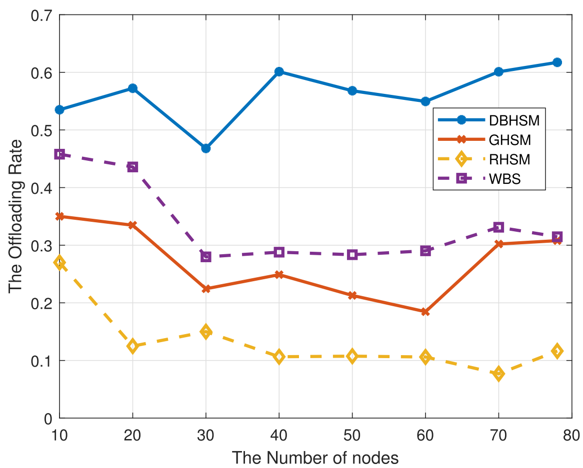


Fig. 6. Performance comparison in terms of the offloading rate in the Infocom 06 trace.

but unlike WBS, DBHSM adds a decay factor to update the offloading potential of each node, not just by eliminating the offloading probability with the helpers. As expected, the performance of RHSM is the worst as RHSM selects helpers randomly. In Fig. 6, the tolerant delay is set as $T = 60$ mins. It can be seen that the proposed DBHSM also performs best, and RHSM performs worst. Therefore, it can be proved that the proposed DBHSM performs best in terms of the offloading rate in both traces.

In summary, we show that DBHSM performs best in both traces under different scenarios, and WBS outperforms GHSM, RHSM and method without helpers.

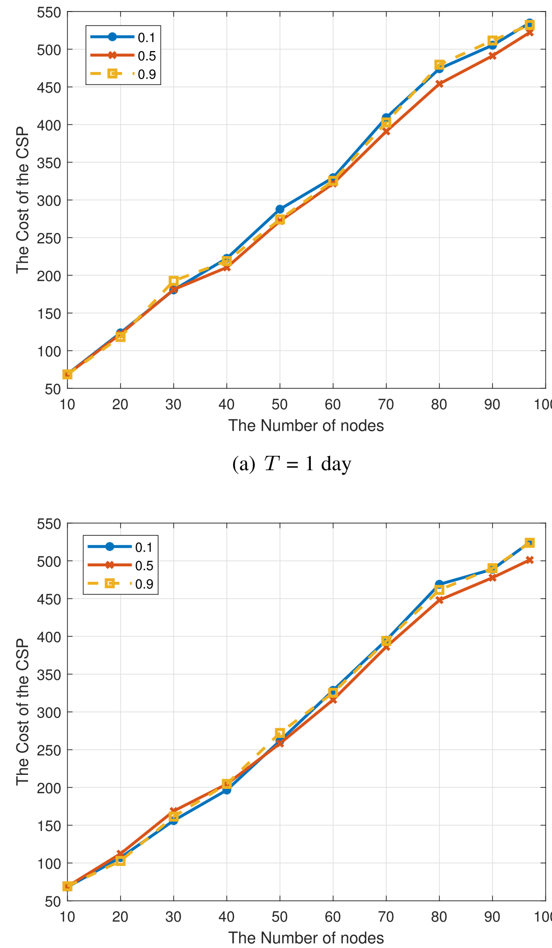
C. Impact of the Decay d

This part evaluates the impact of the decay d on the performance of DBHSM in terms of the CSP's cost.

Fig. 7 shows the impact of d on the performance of DBHSM in the MIT Reality trace when T is 1 d and 2 days, respectively. As shown in Fig. 7, DBHSM's performance is better when d is moderate in the MIT Reality trace. For example, DBHSM performs best when d is 0.5, and performs worst when d is 0.1.

Fig. 8 shows the impact of d on the performance of DBHSM in the Infocom 06 trace when T is 60 minutes and 90 minutes, respectively. As shown in Fig. 8, DBHSM's performance is also better when d is moderate in the Infocom 06 trace.

In summary, the decay value d has a significant impact on the performance of DBHSM, and it performs better when d is moderate in both traces. If d is too large, or too small, it may have a negative impact on the performance of DBHSM, especially when d is too small. According to the simulation results reported above, we set d as 0.5 in both traces.



(a) T = 1 day

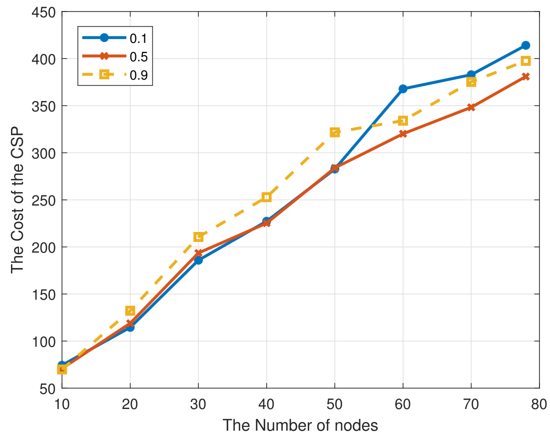
(b) T = 2 days

Fig. 7. Performance evaluation in the MIT Reality trace with different Decay d (e=0.8).

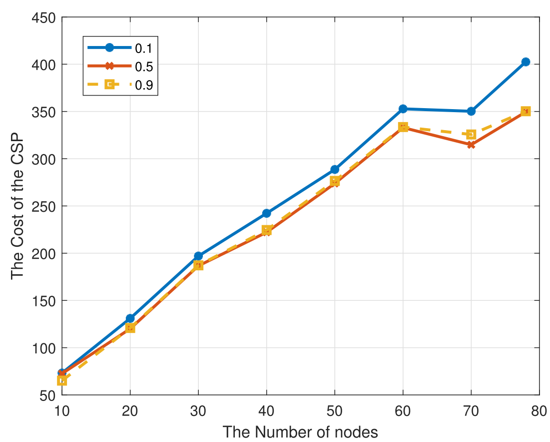
D. Evaluation of Truthfulness and Individual Rationality

This part verifies the truthfulness and individual rationality of our proposed payment determination algorithm in DBHSM. We verify the truthfulness by randomly selecting a certain helper and allowing it to submit a bid that does not equal its true value. In addition, we verify the Individual Rationality by comparing the payment of each helper and its corresponding true value. In the simulation, the originally submitted bid is set as the true value which is fixed and given.

Figs. 9 and 10 show the truthfulness and Individual Rationality of our proposed payment determination algorithm in the MIT Reality trace. In Fig. 9, we randomly select a certain node for analysis, the true value of which is 27.44. In the experiment, we update the expected unit traffic price b_i of the selected node in steps of 0.001. Then, it can be found that when its claimed bid is less than the true value, the selected



(a) T = 60 mins



(b) T = 90 mins

Fig. 8. Performance evaluation in the Infocom 06 trace with different Decay d (e=0.8).

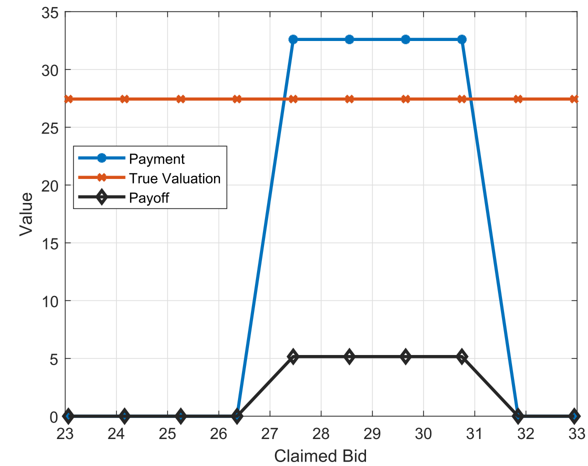


Fig. 9. Truthfulness.

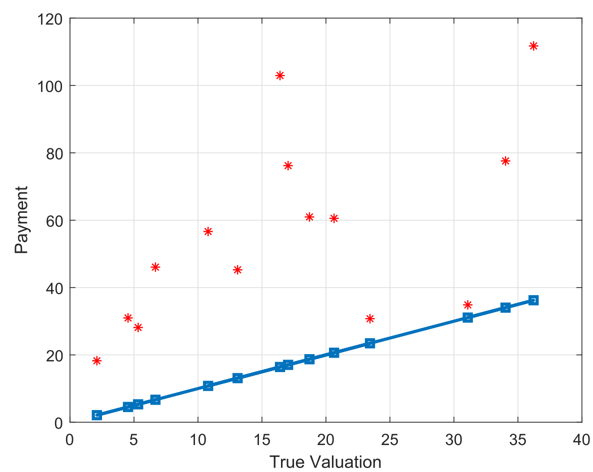


Fig. 10. Individual Rationality.

node will not be willing to serve as the helper, and if the claimed bid is too large, the CSP will not choose it as the helper as the CSP wants to reduce its cost. Only when the claimed bid is within an appropriate range, this node can be selected as the helper, and its payment is always 32.5989 with the increase of the claimed bid, thus its payoff is a constant that is equal to the payment minus its true value. Therefore, it can be found that the helpers cannot increase their utilities from untruthful bids in the proposed DBHSM.

In Fig. 10, we assume that each node submits a truthful bid, and 14 nodes are selected as helpers in the proposed DBHSM. The red dots indicate the payment for each helper and the dots on the solid line represent the corresponding true values. It can be found that the payment of each helper is higher than its true value, which means that each helper can get a positive reward with a truthful bid. Therefore, the proposed payment determination algorithm can guarantee the individual rationality of helpers in DBHSM, which is consistent with the analysis in Section VI.

In summary, the simulation results show that the helpers cannot increase their utilities from untruthful bids, and the payment of each helper is higher than its true value in the proposed DBHSM. Therefore, the proposed payment determination algorithm satisfies truthfulness and individual rationality properties in DBHSM, which can urge each node to claim a truthful bid to maximize the utility of itself and minimize the cost of the CSP.

VIII. Conclusion

In this paper, a Reverse Auction-based Incentive Mechanism, named RAIM, has been proposed to motivate nodes in OMNs to provide data offloading services. The incentive-driven data offloading process was formulated as an NLIP problem. To solve this problem, a heuristic algorithms named Decay-based Helper Selection Method (DBHSM) was proposed. Moreover, a standard VCG scheme-based payment rule was proposed to ensure the individual rationality and truthfulness properties of the DBHSM. Real mobility trace-driven simulation results demonstrated that DBHSM outperforms the other methods in terms of the CSP's cost and the offloading rate under different scenarios, and the proposed payment rule can ensure the individual rationality and truthfulness properties of the DBHSM.

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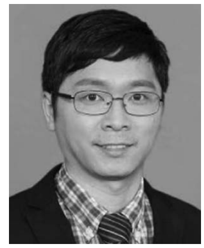

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