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Optimal Cooperative Wireless Communication for Mobile User Data Offloading

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ABSTRACT We study the mobile data offloading problem in cooperative cellular networks, in which the cellular base station can offload a fraction of data traffic to its cooperative Wi-Fi networks. Both user satisfaction and benefit are important for the cellular network. Under the case that the cellular network cannot provide sufficient transmission resources, part of data traffic can be offloaded to its cooperative Wi-Fi networks to guarantee the user satisfaction, even though the benefit loss of the cellular network will be incurred. Meanwhile, considering the users are price sensitive, the operators, including cellular and Wi-Fi, can issue an appreciate unit price to attract more users and more traffic requirements to increase their total benefit. In this paper, we intend to design an optimal pricing scheme to maximize the user satisfaction and minimize the benefit losses of the operators simultaneously. First, we formulate the mobile data offloading problem as a joint optimization of ''min–max'' problem. Then, we convert the problem into a bi-level optimization problem, in which the lower level is to maximize the user satisfaction and the upper level is to minimize the benefit losses of the operators. Since the lower-level problem is convex, a centralized scheme based on the dynamic coordinate search-based method is employed to find the optimal solution of the bi-level problem. In addition, a distributed method is proposed to obtain the near-optimal solution quickly, where one-third-party agent is used to adjust the data traffic allocation. Simulation results show that the proposed method achieves the near-optimal solutions with limited iterations.

INDEX TERMS Mobile data offloading, bi-level optimization, utility function, user satisfaction, cooperative transmission.

I. INTRODUCTION

According to Cisco statistics, global mobile data traffic has risen 18 times in the past five years, and mobile data surged to an average of 7.2 EB per month by the end of 2016, of which 4G traffic accounted for 69%. With the explosive growth of smart terminals, the development of cellular networks is far below that of the user demand for mobile data. As a result, the cellular network might not satisfy the mobile user demands [1]. Especially when a hot event occurs, massive mobile users are aggregated and burst traffic is generated shortly, which can lead to the network unavailable or low user satisfaction due to poor quality of services. Mobile data offloading is one of the most promising technologies for the cellular network to deal with such problems by offloading excessive data traffic to its cooperative partners [2], [3].

Different from the traditional transmission via a single BS or Wi-Fi hotspot, user data can be delivered concurrently through multiple networks in mobile data offloading. Since all the packets transmitted through different paths are aggregated at the terminal devices, the user experience will not be affected. One representative of mobile data offloading is the BT Fon community [3], co-founded by BT and Fon in 2007, wherein BT invites 3 million home users to join the community and shares their free or charged idle bandwidth resources.[1] Existing studies on mobile data offloading can generally be classified into two major categories, namely, infrastructure-assisted and infrastructure-free schemes [4]. The first type of scheme utilizes some existing facilities with capabilities of communication, calculation and storage for

[1]Fon is the world's first global Wi-Fi network and aims to give all its members access to wireless broadband wherever they are in the world. Since March 2009, all new BT Broadband customers are automatically members of the Fon community and agree to securely share a portion of their Wi-Fi bandwidth through a separate channel on their hub.

data transmission, e.g., Wi-Fi hotspot [5] and Internet of Vehicles [6]. The second one refers to infrastructure-free offloading, wherein the cooperative transmission is implemented via other local networks composed of various mobile terminals, e.g., delay tolerance networks (DTN) [7] and device to device (D2D) networks [8].

From the point of view of incentive cooperation, designing effective strategies to motivate the partners participating in data offloading has attracted lots of attentions. Generally, such approaches leverage economic principles [9], e.g., benefit sharing [10] or unilateral benefit maximization [11], on the incentive strategies for sharing the idle bandwidth resources. However, most of them only consider one type of cooperative partner, which limits the transmission performance. In this work, we study the mobile data offloading in consideration of the incentive cooperation between cellular and various Wi-Fi networks, in which different Wi-Fi operators can offer different price plans based on their own needs. The system objective is to maximize the user satisfaction and minimize the operator benefit loss for giving up a fraction of user data traffic to its cooperative partners. The major contributions of this work are summarized as follows.

- An S-shaped utility function are introduced into the system design, which could be more suitable for the benefit expectation among multiple partners' cooperation. To our best knowledge, it is the first time that the S-shaped utility is used to measure the user satisfaction in mobile data offloading.
- The mobile data offloading problem is formulated as an "Min-Max" joint optimization problem, where the system objective is to minimize the operator benefit loss and maximize the user satisfaction. We design a centralized scheme based on the dynamic coordinate search-based method (DYCORS) to solve this bi-level optimization problem.
- A fast convergent distributed approach is presented to solve the joint optimization problem, in which a third-party agent is introduced to calculate the optimal data traffic allocation.

The rest of this paper is organized as follows. Section II introduces the network model and the two-stage offloading scheme. Section III formulates the offloading problem as a joint optimization problem w.r.t. the minimization of the benefit losses of operators and the maximization of user satisfaction. In Section IV, we convert the joint optimization problem into a bi-level optimization problem, and solve it by DYCORS and the distributed methods, respectively. Section V evaluates the proposed methods with extensive simulations, followed by the concluding remarks in Section VI.

II. SYSTEM MODEL

A. NETWORK MODEL

Considering a cooperative LTE network scenario (as shown in Fig. 1), there are I user equipments (UEs) and K Wi-Fi access points in the same cell. Each UE is equipped with two

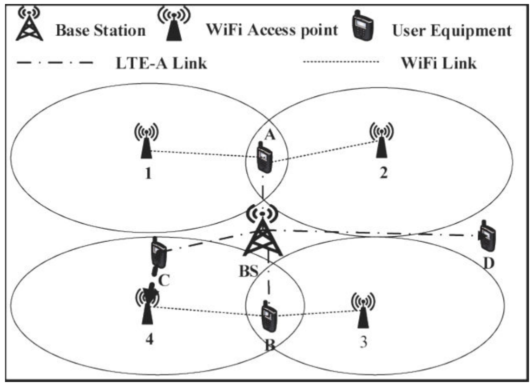

FIGURE 1. A network model illustration. If the micro BS in one public area, e.g., in a train station, is overloaded, different types of users (user A, B, and C), can utilize their own mobility to obtain data services from multiple operators after they announce the unit price of data traffic and location information.

interfaces, namely, one LTE interface and one Wi-Fi interface, such that the UE can receive data from the cellular and Wi-Fi networks simultaneously. The cellular BS can offload a fraction of user data traffic to the Wi-Fi networks such that the users can obtain a higher transmission bandwidth. Denote f_{ij} $(i \leq I, j \leq J)$ the amount of data traffic required by user i, where j and J denote the traffic type and its total amount, respectively. Generally, different mobile users may have different requirements for traffic type and amount. Suppose user i's data traffic amount transmitted by cellular network is g_{ij}, and transmitted by Wi-Fi k $(k \leq K)$ is f_{ijk}, respectively. Thus, f_{ij} should satisfy

$$f_{ij} \leq g_{ij} + \sum_{k=1}^{K} f_{ijk}. \tag{1}$$

Here, the cooperative Wi-Fi hotspots serve as the third-party operators to offload partial user data traffic in case of the corresponding BS overloaded. The main notations used in this paper are summarized in Table 1.

B. A TWO-STAGE OFFLOADING SCHEME

Considering that the users are price sensitivity, the different unit prices at different network operators may affect the data transmission scheme. Generally, each network operator can determine its unit price of data traffic independently [12]. In order to manage the data transmission, the cellular operator can motivate the Wi-Fi operators with better link conditions to cooperatively transmit for the covered users via the pricing strategy. Such that the overall user satisfactory can be maximized and the benefit losses of all operators, including the cellular and Wi-Fi networks, can be minimized simultaneously. In a centralized offloading scheme, the Wi-Fi operators will report their hotspot locations and the data traffic unit prices to the BS, which can be broadcasted to the covered users via the cellular downlink [13].

Basically, the offloading scheme can be depicted by a two-stage decision process (as shown in Fig. 2).

TABLE 1. Mainly used notations in this paper.

Notation	Description
f_{ij}	The data traffic amount of type j required by user i
g_{ij}	The data traffic amount of type j provided by the BS for user i
f_{ijk}	The data traffic amount of type j provided by Wi-Fi k for user i
c_{bs}	The standard unit price of the BS
c_k	The standard unit price of Wi-Fi k
v_i	The unit price of BS provided for user i
c_{ik}	The unit price of Wi-Fi k provided for user i
U	The utility function
a_i	The preference factor of user i to the BS
a_{ik}	The preference factor of user i to Wi-Fi k
d_{ij}	The access threshold to the BS
d_{ijk}	The access threshold to Wi-Fi k
b_i	User i's sensitivity to the unit price of the BS
b_{ik}	User i's sensitivity to the unit price of Wi-Fi k
P	the price sensitive function
F	The set of the mobile data offloading scheme
C	The set of the unit price scheme for Wi-Fi/BS
S	The summation of all users satisfaction
α	The weight factor of the cellular network
β	The weight factor of the Wi-Fi networks

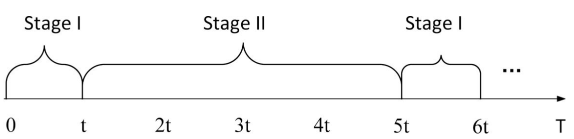

FIGURE 2. The two-stage strategy is an iterative process. In Stage I, the operators will announce their unit prices. According to the unit prices, the users will make a decision on the optimal data traffic allocation in Stage II, i.e., the optimal data traffic amount from different networks can be calculated out. Correspondingly, the data usage from different networks will influence the unit price in next round.

Stage I: The cellular network and each Wi-Fi hotspot set or adjust the unit prices of data traffic to ensure their benefits and then broadcast the prices to all users in their coverage area.

Stage II: According to the unit prices announced in **Stage I**, each user allocates their data traffic requirements to different operators, such that the user satisfaction can be maximized.

The above two stages are conducted one by one iteratively until reaching the best tradeoff between the operators and users.

III. PROBLEM FORMULATION

A. MAXIMIZATION PROBLEM OF THE USER SATISFACTION

In this paper, an S-shaped utility function is adopted to evaluate the user satisfaction in the mobile offloading scheme. The utility function means that the user utility curve changes like a capital letter of 'S' as the user gets more required resources. It is more suitable for the user satisfaction thanks to the good marginal effect [14], [15], as shown in Fig. 3, which denotes the user satisfaction versus resource amount. Before the resource amount reaching to the user's expectation, the utility function is concave with the resource amount increasing. Thereafter, it becomes convex.

According to [14], the S-shaped utility function of cellular network, namely $U(g_{ij})$, is defined by

$$U(g_{ij}) = \frac{1}{1 + \mathrm{e}^{-a_i(g_{ij}-d_{ij})}}, \tag{2}$$

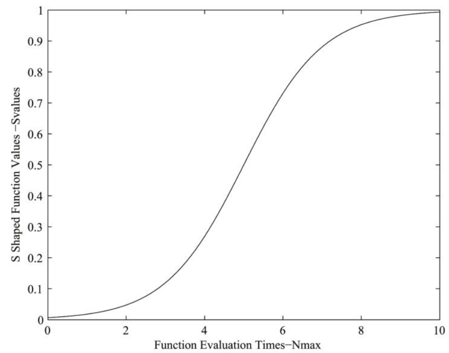

FIGURE 3. An S-shaped utility function to depict the user satisfaction.

and the utility function of Wi-Fi network k, namely $U(f_{ijk})$, is defined as

$$U(f_{ijk}) = \frac{1}{1 + \mathrm{e}^{-a_{ik}(f_{ijk}-d_{ijk})}}, \tag{3}$$

where a_i denotes user i's preference factor to the BS, and a_{ik} denotes user i's preference factor to Wi-Fi k. Parameters a_i and a_{ik} determine the convergence speeds of the S-shaped utility functions in reality. Parameters d_{ij} and d_{ijk} denote the access thresholds, i.e., user i expects a certain amount of data traffic of type j from the BS or Wi-Fi k, such that it can get a basic access service from the specific network.

Notice that the two kinds of access thresholds are set by the corresponding network operators independently, and also correspond to the expected values of the utility functions. When the data traffic from one network below the threshold, the user will require to increase the data traffic provision to the threshold from the network correspondingly, such that the basic access service can be guaranteed. Therefore, the utility function is concave. Otherwise, the utility function is convex if the received data traffic is larger than the access threshold (as shown in Fig. 3). It can be found that the utility function follows the cumulative effect of the general utility function and has the first derivative (greater than 0). Therefore, the utility functions $U(g_{ij})$ and $U(f_{ijk})$ are quasi-convex.

According to the principle of economic supply [16], the commodity price will rise as the goods supply increases. The slope of the supply curve is positive and can be approximated by a straight line. Similarly, to ensure a higher cumulative effect of the cellular and Wi-Fi networks, the access thresholds, i.e., d_{ij} or d_{ijk}, will be improved as the increasing amount of data traffic provision (g_{ij} or f_{ijk}). As the principle of economic supply shows, the larger g_{ij} or f_{ijk} is, the larger d_{ij} or d_{ijk} is. The access thresholds can be defined by

$$d_{ij} = q_i \cdot g_{ij}, \tag{4}$$

$$d_{ijk} = q_{ik} \cdot f_{ijk}, \tag{5}$$

where q_i and q_{ik} are the access slope of the BS and Wi-Fi k, respectively, which represent the percentage of the access thresholds to the amount of data traffic required by user i. To simplify our formulation, substituting (4) and (5) into (2) and (3) respectively, we can obtain that

$$U(g_{ij}) = \frac{1}{1+\mathrm{e}^{-a_i(g_{ij}-q_i g_{ij})}}, \tag{6}$$

$$U(f_{ijk}) = \frac{1}{1+\mathrm{e}^{-a_{ik}(f_{ijk}-q_{ik} f_{ijk})}}. \tag{7}$$

Let $h_i = a_i(1-q_i)$ and $h_{ik} = a_{ik}(1-q_{ik})$, and we can obtain that

$$U(g_{ij}) = \frac{1}{1+\mathrm{e}^{-h_i g_{ij}}}, \tag{8}$$

$$U(f_{ijk}) = \frac{1}{1+\mathrm{e}^{-h_{ik} f_{ijk}}}, \tag{9}$$

where h_i and h_{ik} denote the user i's sensitivity of the data traffic service provided by the BS and Wi-Fi k, respectively. A larger value of h_i or h_{ik} means a faster convergence speed of its utility function. According to the first derivative of the utility functions, both $U(g_{ij})$ and $U(f_{ijk})$ are monotonically increasing. In the case of $g_{ij} \geq 0$ and $f_{ijk} \geq 0$, the second derivatives of $U(g_{ij})$ and $U(f_{ijk})$ are negative, which means that $U(g_{ij})$ and $U(f_{ijk})$ are convex in the defined domain.

Each user need to pay fee to the operators according to their data traffic usage in **Stage II** and the unit price announced in **Stage I**. To represent the price sensitivity to the data traffic provided by the cellular and Wi-Fi networks, the price sensitive functions are defined by

$$P(g_{ij}) = b_i \cdot v_i \cdot g_{ij}, \tag{10}$$

$$P(f_{ijk}) = b_{ik} \cdot c_{ik} \cdot f_{ijk}, \tag{11}$$

where b_i and b_{ik} represent the user i's sensitivity to the unit price of the cellular network and Wi-Fi k, which are constants. In this work, the utility functions $U(g_{ij})$ and $U(f_{ijk})$ describe the user's satisfaction of the services provided by the cellular and Wi-Fi networks, and the price sensitive functions, i.e., $P(g_{ij})$ and $P(f_{ijk})$, are used to describe the satisfaction with expenses. Combining the user expense and utility, the user satisfaction function, i.e., S, can be given by

$$S = \sum_{i=1}^{I}\sum_{j=1}^{J}\left\{\alpha(U(g_{ij}) - P(g_{ij})) + \sum_{k=1}^{K}\beta(U(f_{ijk}) - P(f_{ijk}))\right\}, \tag{12}$$

where α and β are the weights of the cellular and Wi-Fi networks, respectively.

The strategy to allocate data traffic among different networks in **Stage II** is to maximize user payoff, which can be formulated as the maximization of the user satisfaction.

Problem 1 (Maximizing the User Satisfaction):

$$\begin{aligned} &\max\ S \\ &s.t.\ (1), g_{ij} \geq 0, \quad f_{ijk} \geq 0 \\ &var:\ \{\sum_{i=1}^{I}\sum_{j=1}^{J} g_{ij}, \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} f_{ijk}\} \in F \end{aligned}$$

B. MINIMIZATION PROBLEM OF NETWORK BENEFIT LOSS

The data traffic allocation in **Stage II** has a significant effect on the revenues of the cellular and Wi-Fi networks. Thus, the corresponding networks can adjust their unit prices to attract more users to use their transmission services. Price discount is one of the most commonly used methods, but it will possibly result in benefit losses of the networks.

1) THE CELLULAR BENEFIT LOSS

To incentive more users to use the cellular transmission service, the cellular operator can offer a discounted price on the basis of the standard unit price, which can lead to the benefit loss of the cellular operator. Denote $c_{\mathtt{bs}}$ and v_i the standard unit price and the discounted unit price to user i in the cellular network, respectively. The discounted unit price v_i is no larger than the standard unit price $c_{\mathtt{bs}}$. Therefore, the cellular benefit loss can be calculated by

$$H_1 = \sum_{i=1}^{I}\sum_{j=1}^{J}(c_{\mathtt{bs}} - v_i)g_{ij}. \tag{13}$$

2) THE WI-FI BENEFIT LOSS

When the cellular network is overloaded, it will seek the potential offloading partners from the cooperative Wi-Fi networks. Similar to the benefit loss of the cellular network, the Wi-Fi benefit loss can be caused by the price discount. Correspondingly, the Wi-Fi benefit loss can be given by

$$H_2 = \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K}(c_k - c_{ik})f_{ijk}, \tag{14}$$

where c_k and c_{ik} are the standard unit price and discounted unit price of Wi-Fi k, respectively. Consequently, the total benefit loss can be represented by

$$H(c) = H_1 + H_2. \tag{15}$$

The minimization of benefit loss problem can be formulated as **Problem 2**.

Problem 2 (Minimizing the Benefit Loss):

$$\begin{aligned} &\min\ H(c) \\ &s.t.\ 0 < v_i < c_{\mathtt{bs}}, \quad 0 < c_{ik} < c_k \\ &var:\ \left(\sum_{i=1}^{I} v_i, \sum_{i=1}^{I}\sum_{j=1}^{J} c_{ik}\right) \in C \end{aligned} \tag{16}$$

Notice that, the mobile data offloading problem is formulated as a joint optimization of "min-max" problem, where the upper level is to minimize the benefit losses of the operators and the lower one is to maximize the user satisfaction.

IV. THE SOLUTION OF BI-LEVEL OPTIMIZATION PROBLEM

In this section, we first transform **Problem 1** and **Problem 2** into a bi-level optimization problem. Since the lower-level problem is convex, the optimal solution of the bi-level problem can be found by the dynamic coordinate search-based method, e.g., DYCORS.

A. PROBLEM TRANSFORMATION

The unit prices, announced by the cellular and Wi-Fi networks, can be treated as constants. It can be found that **Problem 1** is convex and it can be solved according to the KKT conditions, which are given by (17)-(20) (see next page).

$$\sum_{j=1}^{J}\sum_{i=1}^{I}\left\{\alpha b_i v_i - \frac{\alpha h_i e^{-h_i g_{ij}}}{(1+e^{-h_i g_{ij}})^2} + \lambda\right\} \geq 0, \tag{17}$$

$$\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I}\left\{\beta b_{ik} c_{ik} - \frac{\beta h_{ik} e^{-h_{ik} f_{ijk}}}{(1+e^{-h_{ik} f_{ijk}})^2} + \lambda\right\} \geq 0, \tag{18}$$

$$\sum_{j=1}^{J}\sum_{i=1}^{I}\left\{\alpha b_i v_i - \frac{\alpha h_i e^{-h_i g_{ij}}}{(1+e^{-h_i g_{ij}})^2} + \lambda\right\} = 0, \tag{19}$$

$$\sum_{k=1}^{K}\sum_{j=1}^{J}\sum_{i=1}^{I}\left\{\beta b_{ik} c_{ik} - \frac{\beta h_{ik} e^{-h_{ik} f_{ijk}}}{(1+e^{-h_{ik} f_{ijk}})^2} + \lambda\right\} = 0. \tag{20}$$

Since **Stage I** and **Stage II** are iterative w.r.t. **Problem 1** and **Problem 2**, it is necessary to ensure that the total benefit losses of the cellular and Wi-Fi networks are minimized after the data traffic allocation. **Problem 2** can be seen as a bi-level optimization problem based on **Problem 1**. Mathematically, it can be described as **Problem 3**:

Problem 3 (The Bi-Level Optimization Problem):

$$\begin{aligned}
&\min \sum_{i=1}^{I}\sum_{j=1}^{J}\left((c_{\text{bs}} - v_i)g_{ij} + \sum_{k=1}^{K}(c_k - c_{ik})f_{ijk}\right)\\
&s.t.\ (16)-(20)\\
&var:\ \left\{\sum_{i=1}^{I}\sum_{j=1}^{J} g_{ij}, \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} f_{ijk}\right\} \in F\\
&\qquad\ \left\{\sum_{i=1}^{I} v_i, \sum_{i=1}^{I}\sum_{j=1}^{J} c_{ik}\right\} \in C
\end{aligned} \tag{21}$$

All the KKT conditions (17)-(20) are functions of g_{ij}, f_{ijk} and λ, which depend on v_i and c_{ik}. Therefore, **Problem 3** can be converted into **Problem 4**.

Problem 4 (Minimizing the Benefit Loss Given the Data Traffic Usage):

$$\begin{aligned}
&\min\ H(c)\\
&s.t.\ (16)\\
&var:\ \left\{\sum_{i=1}^{I} v_i, \sum_{i=1}^{I}\sum_{j=1}^{J} c_{ik}\right\} \in C
\end{aligned}$$

The solution of **Problem 4** is based on the condition that the data traffic usage is known. As shown in **Stage II**, the data traffic usage is based on the initial unit prices announced by the operators in **Stage I**. Thus, solving **Problem 4** is equivalent to solve **Problem 5**.

Problem 5 (Minimizing the Benefit Loss When the Unit Price Is Known at Stage I):

$$\begin{aligned}
&\min\ H(c)\\
&s.t.\ (1), (17)-(20)\\
&var:\ \left\{\sum_{i=1}^{I}\sum_{j=1}^{J} g_{ij}, \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{k=1}^{K} f_{ijk}\right\} \in F, \lambda
\end{aligned}$$

Problem 5 is the simplified problem of **Problem 3** when the unit price at **Stage I** is known. Because constraint (1) is linear, and constraints (17)-(20) are the KKT conditions of the convex-optimization **Problem 1**, **Problem 5** is also convex. Because the utility functions $U(g_{ij})$ and $U(f_{ijk})$ are quasi-convex, the price sensitive functions $P(g_{ij})$ and $P(f_{ijk})$ are linear, and the second derivative of the satisfaction function S is negative, the maximum value of S exists. Similarly, the solution of **Problem 5** also exists.

Problem 5 can be solved after g_{ij}, f_{ijk} and λ being calculated by the KKT conditions (17)-(20). Accordingly, g_{ij} and f_{ijk} can be expressed by the combination of v_i, c_{ik} and λ based on (19) and (20), which are given by

$$g_{ij} = \max\left\{g_{ij}(v_i, \lambda), 0\right\}, \tag{22}$$

$$f_{ijk} = \max\left\{f_{ijk}(c_{ik}, \lambda), 0\right\}. \tag{23}$$

Moreover, the upper and lower bounds of λ can be calculated according to (17) and (18), which are given by

$$\frac{\alpha h_i e^{-h_i g_{ij}}}{(1+e^{-h_i g_{ij}})^2} - \alpha b_i v_i \leq \lambda \leq 1. \tag{24}$$

According to the dichotomy, the values of g_{ij} and f_{ijk} can be determined by substituting λ into (1). According to (19) and (20), the upper and lower bounds of λ can be given by

$$0 \leq \frac{\lambda + \alpha b_i v_i}{\alpha h_i} \leq 1 \tag{25}$$

B. THE DYCORS-BASED SOLUTION

DYCORS can be used to solve the optimization problem with high dimensional bounds [17], which establishes an agent model of the objective function in each iteration, and generate an experimental solution by dynamic coordinate perturbation method. The optimal solution can be obtained by perturbing a small fraction of the local optimal solution at present. When the coordinate probability of the local optimal solution is reduced to the given threshold, it is considered that the optimal solution is obtained.

Ma *et al.* [18] use the DYCORS algorithm to solve offloading problem. Different from the work [18], the proposed optimization problem introduces the S-shaped utility function into the system design, and further convert it into a quasi-convex optimization problem.

As shown in Algorithm 1, **Problem 4** can be solved by the DYCORS, and **Problem 5** is also solved with the solution of **Problem 4** simultaneously.

Algorithm 1 CDP: Centralized DYCORS for **Problem 4**

Input: $c_{\mathtt{bs}}, c_k, h_i, h_{ik}, b_i, b_{ik}, \alpha, \beta$
Output: c^*
1. Initialize $n_{ini}, N_{\max}$;
2. $Ini = \left\{\sum_{i=1}^{I} v_i^{n_{ini}}, \sum_{i=1}^{I}\sum_{k=1}^{K} c_{ik}^{n_{ini}}\right\}$;
3. Evaluate $H(c)$ at the initial points Ini;
4. c^* is best point found so far;
5. Set $n = n_{ini}$, $C_n = Ini$;
6. **while** $n < N_{\max}$ **do**
   1) Select a suitable response surface model $s_n(c)$ according to the data points in $B_n = \{(c, H(c)) : c \in C_n\}$;
   2) Determine the probability $\phi(n)$;
   3) Generate the trial points $\Omega(n) = \{y_{n1}^1, \cdots, y_{nm}^I\}$ by the following steps;
      (1) Select the appropriate coordinates to perturb;
      (2) Generate the trial points randomly;
      (3) Substitute them into (16);
   4) Select the next iterate c_{n+1} from $\Omega(n)$ that minimizes $s_n(c)$;
   5) Calculate $H(c_{n+1})$ by solving convex **Problem 5**;
   6) **if** $H(c_{n+1}) < H(c^*)$ **then**
      $c^* = c_{n+1}$;
   end
   7) $C_{n+1} = C_n \cup \{c_{n+1}\}$;
   8) $n = n + 1$;
end

C. THE DISTRIBUTED APPROACH

The proposed optimization problem can be considered as a dual optimization problem, which can be addressed by the dual auction. But it is difficult to deploy and implement [19]–[23]. In the distributed method, assume that the unit prices are set by the operators including BS and Wi-Fi independently and no collusion exists. Each user cannot know the base unit prices of the operators. Therefore, all the users needs to submit the acceptable unit prices and obtain the optimal data traffic allocation via a third-party agent, i.e., all users can interact with operators through the agent by submitting different unit prices.

Basically, the distributed solution unfolds three phases:

Phase I (Bids and Requirements of All Users): All users submit their target unit prices and data traffic requirements to the agent, and predefine a minimum satisfaction.

Phase II (Bids of All Operators): The operators, including BS and Wi-Fi, submit their own data traffic unit prices to the agent.

Phase III (Data Traffic Allocation): According to the submissions of the users and operators, the optimal allocation strategy could be obtained by the water filling approach [24], which are returned to the users and operators.

Notice that the users and operators are interactive with each other at **Phase I** and **Phase I** according to the allocation policy obtained at **Phase III**.

To facilitate the distributed method design, denote subscript $k = 0$ the cellular network, and $k = 1, 2, \cdots, K$ the Wi-Fi networks in the following sections. Denote $Q_i(f_{ijk})$ the total data traffic cost of the user i, which can be represented by

$$Q_i(f_{ijk}) = \sum_{k=0}^{K} D_k(f_{ijk}) + \sum_{k=0}^{K} f_{ijk} * c_{ik}. \tag{26}$$

where c_{ik} is the unit price of the operator k, and $D_k(f_{ijk})$ is the data traffic cost function w.r.t. f_{ijk}. The marginal cost of f_{ijk} can be given by

$$\frac{dQ_i(f_{ijk})}{df_{ijk}} = D'_k(f_{ijk}) + c_{ik}. \tag{27}$$

where $D_k(f_{ijk})$ is strictly convex, i.e., $D'_j(f_{ijk})$ will be increased with f_{ijk} increasing. Notice that each operator only bid the unit price whatever the traffic type is.

Accordingly, the agent will select the operator with the lowest marginal cost as the candidate to undertake the data traffic of some specific users. The agent will gradually increase the data traffic amount for one specific user until the specific operator cannot offer the lowest marginal cost. Thereafter, the agent will continue to select the operator with the lowest marginal cost as the candidate and repeat the aforementioned process. The agent can always assign the operator with the lowest marginal cost to the user, and thus the optimal allocation strategy can be obtained.

All users will be sorted by descending order according to their bids, and the operators can repeatedly select the users from the front one to the next until all users' requirements are satisfied. Each user can adjust his own target price according to whether the data traffic allocation meets his needs. If the data traffic allocation cannot meet the users' needs in one round, the users will lower their target prices in next round. Otherwise, the users increase their prices. Correspondingly, the agent can initialize the water filling method based on the bids. Notice that the users not only consider the price factor of the operators, but also the cost of acquiring the data traffic, i.e., the users are willing to pay a higher price given a lower data traffic cost.

Notice that the data traffic cost function $Q_i(f_{ijk})$ is strictly convex and second differentiable. Therefore, the marginal cost function, i.e., $Q'_i(f_{ijk})$, is continuous, and the agent can uniquely assign the optimal data traffic allocation to all users by **Algorithm 2**.

V. SIMULATION RESULTS

A. EXPERIMENTAL SETTINGS AND SIMULATION RESULTS OF THE CENTRALIZED METHOD

There are four Wi-Fi hotspots and one cellular BS in the experimental scenario, i.e., $K = 4$. Under the ideal conditions, the transmission rate of 4G cellular downlink can reach to 150 Mbps, and that of Wi-Fi can reach to 54 Mbps [25]. To simplify the experiments, assume that there are three types of user data traffics, which are 5M, 10M and 15M, respectively. Meanwhile, there are three different types of data

Algorithm 2 BATA: the Distributed Algorithm Based on the Third-Party Agent

Input: I, J, K, S', $N_{\max}$, a, b
/*S', the predefined user satisfaction, $N_{\max}$ is the maximum evaluation times of the algorithm, $a < 1$, $b > 1$*/
Output: c^*
/*c^*, the unit price set, include the unit prices of BS and Wi-Fi operators*/
while $n < N_{\max}$ **do**
  1) The user submits target price c_{pre} and current requirement f_{ij} to the agent;
  2) The operator submits the unit price c_{ik} to the agent;
  3) The agent uses **OWI Algorithm 3** to get the optimal data traffic allocation, and the agent submit the allocation to the user and operator, respectively;
  4) The user calculates the satisfaction S_{cur} based on the allocation and adjusts the price;
  5) **if** $S_{cur} > S'$ **then**
    $c_{pre} = c_{pre} * a$;
  end
  6) **if** $S_{cur} < S'$ **then**
    $c_{pre} = c_{pre} * b$;
  end
  7) The operator adjusts its submission price according to the allocation strategy of the agent;
  8) **if** $f_{ijk_n} <= f_{ijk_{n-1}}$ **then**
    $c_{ik} = c_{ik} * a$;
  end
  9) **if** $f_{ijk_n} > f_{ijk_{n-1}}$ **then**
    $c_{ik} = c_{ik} * b$;
  end
  10) $n = n + 1$;
end

Algorithm 3 OWI: Data Traffic Allocation by Water Filling Approach

Input: f_{ij}, c_{pre}, c_{ik}, CP_k
/*CP_k, the maximum capacity of cellular or Wi-Fi operator that can provide*/
Output: f^*
/*f^*, the optimal data traffic allocation strategy*/
while $\sum_{k=0}^{K} f_{ijk} < f_{ij}$ **do**
  1) Compare c_{ik} with c_{pre};
  2) **if** $c_{pre} < c_{ik}$ **then**
    return;
  end
  3) **if** $c_{pre} >= c_{ik}$ **then**
    According to (27) to calculate each operator marginal cost, and choose the minimum value to increase the operators data traffic;
    if $f_{ijk} >= CP_k$ **then**
      Choose another operator to provide the data traffic;
    end
  end
end

traffic sensitivity parameters for h_i and h_{ik}, which are LOW, MID and HIGH, as shown in Table 2. Similarly, there are three kinds of unit price sensitivity parameters for b_i and b_{ik}, which are LOW, MID and HIGH, as shown in Table 3. The maximum evaluation times of $N_{\max}$ is 300, the coefficients α and β are set to 1.

To generate initial discounted unit price for v_i and c_{ik}, the values of their lower and upper bounds on unit price are set in advance, as shown in Table 4. Similarly, the values of standard unit price for c_{bs} and c_k are shown in Table 5.

We analyze the results of the bi-level optimization problem when the mobile users are the same type and their data traffic requirements f_{ij} are consistent with the three specific types. Furthermore, the data traffic sensitivity parameters h_i and h_{ik} are set to type of LOW. Similarly, the unit price sensitivity parameters b_i and b_{ik} are also set to LOW. Fig. 4 shows the benefit losses of the operators versus the times of iterations. With the iterations of evaluation increasing, the benefit losses of all operators tend to converge. Moreover, when the data

TABLE 2. Three types of data traffic sensitivity parameters.

	h_i	h_{i1}	h_{i2}	h_{i3}	h_{i4}
LOW	0.35	0.22	0.17	0.43	0.55
MID	0.7	0.44	0.34	0.86	1.1
HIGH	1.05	0.66	0.51	1.29	1.65

TABLE 3. Three types of unit price sensitivity parameters.

	b_i	b_{i1}	b_{i2}	b_{i3}	b_{i4}
LOW	0.62	0.81	0.54	0.71	0.92
MID	1.24	1.62	1.08	1.42	1.84
HIGH	1.86	2.43	1.62	2.43	2.76

TABLE 4. The lower and upper bounds on unit price.

	v_i	c_{i1}	c_{i2}	c_{i3}	c_{i4}
Lower Bound	0.5	0.3	0.6	0.4	0.2
Upper Bound	1.5	1.3	1.2	2	1.6

TABLE 5. The standard unit prices.

	c_{bs}	c_1	c_2	c_3	c_4
Standard unit price	2	1.5	1.6	2.4	1.8

traffic requirement f_{ij} increases, the value of $H(c)$ almost identically increases. In other words, the benefit losses of the operators are proportional to the data traffic undertaken by them.

The experimental results of the user satisfaction are shown in Fig. 5. It can be found that the satisfaction of all users converges rapidly with the evaluation times increasing. With the data traffic requirement f_{ij} increases, the user satisfaction decreases in proportion correspondingly. Different form

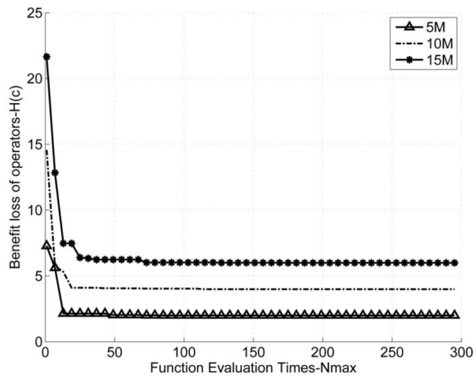

FIGURE 4. The results of benefit losses of the operators when the data traffic requirements of users are different.

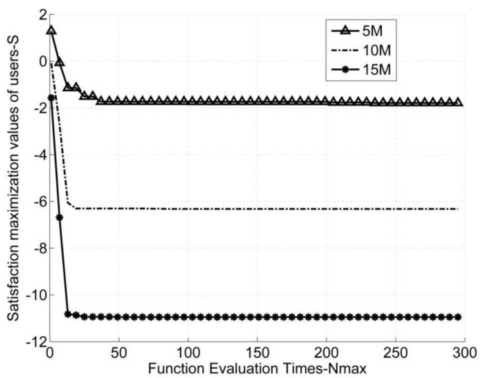

FIGURE 5. The results of the user satisfaction when the user data traffic requirements are different.

Fig. 4, the more the user data traffic requirement is, the less the user satisfaction is. It is a fact that the users' needs would not be satisfied if their data traffic requirements exceed the total provision by the networks.

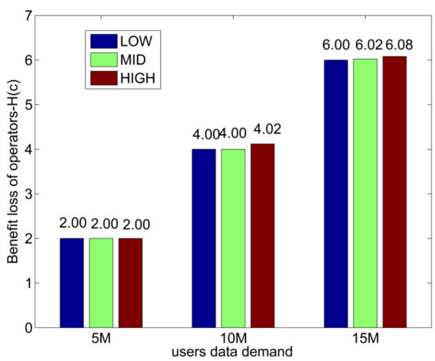

FIGURE 6. The results of the benefit losses of the operators when the users are sensible to traffic service and their data traffic requirements are different.

Fig. 6 shows the benefit losses of operators, in which the users are sensible to data traffic services, i.e., their data traffic sensitivity parameters h_i and h_{ik} are different. It can be found that the benefit losses of the operators are nearly the same under the case that the user data traffic requirements are equal and their data traffic sensitivity parameters h_i and h_{ik} are increased as equal for the three specific types. In comparison, Fig. 7 shows the benefit losses of the operators, in which the three types of users are sensible to the unit price of data traffic, i.e., the unit price sensitivity parameters b_i and b_{ik} are different. Given the same user data traffic requirements and different unit price sensitivity, the benefit losses of operators are nearly the same.

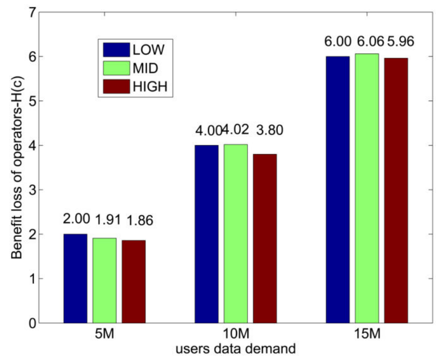

FIGURE 7. The results of the benefit losses of operators when the users are sensible to unit price and their data traffic requirements are different.

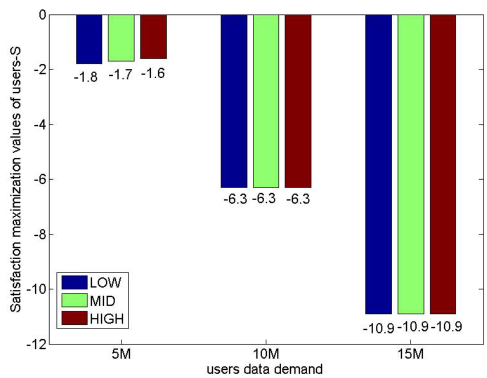

FIGURE 8. The results of the users satisfaction when the users are sensible to traffic service and their data traffic requirements are different.

Fig. 8 shows experimental results of user satisfaction under three type of users who are sensible to traffic service. When the data traffic requirements of users are equal and their data traffic sensitivity parameters h_i and h_{ik} are increased as equal for the three types, their satisfaction values are reduced nearly the same. In comparison, Fig. 9 shows the satisfaction of users, in which the users are sensible to unit price of data traffic. When the data traffic requirements of users are equal and their sensitivity parameters of unit price, i.e., b_i and b_{ik}, are increased as equal for the three specific types, the user satisfaction is nearly decreased as equal. But it can be found that the users under the same data traffic requirement and different sensitivities of unit price can achieve different satisfaction. The higher the sensitivity of unit price is, the lower user satisfaction is. The reason is that the b_i and b_{ik} are the coefficients of the linear function of P, which have a significant effect on the simulation results, while h_i and h_{ik}

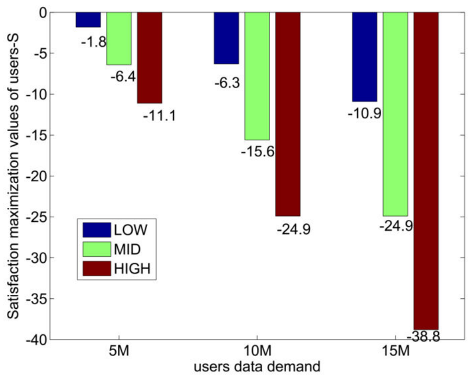

FIGURE 9. The results of the user satisfaction when the users are sensible to unit price and their data traffic requirements are different.

are the coefficients of the convex functions and have little effect on the simulation results.

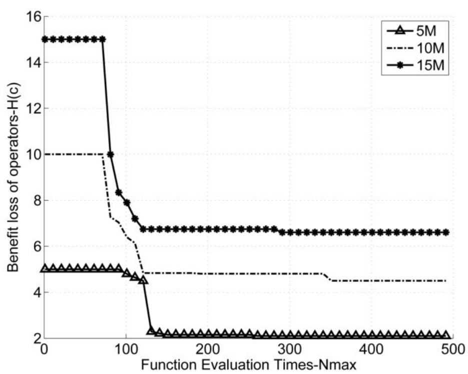

FIGURE 10. The benefit losses of the operators when the user data traffic requirements are different.

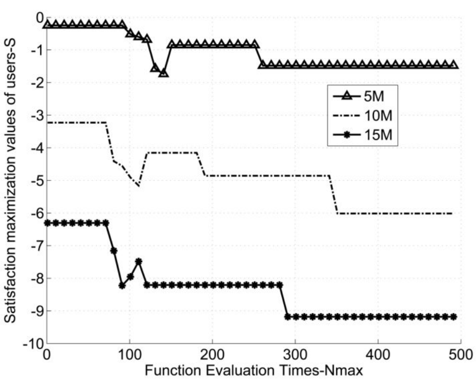

FIGURE 11. The results of the user satisfaction maximization problem when the user data traffic requirements are different.

B. SIMULATION RESULTS OF THE DISTRIBUTED ALGORITHM

In this subsection, we evaluate the proposed distributed algorithm with the same experimental scenario. From Fig. 10 and 11, it can be found that the results can converge with the increasing of the evaluation iterations.

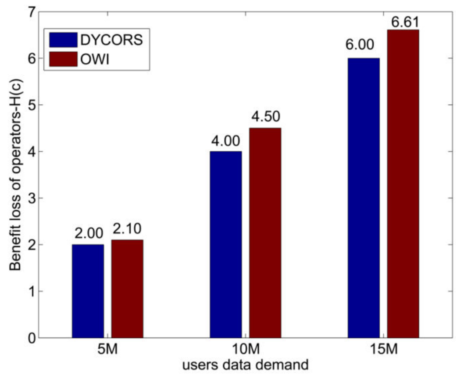

FIGURE 12. The comparison of the benefit losses of operators between DYCORS and the distributed algorithm.

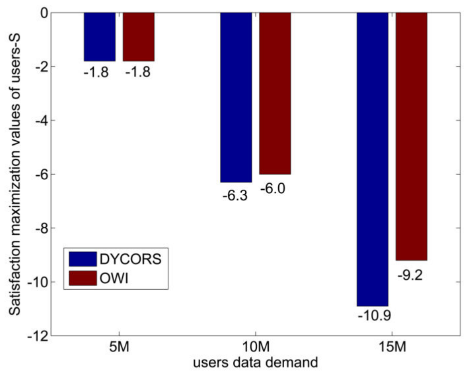

FIGURE 13. The comparison of satisfaction of users between DYCORS and the distributed algorithm.

Fig. 10 shows the benefit losses of the operators versus the iteration times. When the data traffic requirement f_{ij} increases, the value of $H(c)$ increases identically. Fig. 11 shows the simulation results of user satisfaction versus the iteration times. Obviously, the user satisfaction is varying sharply with the evaluation times increasing. This is because the users can be satisfied by several operators when their unit prices are discounted. As the algorithm runs continuously, the unit prices of the operators are towards to stability and the algorithm converges.

Fig. 12 shows the comparison of the benefit losses of the operators, i.e., $H(c)$, between DYCORS and the distributed algorithm, in which the user types are the same, and the data traffic requirements are also 5M, 10M and 15M. It can be found that the difference of $H(c)$ between DYCORS and the distributed algorithm is 0.1 under the case of 5M data traffic requirement. As the data traffic requirement increases to 10M or 15M, the differences does not increase obviously. Fig. 13 shows the comparison of user satisfaction between DYCORS and the distributed algorithm. It can be found that the value of $H(c)$ under the distributed algorithm is better than DYCORS, while the distributed algorithm requires more iterations to converge.

VI. CONCLUSION AND REMARKS

We proposed the bi-level optimization problem for mobile data offloading based on the cooperation of multiple Wi-Fi operators and one cellular operator. The problem of maximizing the user satisfaction and minimizing the benefit losses of the operators was convert into a quasi-convex problem firstly, and then we used the DYCORS method to solve it. Meanwhile, we designed a distributed algorithm to solve the bi-level optimization problem. We verified the performance of the proposed methods under different situations. The simulation results show that the DYCORS-based method can converge more quickly than the distributed algorithm, but the later one can achieve a better result with more iterations.

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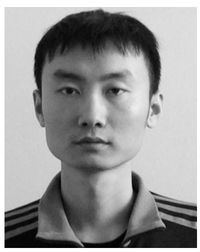

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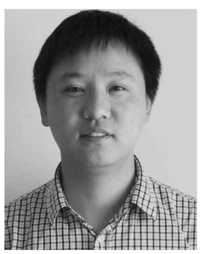

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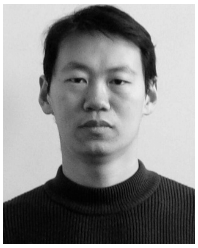

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