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Incentive mechanisms for mobile data offloading through operator-owned WiFi access points

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A R T I C L E I N F O

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A B S T R A C T

Due to the explosive growth of mobile data traffic, it has become a common practice for Mobile Network Operators (MNOs, also known as operators or carriers) to utilize cellular and WiFi resources simultaneously through mobile data offloading. However, existing offloading technologies are mainly established between operators and third-party WiFi resources, which cannot reflect users dynamic traffic demands. Therefore, MNOs have to design an effective incentive framework, encouraging users to reveal their valuations on resources. In this paper, we propose a novel bid-based Heterogeneous Resources Allocation (HRA) framework. It can enable operators to efficiently utilize both cellular and operator-own WiFi resources simultaneously, where the decision cost of user is strictly controlled. Through auction-based mechanisms, it can achieve dynamic offloading with awareness of users valuations. And the operator-domain offloading effectively avoids anarchy brought by users selfishness and lack of information. More specifically, *HRA-Profit* and *HRA-Utility*, are proposed to achieve the maximal profit and social utility, respectively. addition, based on Stochastic Multi-Armed Bandit model, the newly proposed *HRA-UCB-Profit* and *HRA-UCB-Utility* are able to gain near-optimal profit and social utility under incomplete user context information. All mechanisms have been proven to be truthful and satisfy individual rationality, while the achieved profit of our mechanism is within a bounded difference from the optimal profit. In addition, the trace-based simulations and evaluations have demonstrated that *HRA-Profit* and *HRA-Utility* increase the profit and social utility by up to 40% and 47%, respectively, compared with benchmarks. And the cellular utilization rate is kept at a favorable level under the proposed mechanisms. *HRA-UCB-Profit* and *HRA-UCB-Utility* restrict pseudo-regret ratios under 20%.

1. Introduction

With the explosive growth of intelligent mobile devices and bandwidth-consuming mobile applications, mobile data traffic has experienced dramatic growth in the past decade [1]. There exists a shortage of cellular capacity, especially in busy regions during peak periods. It is often too expensive or sometimes even impossible for Mobile Network Operators (MNOs) (we use the terms MNO, operator and carrier interchangeably in this paper) to deploy enough cellular resources that can meet the peak traffic demand [2–4]. Once excessive traffic exceeds the cellular capacity, it will introduce high congestion cost to MNOs [5–7]. Therefore, MNOs have to utilize other complementary technologies to enhance transmission capability.

To reduce the pressure on the cellular networks, WiFi has been widely used by mobile users to offload mobile data from cellular networks at specific scenarios. It has been envisioned that one of the future trends for MNOs is to utilize both licensed (*e.g.*, cellular) and unlicensed (*e.g.*, WiFi) spectrums in Heterogeneous Networks (HetNet) [8–13]. For example, Bennis et al. [8] constitute a cost-effective integration of multiple infrastructures, efficiently coping with peak traffic and heteroge-

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neous Quality of Service (QoS) requirements. Unlicensed Long-Term Evolution (LTE-U) is also proposed by industries to introduce Long-Term Evolution (LTE) in unlicensed spectrums [14], which will improve the throughput of radio access networks.

WiFi can be divided into third-party WiFi and carrier WiFi (i.e., operator-owned WiFi). Third-party WiFi has provided widely deployed infrastructures for mobile data offloading. In contrast, infrastructures of carrier WiFi are deployed and operated by carriers. Existing offloading technologies [11,12,15,16] mainly focus on how to utilize third-party WiFi, rather than carrier WiFi. In fact, carrier WiFi should also be explored and exploited considering the following advantages. First, many MNOs (*e.g.*, AT&T, Verizon, China Mobile, and Vodafone) have widely deployed WiFi Access Points (APs) [17]. Most of these APs are deployed in busy regions, so they can offload the peak traffic from cellular networks. Second, operator-owned WiFi APs can help improve the QoS. During peak hours, third-party WiFi APs may also serve heavy traffic. In comparison, operators can reserve bandwidth on self-owned APs for peak-hour cellular offloading. In addition, the security and privacy issues [18] brought by third-party WiFi can also be solved by controlling the access to operator-owned WiFi APs. Moreover, third-party WiFi APs can also be utilized by MNOs to provide offloading services [11,19], which can be regarded as the resources of MNOs. Therefore, we focus on how to utilize carrier WiFi resources from the perspective of economics, to alleviate the pressure on cellular networks.

To achieve the integrated utilization of cellular and carrier WiFi resources, user context information about their valuations on resources cannot be neglected. It is the foundation for achieving economic optimization targets [20,21], like the maximal profit of the operator and social utility (i.e., the sum of utilities of all users). On the other hand, operator-dominant offloading (i.e., dynamic resource allocation is dominated by the operator), which has the ability to take into account user context information, can achieve better resource allocation performance, because the operators are better aware of network status. In addition, small-scale central control with users' valuations cannot deal with the anarchy brought by users' local views on the global network condition as well as their selfish behaviours, but also satisfy delay requirements. These relevant factors have been considered in our work, which are further verified through the trace-based evaluations.

However, several challenges are brought forth considering users' valuations in heterogeneous resource utilization. First, incentive mechanisms are required to motivate users to reveal their true valuations on resources. Second, the operator profit and social utility must be considered under the premise of true users' valuations. Third, the interactions among users and MNOs should minimize the costs of users.

To solve the above issues under such circumstances, we propose a novel bid-based operator-dominant mobile data offloading framework between cellular and carrier WiFi networks, to achieve the Heterogeneous Resource Allocation (HRA). In summary, the proposed HRA framework in this paper is mainly due to the following motivations.

- Different from a simpler resource scheduler operated by the MNO alone, the newly proposed offloading mechanisms should enable users to express their willingness to use WiFi resources according to different scenarios.
- In addition to alleviating the pressure of cellular networks, the newly proposed framework should also encourage users to reveal their true valuation on WiFi resources, so that operators can achieve economic optimization targets.
- Different from allowing users to freely decide whether to use WiFi resources, the operator should achieve offloading on the basis of considering the global network condition, avoiding the anarchy brought by users local views.

Thus, MNOs can realize dynamic WiFi pricing and resource allocation, while mobile users can achieve dynamic data offloading according to their bids. More specifically, all auction mechanisms proposed in this paper are established between MNOs and mobile users, instead of MNOs and third-party resource owners. And it has been demonstrated through theoretical analysis that, they can solve the above challenges to encourage users to claim their true valuations and help MNOs make better use of heterogeneous resources.

The implementation of HRA framework needs the support of MNOs or regulators. For operators, the goal is to maximize their profits with some constraints such as traffic performance and user experience assurance. For regulators, the policy is formulated in order to maximize social utility. Thus, from the perspectives of both operators and regulators, two auction mechanisms, *HRA-Profit* and *HRA-Utility*, are designed to achieve the maximal profit and social utility, respectively. In addition, *HRA-UCB-Profit* and *HRA-UCB-Utility* are proposed to gain near-optimal profit and social utility under incomplete user information. The following summarizes the contributions of this paper.

- Through offloading between cellular and carrier WiFi networks, the bid-based operator-dominant offloading framework for the first time takes users' valuations on resources into consideration, and effectively avoids anarchy brought by users selfishness and lack of information.
- To enable the newly proposed framework to be applied to more complex scenarios with incomplete information, *HRA-UCB-Profit* and *HRA-UCB-Utility* are proposed to optimize operator profit and social utility.
- Compared with classical auction-based mechanisms, we cope with the challenges brought by HRA's distinct features. And the proposed mechanisms have been proven to be *truthful* and satisfy *individual rationality*.
- Through theoretical analysis, the profit of *HRA-Profit* has been proven to be within the bound of the optimal profit. And extensive evaluations demonstrate the efficiency of the proposed mechanisms, compared with benchmarks.

The rest of this paper is organized as follows. Section 2 builds the system model to formulate the problem. Section 3 proposes and theoretically analyzes the bid-based dynamic resource allocation framework. Furthermore, Section 4 proposes a model to analyze the resource allocation with incomplete information. And Section 5 sets up trace-based simulations and analyzes the performance of the proposed framework. Section 6 analyzes the implementation issues of the framework. Section 7 introduces the related work. Finally, Section 8 concludes the paper.

2. System model and problem formulation

The key problem is to determine the allocation of cellular and operator-owned WiFi resources, especially properly pricing WiFi resources, so as to achieve dynamic resource allocation with considering MNO's profit, social utility, resource utilization efficiency and QoS. In this section, we first introduce the system model through an example, illustrated in Fig. 1. After explaining the relationship between the system participants and the main parameters through Fig. 1, we further

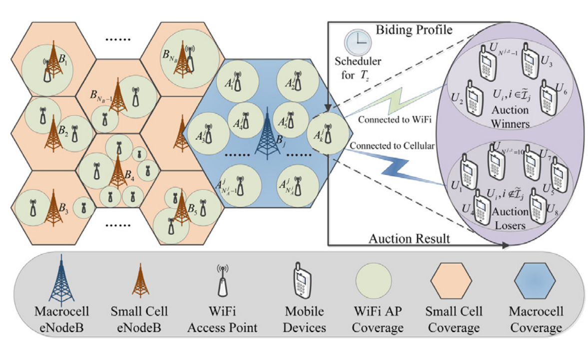


Fig. 1. An Example of the System Model.

provide a high level description of the problem. And then, we present the user model and operator model separately. Finally, we discuss the congestion control of the system model.

2.1. Overview

In this paper, we consider one specific MNO[1], like some studies under monopoly scenarios [3,22,23]. Considering the differences in traffic demand between different regions, the MNO deploys two types of cellular base stations (BSs), i.e., macrocell and small cell. Note that the number of macrocell is more than one, and Fig. 1 merely illustrates that the BSs may be of different types. In our system model, the MNO has N_B BSs, denoted by $\mathcal{B} = \{B_1, B_2, \ldots, B_{N_B}\}$. Since the infrastructures are deployed by the same operator, the BSs are assumed to have no overlaps between each other [12], and so are the WiFi APs. But each B_j may cover multiple APs. For a specific BS $B_j \in \mathcal{B}$ (*e.g.*, the macrocell in Fig. 1), within its coverage there are N_A^j WiFi APs, denoted by $\mathcal{A}^j = \{A_1^j, A_2^j, \ldots, A_{N_A^j}^j\}$. And the number of APs in the coverage of different BSs can be different, illustrated in Fig. 1, so N_A^j is related to BS index j. To differentiate the capacity of different BSs or APs, the capacity of B_j is denoted by $\widehat{C}_j$ and that of A_k^j is denoted by $\widetilde{C}_k^j$. Note that the capacity of AP refers to that of the idle WiFi resources.

It has been found that the mobile data traffic shows a daily pattern [24,25]. Thus, we consider a one-day time scale. Moreover, one-day is divided equally into N_T time-slots $\mathcal{T} = \{T_1, T_2, \ldots, T_{N_T}\}$. And the length of each time-slot is denoted by $\overline{T}$ on average. For example, one day has 1440 *min*, and if $N_T = 24$, then $\overline{T} = 60$. And T_z is a specific time-slot with an index of z. At time-slot T_z, the dynamic load of B_j is $\widehat{L}_j^z$ and that of A_k^j is $\widetilde{L}_k^{j,z}$, which shows the dynamic traffic demand on the BS or AP. When the total demand exceeds the corresponding capacity, network congestion happens [5].

Mobile data of users who are within the coverage of both cellular and WiFi networks can be transmitted via either one, thus mobile users within the coverage of different BSs or APs can be different during different time-slots. Specifically, the number of mobile users within the coverage of both B_j and A_k^j during time-slot T_z is $N_k^{j,z}$. Note that $N_0^{j,z}$ indicates the number of users who are out of any AP coverage, while in the coverage of B_j. $N^{j,z} = \sum_{k\in[1,N_A^j]\cup\{0\}} N_k^{j,z}$ denotes the number of all users within the coverage of B_j. Since some users are not in the coverage of B_j, but in the coverage of other BSs, the total number of users N_U in the market is different from $N^{j,z}$, i.e., $N^{j,z} \le N_U$. If $N^{j,z} = N_U$, it means that there is only one BS in the market, or other BSs don't have any users. Each user in the market can be denoted by U_i, where $i \in \mathcal{I} = \{1, 2, \ldots, N_U\}$, and $\widetilde{\mathcal{I}}$ denotes the index set of the users connected to WiFi, where $\widetilde{\mathcal{I}} \subseteq \mathcal{I}$. We use $\mathcal{I}_j$ to denote the index set of the users who are within the coverage of B_j in some time-slot, where $|\mathcal{I}_j| = N^{j,z}$. And $\widetilde{\mathcal{I}}_j$ denotes the index set of the users who are within the coverage of B_j and connected to WiFi. For example, $\widetilde{\mathcal{I}}_j = \{U_2, U_3, U_6, U_9\}$ and $N^{j,z} = 10$ with the example illustrated in Fig. 1.

For the sake of clarity, Table 1 lists the major notations used in this paper. It is worth noting that the specific meaning of the symbol also depends on its superscript and subscript. For example, the loads of a specific base-station B_j during time-slot T_z is denoted by $\widehat{L}_j^z$. The actual profit under *HRA-Profit* is denoted by π^z, while the theoretically maximal profit is denoted by π^{*z}. And some notations, which are easy to understand through the context, are not listed in Table 1, such as N_W^z, which is the simplified version of $N_W^{j,z}$ and represents the number of winners who are in the coverage of B_j during time-slot T_z.

Table 1
Major Notation List.

Symbol	Description
$\mathcal{B}$	Set of base-stations, and $N_B = \lvert\mathcal{B}\rvert$
B_j	A specific base-station with an index of j, where $B_j \in \mathcal{B}$
$\mathcal{A}^j$	Set of WiFi access points, which are in the coverage of B_j, and $N_A^j = \lvert\mathcal{A}^j\rvert$
A_k^j	A specific WiFi access point with an index of k, which is in the coverage of B_j, where $A_k^j \in \mathcal{A}^j$
$\widehat{C}_j$, $\widetilde{C}_k^j$	Capacity of B_j and A_k^j
$\widehat{L}_j^z$, $\widetilde{L}_k^{j,z}$	Loads of B_j and A_k^j during time-slot T_z
δ_i^z	Connection state of U_i during time-slot T_z
$\widehat{p}_i$	Price of the unit cellular traffic for U_i
$\widetilde{p}^z$	Price of unit WiFi traffic during time-slot T_z
$\overline{v}_i^z$	Average data-rate of U_i during time-slot T_z
s_i^z	Marginal surplus of U_i during time-slot T_z
φ_i^z, φ'^z_i	Ideal and actual marginal utility of U_i during time-slot T_z
$\widehat{e}_j^z$, $\widetilde{e}_j^z$	Marginal operating expense of cellular and WiFi networks during time-slot T_z
$\breve{e}^z$	Marginal allocation cost during time-slot T_z
b_i^z, b'^z_i	Truthful and claimed bid of U_i for WiFi during time-slot T_z
r_j^z	Marginal revenue within B_j during time-slot T_z
π_j^z	MNO's profit obtained from users of B_j during time-slot T_z
$\overline{T}$	Length of each time-slot

Since user's connection states and data consumption behaviors are independent among different BS coverage areas, we focus on the heterogeneous resource allocation problem within the coverage of one BS, and the detailed reason will be introduced in Section 2.3. In this paper, we assume that automatic access and transparent handover between cellular and WiFi networks is achieved, for instance, through protocols or application level technologies [26–28]. Therefore, what is urgently needed to be solved is how to allocate heterogeneous resources dynamically. Considering that mobile users valuations on resources are very important in the market, the auction mechanisms for heterogeneous resource allocation, therefore, are established between the MNO and mobile users. To achieve efficient resource allocation, the dynamic resource allocation is dominated by the operator. This is because the operator is better aware of network status and has the ability to take into account user context information. More specifically, in the operator-dominant offloading, mobile users submit bids to the operator, which can reflect their true valuations on WiFi resources. Subsequently, the operator comprehensively considers the bidding profile and network status (*e.g.*, the capacity of BS and WiFi AP), and carries out a series of decision-making operations, including WiFi pricing and winner determination. After the operator completes the decision-making process, users are divided into two groups, i.e., winners and losers. The winners and the losers enjoy the operator's network services through WiFi and cellular networks, respectively. And the example illustrated in Fig. 1 can provide a more concise overview of these interactions between the operator and mobile users. Note that when the operator makes decisions, there are two types of maximization targets (i.e., maximizing profit and maximizing social utility). Meanwhile, although these mechanisms for different maximization targets have to encourage users to claim their true valuations on WiFi resources through their bids, the details of the auction mechanism used for different maximization targets are different, which can be found in Section 3. In addition, the dynamic resource allocation is achieved by executing the auction mechanism within limited time at the beginning of each time-slot T_z. Therefore, we need to analyze the complexity of relevant algorithms while integrating users' valuations on WiFi resources to achieve economic improvement.

[1] We set up this not only for mathematical simplicity, but also capture one MNO's monopoly access power for a majority of users. In addition, if the multiple MNOs could form an unified coalition, our analysis can be extended into the market with multiple MNOs, and our conclusions on the newly proposed framework and mechanisms will hold. Without doubt, it would be interesting to study how the presence of multiple competing MNOs could affect the pricing policy. However, due to the complexity of the work, this point could be studied as future work.

2.2. User model

As formerly notified in Section 2.1, each user has two types of states at any time, *being connected to cellular* or *being connected to WiFi*. We define the *connection state* (i.e., δ_i^z) of U_i during time-slot T_z, which is shown as Eq. (1).

$$\delta_i^z = \begin{cases} 1, & \text{if } U_i \text{ is connected to cellular;} \\ 0, & \text{if } U_i \text{ is connected to WiFi.} \end{cases} \tag{1}$$

In the real-world wireless data market, the operator provides users with a choice of different cellular plans to meet diverse needs. These cellular plans fall into three main categories, i.e., the usage-based pricing [6], the flat-rate pricing [25] and tiered pricing [29]. For the usage-based pricing (also know as *pay-as-you-go*, usage-sensitive, *etc.*), users are charged by the volume of consumed mobile data. Instead, the flat-rate pricing charges a fixed service fee for unlimited data usage within a period of time (*e.g.*, one month). And the tiered pricing refers to a mixture of flat-rate pricing and usage-based pricing, where extra charges per unit usage are imposed on the metered usage beyond the predefined data cap. The volume of consumed mobile data by different users can be different, thus we use $TotalVolume_i$ to represent the total volume of consumed mobile data by U_i within one billing cycle. To be consistent with reality, different users may have different traffic prices (*e.g.*, the difference between plans of different categories, or the difference between different plans of the same category), which is denoted by $\hat{p}_i$. Without any doubt, it can describe the usage-based pricing. Regarding the flat-rate pricing, the fixed service fee for U_i is denoted by $FixedFee_i$. And then, we have $\hat{p}_i = \frac{FixedFee_i}{TotalVolume_i}$. As for the tiered pricing, the fixed service fee for U_i is also denoted by $FixedFee_i$, which can cover the predefined data cap $DataCap_i$. Zheng et al. [30,31] have demonstrated that users with such data cap have strong incentive to plan their usage per billing cycle. That is, in reality, users do usually limit their usage below this cap (i.e., $TotalVolume_i \le DataCap_i$), due to the high fee charged for beyond. For users with tiered pricing, therefore, we have $\hat{p}_i = \frac{FixedFee_i}{DataCap_i}$. Overall, $\hat{p}_i$ has the ability to describe different traffic prices for different users, even if these users use different categories of plans. More specifically, we have $\hat{p}_i \in (\$0, \$2)/GB$ in our simulation experiments, and all values of $\hat{p}_i$ follows the specific Gaussian distribution, i.e., $\{\hat{p}_i | i \in \mathcal{I}\} \sim N(\mu = 1, \sigma^2 = 4)$. After subscribing MNO, U_i will be assigned a Maximum Information Rate (MIR), denoted by V_i, which limits the instant data-rate. The actual instant data-rate depends on the data requests of mobile applications, and the average data-rate of U_i during time-slot T_z is denoted by $\bar{v}_i^z$, where $\bar{v}_i^z \le V_i$, $\forall i \in \mathcal{I}$.

From the perspective of social utility, the goal of the dynamic resource allocation is to maximize the sum of user utilities. And the user utility describes the value that the user gains from consuming mobile data. The alpha-fair utility model [32,33] is often used to model user utility on the Internet, where an increasing and concave utility function emulates a decreasing marginal benefit to user's additional bandwidth. However, the alpha-fair utility model ignores the temporal distribution of mobile traffic demands. For example, although the utility of checking an email at night is as much as that of checking an email in the morning, the alpha-fair utility model generates different utilities. The reason is, in the alpha-fair utility model, the marginal benefit gradually decreases with the increase of traffic, so the utility in the evening is smaller than that in the morning at the same day. Therefore, we introduce a new definition of *marginal utility*.

Definition 1. U_i's **marginal utility** $\varphi_i^z \ge 0$ indicates the monetary value gained from consuming one unit mobile traffic without congestion, i.e., the intrinsic value of per unit mobile traffic to U_i during time-slot T_z.

For the design of a practical resource allocation mechanism, the user utility should also take the network congestion into account, which is a consensus in many real-world scenarios [7,34–36]. That is, the *marginal utility* should also have the ability to reflect the influence of network congestion. In these studies, it is consistently agreed that network congestion has a negative impact on the user utility. Meanwhile, the related utility function can be defined as an abstract function with characteristic restrictions, and the specific form may be different. For example, Gong et al. [35] define the user utility as the intrinsic value minus the negative impact of congestion, where the negative impact is determined by the user's congestion coefficient and network congestion level. And Zou et al. [7] define the user utility as the product of intrinsic value and satisfaction discount function. The satisfaction discount function (i.e., $\nu(\cdot)$ in [7]) can captures the negative effect of congestion on user's intrinsic values. More specifically, the user cannot get any utility (i.e., $\upsilon(\cdot) = 0$) when the network congestion level reaches the maximum, while the user can get all the intrinsic value (i.e., $\upsilon(\cdot) = 1$) when there is no network congestion. To this end, we propose the *actual marginal utility* to integrate network congestion, which is defined as Eq. (2).

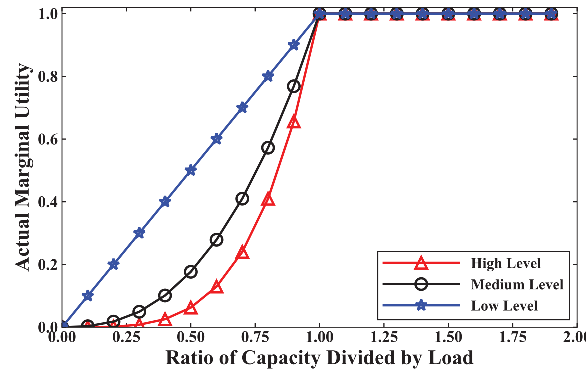


Fig. 2. Actual Marginal Utility with Different Sensitivity levels.

$$\varphi'^z_i = \varphi_i^z \cdot \gamma^\alpha = \varphi_i^z \cdot \left(\min\left\{ \frac{\hat{C}_j}{\hat{L}_j^z}, 1 \right\} \right)^\alpha \tag{2}$$

where $\gamma = \min\{\frac{\hat{C}_j}{\hat{L}_j^z}, 1\}$ is used to reflect the *satisfaction level*, which is related to the *network congestion level*. For example, when the network capacity (i.e., $\hat{C}_j$) is greater than the network load (i.e., $\hat{L}_j^z$) during time-slot T_z, the user can get all the intrinsic value (i.e., φ_i^z) without congestion. And when $\hat{C}_j < \hat{L}_j^z$, network congestion occurs and the *satisfaction level* (i.e., γ) will be less than 1. In particular, if the *network congestion level* research the maximum (i.e., $\hat{C}_j \gg \hat{L}_j^z$ and $\gamma \to 0$), the user cannot get any utility. And $\alpha \in [1, +\infty)$ represents the sensitivity of the *satisfaction level*[2], indicating how sharply user's marginal utility will decrease with congestion. To better understand the impact of α, we plot the curves in Fig. 2 to illustrate some examples.

Fig. 2 shows the effect on actual marginal utility at different sensitivity levels, where the marginal utility without congestion (i.e., the intrinsic value of per unit mobile traffic without congestion, defined in Definition 1) is assumed to 1.0. And $\alpha = 1$, $\alpha = 2.5$, and $\alpha = 4$ are represented by three levels of low, medium and high. It can be found in Fig. 2 that, when there is no network congestion (i.e., $\hat{C}_j \ge \hat{L}_j^z$), the sensitivity level has no effect on the *actual marginal utility*. Once the network is congested (i.e., $\gamma < 0$), the *actual marginal utility* is gradually reduced with the decrease of γ (i.e., more serious network congestion). In particular, when the *network congestion level* is relatively small (i.e., γ is close to 1, which is a more likely scenario), the decrease in the *actual marginal utility* is sharper with a higher sensitivity level. This demonstrates that

[2] Since the *satisfaction level* is directly related to the *network congestion level*, α can also be regarded as the sensitivity of the *network congestion level*. Meanwhile, α has the similar effect to the congestion coefficient in [35], both of which are used to further refine the negative effects of network congestion.

α can indicate how sharply user's marginal utility will decrease with congestion. In contrast, when the *network congestion level* is extremely severe (i.e., γ is close to 0, which is a rare scenario), the decrease in the *actual marginal utility* is sharper with a lower sensitivity level. This is because the *actual marginal utility* with higher sensitivity level is closer to 0 earlier. Note that the sensitivity level is assumed to be the same for all users in this paper, as indicated in Eq. (2), i.e., α is not associated with the user index *i*. We stress that this is for convenience of analysis, and the conclusions of this paper are not affected with different α. Similar simplifications can be found in other studies [35], where the congestion coefficient in the utility function of all users is assumed to be the same. With regard to this hyperparameter, we have $\alpha = 2.5$ (i.e., the line of medium level in Fig. 2) in the simulation experiments[3]. And different users can have different intrinsic valuation of the wireless services [35], which is similar to the marginal utility without congestion in this paper, as indicated in Eq. (2), i.e., φ_i^z is associated with the user index *i*.

Definition 2. U_i's **marginal surplus** s_i^z indicates the difference between the marginal utility φ_i^z and the payment for the unit mobile traffic m_i^z, i.e., $s_i^z = \varphi_i^z - m_i^z$.

Users are assumed to be *rational* in this paper, meaning that the maximum marginal surplus will be the eternal pursue for each user. Following the definition of user connection state, the payment for unit mobile traffic by U_i is expressed as Eq. (3).

$$m_i^z = \delta_i^z \cdot \widehat{p}_i + (1 - \delta_i^z) \cdot \widetilde{p}^z \tag{3}$$

where $\widetilde{p}^z$ is the unit price of WiFi traffic during time-slot T_z, and how to get $\widetilde{p}^z$ will be discussed in Algorithm 1. Note that $\widetilde{p}^z$ is the universal WiFi price for each winner in the auction.

During the allocation of cellular and WiFi resources, we utilize b_i^z to indicate the relative willingness for WiFi connection expressed by U_i's *bid*. And b_i^z can be combined with $\widehat{p}_i$ to express how much money U_i wants to pay for WiFi connection. U_i's highest willingness to pay (*HWTP*) for WiFi traffic is denoted as $\widetilde{P}_i^z$, and the calculation will be described later. And b_i^z is defined as Eq. (4).

$$b_i^z = \frac{\widetilde{P}_i^z}{\widehat{p}_i} \tag{4}$$

From Eq. (4), we can see the real meaning of b_i^z is the ratio value of *HWTP* and cellular data traffic price. In other words, b_i^z does not mean that how much money U_i wants to pay for WiFi connection, but means a relative coefficient. How much money U_i wants to pay for WiFi connection will be introduced later, shown as Eq. (15).

Definition 3 (Individual Rationality (IR)). is satisfied if each user gets the same or a higher surplus by using WiFi than cellular networks.

According to Definition 3, we have Eq. (5).

$$\widetilde{P}_i^z = \underset{\widetilde{P}_i^z}{\operatorname{argmax}}\{\varphi_i^z|_{\delta_i^z=0} - \widetilde{P}_i^z \geq \varphi_i^z|_{\delta_i^z=1} - \widehat{p}_i\} = \varphi_i^z|_{\delta_i^z=0} - \varphi_i^z|_{\delta_i^z=1} + \widehat{p}_i \tag{5}$$

Therefore, according to Eqs. (4) and (5), b_i^z can be expressed by Eq. (6).

$$b_i^z = 1 + \frac{\varphi_i^z|_{\delta_i^z=0} - \varphi_i^z|_{\delta_{i'}^z=1}}{\widehat{p}_i} \tag{6}$$

We further explain why b_i^z means a relative coefficient. For example, $b_i^z = 0$ means that U_i prefers to be offloaded to WiFi only if the WiFi traffic is free. And $b_i^z = 1.5$ means that U_i is willing to pay 50% more for WiFi traffic than cellular traffic during time-slot T_z. Similarly, $b_i^z = 0.5$ means that U_i is only willing to pay half of cellular traffic price for WiFi traffic.

The *claimed bid* of U_i during time-slot T_z is denoted by b'^z_i. It should be noted that users may choose to lie (i.e., $b'^z_i \neq b_i^z$) for higher surpluses, and there will be a more detailed discussion in the rest of this paper.

Definition 4. Truthful means that all the users submit their real bids without lying. Truthful is also called **Incentive Compatible (IC)**.

Both *IR* and *IC* should be satisfied when we design the resource allocation mechanism because they are the foundations for analyzing the optimization goals.

User mobility can be modeled using the dynamic access status of users. The *access status* of U_i during time-slot T_z is denoted by $\mathbf{a}_i^z = (a_{i,1}^z, a_{i,2}^z)$, where $a_{i,1}^z$ indicates the BS index and $a_{i,2}^z$ indicates the AP index. It is assumed that all users will always be under the coverage of cellular networks. But U_i may be out of the access of APs during time-slot T_z, then $a_{i,2}^z = 0$.

Then the BS/AP-level mobility of U_i during one day can be denoted by $\mathbf{a}_i = (\mathbf{a}_i^1, \mathbf{a}_i^2, \ldots, \mathbf{a}_i^{N_T})$. User mobility also shows a daily pattern which is determined by his/her home address, work place, daily schedule, and so on.

2.3. Operator model

For MNOs, we focus on their profit generated from the consumption of mobile data. To this aim, we analyze the cost and revenue of operating mobile networks.

1) Cost: The cost of both cellular and WiFi networks consists of CAPital EXpenditure (*CAPEX*) and OPerating EXpense (*OPEX*). In this paper, we focus on the utilization of the existing wireless resources of operators, so *CAPEX* is ignored in our analysis. *OPEX* consists of the cost for transmitting the mobile data via cellular and WiFi networks.

Definition 5. Marginal OPEX is operator's cost for transmitting mobile traffic during one unit time via cellular or WiFi networks.

When the cellular or WiFi traffic demand is below the corresponding capacity, the marginal cost for transmitting more data is quite low. However, when the capacity is exceeded, the congestion cost will increase dramatically. Therefore, we define the *marginal OPEX* of cellular and WiFi networks during time-slot T_z by piecewise-linear and convex functions [5], which are denoted by $\widehat{e}_j^z(\widehat{L}_j^z, \widehat{C}_j)$ and $\widetilde{e}_k^{j,z}(\widetilde{L}_k^{j,z}, \widetilde{C}_k^j)$, respectively.

2) Revenue: The operator's revenue comes from user's payments for cellular and WiFi networks. We define *marginal revenue* as the operator's revenue within a specific base station (*e.g., B_j*) during a unit time, denoted by $r_j^z = \sum_{i\in\mathcal{I}_j} m_i^z \cdot \bar{v}_i^z$.

3) Profit: The operator profit obtained from the users within the coverage of B_j during time-slot T_z is denoted by π_j^z, which can be derived from its revenue and cost, as shown in Eq. (7).

$$\pi_j^z = \left[r_j^z - \left(\widehat{e}_j^z + \sum_{A_k^j \in \mathcal{A}^j} \widetilde{e}_k^{j,z} \right) \right] \cdot \overline{T} \tag{7}$$

where $\overline{T}$ denotes the length of each time-slot. The goal of MNO is to pursue the maximal profit, as shown in Eq. (8) with constraints (9).

$$\max \sum_{B_j\in\mathcal{B}} \sum_{T_z\in\mathcal{T}} \pi_j^z \tag{8}$$

$$s.t. \begin{cases} b_i^z = b'^z_i, & \forall i \in \mathcal{I}_j \\ s_i^z \geq s_i^z|_{\delta_i^z=1}, & \forall i \in \mathcal{I}_j \\ \widetilde{L}_k^{j,z} \leq \widetilde{C}_k^j, & \forall A_k^j \in \mathcal{A}^j \end{cases} \tag{9}$$

where constraints (9) indicate that users always submit *truthful bids*. Thus, the *individual rationality* is achieved, and WiFi APs, as the alternative access resources, will not be overloaded. It should be noted that,

[3] In fact, users can be divided into different groups with different sensitivity level, and it can cause many complex issues, such as fairness between different groups. For example, users with higher sensitivity level have stronger intrinsic motivation to escape from the congested cellular network, but it also results in a greater cost. Due to the complexity of the work, this article focuses on the auction mechanism.

when deciding which users can use WiFi, MNO will consider the load of APs. In other words, MNO has the right to control the WiFi APs access, it is easy to ensure WiFi APs cannot be overloaded.

The profit of MNO is related to the revenue and costs of each BS, and users may move among different BSs. Therefore, profit optimization needs to consider the collaboration among BSs. However, the HRA mechanisms proposed in this paper carry out periodic resource dynamic allocation, in which the mobility of users will be discovered, so we do not need to consider the collaboration among different BSs. Without considering the coordination among different BSs, the optimization problem can be divided into each BS during each time-slot, expressed as Eq. (10) with constraints (9).

$$\max \quad \pi_j^z \tag{10}$$

As formerly notified, the optimization of different BSs can be simplified to that of each BS. For conciseness of the notions, in the rest of this paper, the notions of the whole market may have the same meanings as the related notions of a certain BS, unless there is special instructions. In other words, in some cases, we can assume that there is only one BS in the market. For example, A_k^j, $\mathcal{A}^j$, $\mathcal{I}_j$, $\widetilde{\mathcal{I}}_j$ can be simplified as A_k, $\mathcal{A}$, $\mathcal{I}$, $\widetilde{\mathcal{I}}$. And some newly defined nations may no longer specifically add the superscripts and subscripts. For instance, N_W^z represents the number of winners who are in the coverage of B_j during time-slot T_z. If not simplified, it can is denoted by $N_W^{j,z}$.

2.4. Congestion control

Oversubscription is a common strategy of MNO [37]. Due to the temporal and spatial dynamics of mobile data demands, congestions can frequently happen at the BSs within busy regions. MNO's congestion control strategies are assumed to control the instant data-rates of the users with proportional to their MIRs mentioned in Section 2.2. In other words, when congestions happen, the whole capacity of the BS will be occupied, and the congestion cost will be derived from the *marginal OPEX* defined in Section 2.3 based on the capacity and the actual mobile data demands.

3. Bid-based resource allocation framework

We propose a bid-based resource allocation framework, as shown in Fig. 3. The allocation of cellular and WiFi resources is achieved through the operator-dominant mobile data offloading, i.e., the cellular data of some users is offloaded to WiFi networks through a decision-making auction. More specifically, we first summary the heterogeneous resource allocation, focusing on the distinctive features from classical auction-based allocation. We then discuss the trigger policy of HRA and how users can participate in resource allocation through bidding. Furthermore, we give the implementation details of the two mechanisms (i.e., *HRA-Profit* and *HRA-Utility*), respectively. Finally, we prove that both mechanisms achieve incentive compatibility and individual rationality, as well as the bounded difference between the actual achieved profit and the theoretically maximal profit.

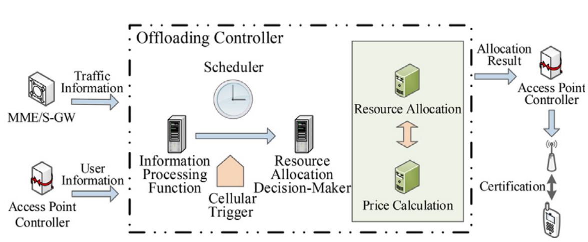


Fig. 3. Heterogeneous Resource Allocation Framework.

3.1. Overview of heterogeneous resource allocation

Users' valuations on cellular resources have been revealed through their purchase and consumption behaviors of cellular data. However, their valuations on WiFi resources remain private. Note that the private property mentioned in this article is mainly due to users' subjective factors, such as the aspiration level of the activities they are engaged in [38], the emotional state they are in, *etc.*. And the uncertainty and dynamics of similar subjective factors can only be actively reflected by users based on their own circumstances. Therefore, we design a bid-based resource allocation framework, which can encourage users to claim their true valuations through some proper auction mechanisms. What is more, to achieve high-efficient resource allocation, central control within each BS area is preferred and feasible. Because the number of users in the coverage of each BS is limited, which is conductive to satisfying delay requirements [39]. Meanwhile, compared to each user's own decision-making, central control of operators can consider more comprehensive information.

We introduce Heterogeneous Resource Allocation mechanism to solve the allocation of cellular and WiFi resources among heterogeneous users. In HRA, the winners of the auction can access the operator's WiFi and the others remain connected to cellular networks. For each U_i, the price of cellular data is predetermined, and may be different for each user. But the price of WiFi data is determined by the dynamic network status and user demands. HRA will complete the resource allocation decision at the beginning of each time-slot T_z, so we focus on the resource allocation problem in each time-slot.

Compared with classical auction-based allocation, HRA has the following distinct features:

- The operator wants to sell WiFi in HRA. However, the amount of resource to be sold is not predetermined. Instead, the sold amount will be dynamically tuned to maximize the operator's profit or social utility.
- Different from traditional auctions, users who fail in HRA can still gain utilities by consuming cellular data. Thus, this feature has to be considered when analyzing the constraint on *individual rationality*.
- Once winning the auction, users can only access WiFi. But, the final utilities gained by the winners are also closely related to their data-rates, like the click-rates in the position auction for online advertisements [40].

In summary, traditional auction theories do not apply to the resource allocation problem in this paper. We design *HRA-Profit* and *HRA-Utility* to achieve the maximal profit and social utility, respectively. To achieve these goals, the allocation rule should make two decisions, including the auction winners who can access WiFi, and the access price. It consists of two phases, namely, winner determination and WiFi pricing.

3.2. Trigger policy of HRA

The *hybrid trigger policy* for HRA involves two triggers, which are mutually independent.

1) Time-driven trigger: MNO can set a time schedule for the resource allocation controller to start HRA. For example, MNO can set a periodic schedule based on the defined time-slot and possibly the daily mobile data traffic pattern within each cellular base station.

2) Event-driven trigger: HRA can also be triggered by cellular load trigger. For example, HRA will be triggered when data requests exceed the capacity of cellular networks.

3.3. Bidding profile

To participate in resource allocation, users only need to submit their *claimed bids* b'^z_i. Users can preconfigure their bids, which will remain unchanged without user's modification. Then the bids can be submitted automatically by user devices, so as to ease user's burden brought by the auction. To achieve the allocation with high efficiency, operators also collect other information besides the *claimed bids* of users. First, as mentioned in Section 2.2, U_i has a data traffic price $\hat{p}_i$, which can reflect U_i's valuations on cellular data. Combined with users' bids, operators can further derive their valuations (claimed) on WiFi traffic. Second, it is useful to know users' historical traffic consumption statistics, on which operators can depend to estimate their consumption behaviors in the following time-slot. To sum up, the bidding profile of U_i is expressed as Eq. (11).

$$\mathbf{f}_i^z = (\hat{p}_i,\ b'^z_i,\ \bar{v}'^z_i,\ \bar{v}_i^{z-1}) \tag{11}$$

where $\bar{v}'^z_i$ is the average data-rate of U_i during time-slot T_z on the previous day, and $\bar{v}_i^{z-1}$ is the average data-rate during time-slot T_{z-1} on the current day.

Note that the actual user data demand during the next time-slot is unknown. To estimate the average data-rate in the following time-slot, we provide the estimation function, which is denoted by Eq. (12).

$$\bar{v}_i^z = \beta \cdot \bar{v}'^z_i + (1-\beta) \cdot \bar{v}_i^{z-1} \tag{12}$$

where $\beta \in [0, 1]$ is the *estimation factor*. The estimation function considers both the daily traffic pattern and the dynamics of mobile data demands. The value of β can be trained from historical data using the least-square method. Furthermore, to study the scenario with incomplete user demand information, a learning-based Upper Confidence Bound (UCB) allocation strategy will be proposed in Section 4. The overhead for dealing with the bidding profile is acceptable considering the distributed controllers and limited user scale in each cell, which is conductive to satisfying delay requirements.

3.4. Allocation rules of HRA-Profit

From operators' points of view, the goal of resource allocation optimization is to maximize their profit. Therefore, ***HRA-Profit*** is proposed to maximize operator's profit, as described in Eq. (10). The pricing strategy of traffic has been widely studied [32,41–45], so we just focus on the profit change resulted from the mobile data offloading in this paper. To capture the variation in operator's profit, we first introduce the concept of *marginal allocation cost*.

Definition 6. Marginal allocation cost is defined as the difference between the operator's *marginal revenue* when all users use cellular networks and users have been connected to heterogeneous networks, i.e., cellular and WiFi networks.

The *allocation cost* $\check{e}^z$ can be expressed by Eq. (13).

$$\check{e}^z = \sum_{i\in\mathcal{I}} \bar{v}_i^z \cdot \hat{p}_i - \left(\sum_{i\in\{\mathcal{I}\setminus\widetilde{\mathcal{I}}\}} \bar{v}_i^z \cdot \hat{p}_i + \sum_{i\in\widetilde{\mathcal{I}}} \bar{v}_i^z \cdot \widetilde{p}^z \right) = \sum_{i\in\mathcal{I}} (1-\delta_i^z) \cdot \bar{v}_i^z \cdot (\hat{p}_i - \widetilde{p}^z) \tag{13}$$

Note that marginal allocation cost can be positive or negative. In other words, the operator may pay incentive cost or earn extra revenue through user's mobile data offloading.

The change of the operator's profit caused by mobile data offloading during time-slot T_z is denoted by $\Delta\pi^z$, which can be derived from Eq. (14).

$$\Delta\pi^z = -(\Delta\hat{e}^z + \Delta\widetilde{e}^z + \check{e}^z) \cdot \overline{T} \tag{14}$$

where $\Delta\hat{e}^z$ and $\Delta\widetilde{e}^z$ are the variation of marginal cost on cellular and WiFi networks, respectively.

1) WiFi Pricing: Due to the strong user mobility and highly dynamic traffic, WiFi pricing is dynamically determined in the proposed mechanism, so as to take advantage of users' valuations and achieve higher profit or social utility.

The pricing of WiFi resources during time-slot T_z is calculated according to the bidding profile $\mathbf{f}^z = \{\mathbf{f}_1^z, \mathbf{f}_2^z, \ldots, \mathbf{f}_{N^{j,z}}^z\}$ and the number of winners N_W^z, which will be determined by the **Winner Determination - HRA-Profit** algorithm (i.e., Algorithm 3). The Claimed Willingness To Pay (*CWTP*) of U_i for WiFi resources can be derived by Eq. (15).

$$\widetilde{p}'^z_i = b'^z_i \cdot \hat{p}_i \tag{15}$$

Then the WiFi pricing function $(\mathbf{f}^z, N_W^z) \to \widetilde{p}^z$ can be demonstrated by Algorithm 1, and the **Biddersort** algorithm in **WiFi Pricing** algorithm is shown in Algorithm 2, which sorts the bidders in a descending order based on their *CWTP*.

Algorithm 1: WiFi Pricing.

Input: $\mathbf{f}^z$, N_W^z, which is determined by **Winner Determination** algorithms (i.e., Algorithms 3, 4)
Use **Biddersort** (i.e., Algorithm 2) to sort the bidders (bidding profile $\mathbf{f}^z$);
if $N_W^z < N^{j,z}$ **then**
  The WiFi price is assigned as the *CWTP* of the (N_W^z+1)-th bidder in the sorted bidder list;
else
  WiFi price is 0, i.e., WiFi will be free for winners;
return $\widetilde{p}^z$, i.e., the determined universal price of WiFi;

Algorithm 2: Biddersort.

Input: The original bidding profile, $\mathbf{f}^z$
Compute *CWTP* for WiFi $\widetilde{p}'^z_i$, of all bidders, i.e., Eq. (15);
Use *quicksort* to sort the bidders (bidding profile $\mathbf{f}^z$) in descending order according to the calculated *CWTP* $\widetilde{p}'^z_i$;
return $\mathbf{f}^z(sorted)$, i.e., the sorted bidding profile;

According to Algorithm 1, the price of WiFi is determined by the *CWTP* of the first user who has failed in *HRA-Profit* in the sorted bidder list. This policy is the key to the truthfulness of the mechanism, which will be proven in Theorem 1. $\widetilde{p}^z$ is the determined universal WiFi price during time-slot T_z.

2) Winner Determination: The process of *HRA-Profit* winner determination can be demonstrated by Algorithm 3, which aims to maximize operator's profit under the constraints mentioned in Eq. (9). Like other common practices in an auction, the bidders are sorted in a descending order based on their *CWTP* using the **Biddersort** algorithm. However, the amount of WiFi resources that will be auctioned is not predetermined. Instead, it will be dynamically explored when the operator profit is dynamically calculated based on the bidding profile. The winners will be determined once the profit-maximizing allocation is found.

Algorithm 3: Winner Determination - *HRA-Profit*.

Input: $\mathbf{f}^z$, $\hat{C}_j$, $\hat{L}_j^z$, $\widetilde{C}_k^j$, $\widetilde{L}_k^{j,z}$
Sort the bidders (bidding profile $\mathbf{f}^z$), i.e., Algorithm 2;
$\Delta\pi' \leftarrow 0$ is the temporary value of profit variation;
$\widetilde{\mathcal{I}}' \leftarrow \emptyset$ temporarily record possible winners;
for *($N_W^z \leftarrow 1; N_W^z \le N^{j,z}; N_W^z \leftarrow N_W^z + 1$)* **do**
  if *(AP is overloaded when the top N_W^z bidders win)* **then**
    break;
  Calculate the WiFi price $\widetilde{p}^z$, i.e., Algorithm 1;
  if *($\Delta\pi^z(\widetilde{p}^z, N_W^z)$(Eq. (14))$> \Delta\pi'$)* **then**
    Add $(\Delta\pi^z(\widetilde{p}^z, N_W^z), N_W^z)$ to $\mathcal{I}'$;
  $\Delta\pi' \leftarrow \Delta\pi^z(\widetilde{p}^z, N_W^z)$;
N_W^z is assigned to the value of N_W^z that maximizes $\Delta\pi^z$ in $\widetilde{\mathcal{I}}'$;
$\widetilde{\mathcal{I}}$ is the set of top N_W^z bidders in the sorted bidder list;
return $\widetilde{\mathcal{I}}$, i.e., the set of winners;

The operator profit can be considered as a function of the traffic demand offloaded from cellular network to WiFi. Therefore, the theoretically maximal profit will be achieved only if the offloaded traffic demand is continuous upon various number of winners, i.e., the demand of a single user is quite small (infinitely close to zero), which is apparently unrealistic for some users. However, the actual profit under *HRA-Profit* has a bounded difference with the theoretically maximal profit, which will be demonstrated and proven in Theorem 3. Moreover, the bound will be quite small compared with the total profit because the demand of a single user is quite small compared with the amount of total traffic volume within a cellular.

3.5. Allocation rules of HRA-Utility

The sum of user utilities indicates the social utility, which will become the optimization goal if considering public interest. Therefore, we also propose ***HRA-Utility*** to maximize user utilities to achieve the optimal social utility, which can be denoted by Eq. (16) with constraints (9).

$$\max \quad \sum_{i\in\mathcal{I}} \varphi'^{z}_{i}\bar{v}^{z}_{i}\overline{T} \tag{16}$$

For the convenience of analysis, we define the difference between the social utility before and after U_i's offloading as $\Delta\varphi^z(\widetilde{\mathcal{I}}, i)$, which is shown as Eq. (17).

$$\Delta\varphi^z(\widetilde{\mathcal{I}}, i) = \left\{ \sum_{i'\in\mathcal{I}\setminus\{\widetilde{\mathcal{I}}\cup\{i\}\}} \varphi'^{z}_{i'}|_{\delta^z_{i'}=1}\cdot\bar{v}^z_{i'} + \sum_{i'\in\widetilde{\mathcal{I}}\cup\{i\}} \varphi'^{z}_{i'}|_{\delta^z_{i'}=0}\cdot\bar{v}^z_{i'} - \sum_{i'\in\mathcal{I}\setminus\widetilde{\mathcal{I}}} \varphi'^{z}_{i'}|_{\delta^z_{i'}=1}\cdot\bar{v}^z_{i'} - \sum_{i'\in\widetilde{\mathcal{I}}} \varphi'^{z}_{i'}|_{\delta^z_{i'}=0}\cdot\bar{v}^z_{i'} \right\}\cdot\overline{T} \tag{17}$$

1) WiFi Pricing: The pricing of WiFi in *HRA-Utility* can also be demonstrated by Algorithm 1. But even so, the final WiFi price of each timeslot is different from that under *HRA-Profit* because one of the inputs of *WiFi Pricing*, i.e., the number of winners, is different from that under Algorithm 3.

2) Winner Determination: The winner determination process in *HRA-Utility* can be demonstrated by Algorithm 4, which aims to achieve maximal social utility, i.e., maximizing the sum of user utilities.

Algorithm 4: Winner Determination - *HRA-Utility*.

Input: $\mathbf{f}^z, \widehat{C}_j, \widehat{L}^z_j, \widetilde{C}^j_k, \widetilde{L}^{j,z}_k$
Sort the bidders (bidding profile $\mathbf{f}^z$), i.e., Algorithm 2;
$\widetilde{\mathcal{I}} \leftarrow \emptyset$;
for *($N^z_W \leftarrow 1; N^z_W \le N^{j,z}; N^z_W \leftarrow N^z_W + 1$)* **do**
  if *(AP is overloaded when the top N^z_W bidders win)* **then**
    break;
  if *($\Delta\varphi^z(\widetilde{\mathcal{I}}, N^z_W)$(Eq. (17))$\ge 0$)* **then**
    Bidder N^z_W in the sorted bidder list is added to $\widetilde{\mathcal{I}}$;
return $\widetilde{\mathcal{I}}$, i.e., the set of winners;

Sorted in a descending order based on *CWTP*, each bidder will be tested if his/her offloading will increase the social utility, given that other bidders remain their connection statuses defined by $\mathcal{I}$ and $\widetilde{\mathcal{I}}$ ($\widetilde{\mathcal{I}}$ is connected to WiFi and $\mathcal{I}\setminus\widetilde{\mathcal{I}}$ is connected to cellular networks).

3.6. Analysis of HRA-Profit and HRA-Utility

As mentioned in constraints (9), both our optimization goals of maximizing profit and maximizing social utility are achieved under the constraints of incentive compatibility and individual rationality. Besides, the actual achieved profit under *HRA-Profit* has a bounded difference with the theoretically maximal profit. These favorable features of the proposed mechanisms are introduced and proven in the following theorems, i.e., Theorems 1, 2 and 3.

Theorem 1. *In both HRA-Profit and HRA-Utility, submitting the truthful bid is a weakly dominant strategy for all users, i.e., $b'^z_i = b^z_i, \forall i \in \mathcal{I}$.*

Proof of Theorem 1. Due to the complexity of the proof, the details can be found in Appendix. Similarly, proofs of Theorems 2 and 3 can also be found in Appendix. □

Theorem 2. *Individual rationality is satisfied in both HRA-Profit and HRA-Utility, i.e., users can gain equal or more surplus by participating in the auction.*

Theorem 3. *There may exist a difference between the actual profit under HRA-Profit, π^z, and the theoretically maximal profit, π^{*z}, due to the atomicity of winners. But the difference between them satisfies $\pi^{*z} - \pi^z < |\frac{\partial\pi(\widehat{L}^z_j, \Delta L)}{\partial\Delta L}|_{\max}\cdot V$, where ΔL is the traffic load that is offloaded to WiFi and $V = \max\{V_i | i \in \mathcal{I}\}$.*

Here we assume a simple scenario with only two users (i.e., U_1 and U_2) to illustrate the rationale behind Theorem 3. Both U_1 and U_2 have high bandwidth requirements and both want to switch to WiFi. Meanwhile, both of them have expressed high willingness to pay for WiFi. However, the load capacity of WiFi is greater than the demand of U_1, but it cannot meet the total demand of U_1 and U_2 at the same time. According to Algorithm 3, only U_1 can be the winner in the auction, which corresponds to the actual profit. Since U_2 also expressed the high willingness to pay for WiFi, if the demand of U_2 can be partially offloaded to WiFi, the operator can obtain more profits, which is the theoretical maximal profit. Therefore, there may exist a difference between the actual profit and the theoretical maximal profit, and the upper bound of this difference can be proved in the proof of Theorem 3.

The time complexity of Algorithm 3 is $O((N^{j,z})^2\log N^{j,z})$ and that of Algorithm 4 is $O(N^{j,z}\log N^{j,z})$. The cost of the algorithms are quite low considering the user scale within the coverage of a single BS.

According to Theorem 1, the proposed mechanisms can well reveal user's true values on WiFi resources, i.e., the *CWTP* is the user's truthful bid. Then based on this fact, the maximal profit and social utility are achieved through *HRA-Profit* and *HRA-Utility*, respectively.

4. Resource allocation with incomplete information

As discussed in Section 3.3, the actual data-rates of users are unknown to MNOs when they determine the winners of the resource allocation. Instead, we use estimated data-rates (i.e., Eq. (12)), which will affect the precision of the optimization result. And the *estimation factor* β in Eq. (12) depends on the historical data. However, in the real-world wireless data market, there are inevitably some new users entering the market, and these users do not have sufficient historical data to support the calculation of β. This scenario is similar to the cold start [46,47] of the recommendation system, which cannot be ignored in a real-world scenario. To be more applicable to real-world scenarios, the proposed framework should have the ability to enable operators to make decisions even if they do not know the exact distributions of user data-rates, and learn from their past performance, addressing the fundamental tradeoffs between exploration and exploitation [48,49].

In this section, the resource allocation problem is modeled by a Stochastic Multi-Armed Bandit (SMAB) problem. And two near-optimal Upper Confidence Bound (UCB) strategies are designed to help operators make decisions on heterogeneous wireless resource allocation.

4.1. Stochastic multi-Armed bandit model

In an SMAB problem, there exist multiple arms on the bandit and the player plays multiple rounds. Each arm corresponds to an unknown

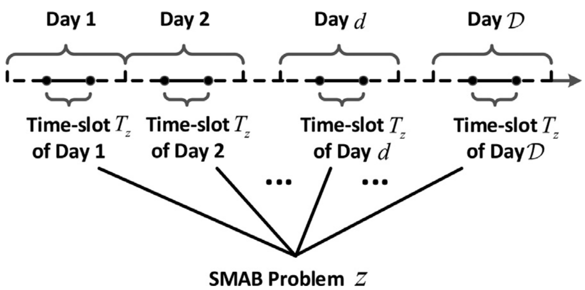


Fig. 4. Time-slots in SMAB Problem z.

probability distribution and the reward of choosing 1 arm in a round is independently drawn from the corresponding distribution. For each round, the player chooses one of the arms and the bandit draws the reward independently from the past, revealing it to the player.

The one-day time scale is divided into N_T time-slots in the proposed model. We consider a $\mathcal{D}$-day period for operators to analyze their strategies, where $\mathcal{D}$ is a large number, reflecting the user's traffic consumption behaviors. Therefore, the operator's resource allocation problem is modeled by N_T homogeneous SMAB problems, each of which corresponds to the resource allocation problem within a specific time-slot of all days. Since the N_T SMAB problems are homogeneous, we focus on a specific one, *e.g.*, the z-th one to analyze the operator's strategies. Specifically, the z-th SMAB problem is defined in Definition 7, and the time-slots considered in SMAB problem z are shown in Fig. 4.

Definition 7. The z-th SMAB problem: The first round is defined as the z-th time-slot of the first day, the second round is the z-th time-slot of the second day, and so on. During each round, the operator should make a decision/choice on how to allocate the heterogeneous wireless resources among users, then a reward (*e.g.*, the profit) will be revealed to the operator. The operator's goal is to maximize the total reward of all the z-th time-slots on the $\mathcal{D}$-day time scale.

1) Choice Set: The group of arms are defined as the choice set in multi-armed bandits. In an SMAB model, the number of choices is required to be no more than the number of time-slots. However, when considering the allocation of two types of radio resources, i.e., cellular networks and WiFi, the number of allocation choices is $2^{N_M^j}$, where N_M^j is the upper bound of user scale that is allowed to be connected to B_j. Apparently, the number of elements in the choice set is a huge number, which is against the requirement of SMAB model.

To fix this problem, we try to reduce the scale of the choice set. We can conclude from Section 3 that, to guarantee the optimization of the allocation result, the strategy of MNO is actually to decide the number of winners after sorting the bidding users according to the optimization goal. And here, in order to make the following statement more concise, we use w to denote N_W. Then for a sorted user list, the choice set becomes $\{0, 1, \dots, N_M^j\}$ and the number of choices can be reduced to $N_M^j + 1$. For example, if $w = 0$ ($w = N_M^j$), it represents all users are connected to cellular (WiFi) networks. And if $w \in (0, N_M^j)$, it means that only the first w users in the sorted user list are connected to WiFi. As mentioned above, a long-term strategy (i.e., $\mathcal{D}$ is a large number) will be provided to the operators. Then considering that the possible values of N_M^j is limited by the capacity of BS, the number of choices will be smaller than that of play rounds. Therefore, the requirement of SMAB model is met.

2) Reward: Following the definition of the SMAB problem in this paper, the "reward" refers to the optimization goal, i.e., operator profit or social utility. Now we analyze operator profit and social utility, respectively.

A. Operator Profit as Rewards

Compared with that when all users connect to cellular networks, there exists a change of operator profit within the coverage of B_j during time-slot T_z when heterogeneous resources are utilized. According to Eq. (7), Eq. (13) and Eq. (14), operator profit as rewards, after the operator make the resource allocation decision, can be expressed as Eq. (18).

$$\pi_j^z(w) = \left\{ \widetilde{p}^z \sum_{i\in\widetilde{\mathcal{I}}} \bar{v}_i^z + \sum_{i\in\mathcal{I}\setminus\widetilde{\mathcal{I}}} \bar{q}_i^z \widehat{p}_i - \left[r_j^z - (\widehat{e}_j^z + \sum_{A_k\in\mathcal{A}^j} \widetilde{e}_k^{j,z}) \right] \right\} \cdot \overline{T} \tag{18}$$

where w denotes the operator choice, i.e., $\widetilde{\mathcal{I}}$ is the first w users in the sorted user list, which is generated by Algorithm 2. Therefore, w has the same meaning as N_W^z.

The $N_M^j + 1$ choices corresponds to $N_M^j + 1$ probability distributions $\chi_0, \chi_1, \dots, \chi_{N_M^j}$, from where the operator profit rewards are drawn independently.

B. Social Utility as Rewards

After the operator reallocate the heterogeneous wireless resources among users, the social utility as rewards within the coverage of B_j during time-slot T_z can be denoted by Eq. (19).

$$\theta_j^z(w) = \left\{ \sum_{i\in\mathcal{I}\setminus\widetilde{\mathcal{I}}} \varphi_i^z \bar{v}_i^z \cdot \left(\min\left\{ \frac{\widehat{C}_j}{\widehat{L}_j^z}, 1 \right\} \right)^\alpha + \sum_{i\in\widetilde{\mathcal{I}}} \varphi_i^z \bar{v}_i^z \right\} \cdot \overline{T} \tag{19}$$

where w denotes the operator choice, i.e., $\widetilde{\mathcal{I}}$ is the first w users in the sorted user list, which is generated by Algorithm 2. Therefore, w has the same meaning as N_W^z.

The $N_M^j + 1$ choices corresponds to $N_M^j + 1$ probability distributions $\chi_0', \chi_1', \dots, \chi_{N_M^j}'$, from where the social utility rewards are drawn independently.

3) Pseudo-regret: Even though the operators know that the profit they gain or the social utility from each choice follow certain distribution, the detailed properties of the distribution remain unrevealed. The profit loss or the utility loss resulted from the incomplete information can be reflected by *pseudo-regret*.

Definition 8. Pseudo-regret of the z-th SMAB problem within the coverage of B_j during the $\mathcal{D}$-day period is defined as

$$\overline{R}_j^z = \max_{w=0,1,\dots,N_M^j} \mathbb{E}\left[\sum_{d=1}^{\mathcal{D}} X_{w,d} - \sum_{d=1}^{\mathcal{D}} X_{W_d,d} \right] \tag{20}$$

where $w \in [0, N_M^j]$ denotes the choice of operator, i.e., the number of winners in the sorted user list. d denotes the d-th round (i.e., the z-th time-slot on day d) and W_d denotes the actual operator choice in round d. $X_{w,d} \sim \chi_w$ or $X_{w,d} \sim \chi_w'$ denotes the reward of round d when the operator choice is w.

In SMAB problems, it is easy to see that if we consider operator profit as rewards, pseudo regret can be written as Eq. (21).

$$\overline{R}_j^z = \mathcal{D}\eta^* - \sum_{d=1}^{\mathcal{D}} \mathbb{E}(\eta_{W_d}) \tag{21}$$

where η_w denotes the mean of χ_w and

$$\eta^* = \max_{w=0,\dots,N_M^j} \eta_w \tag{22}$$

Similarly, if the social utility is considered as the reward, pseudo regret can be written as Eq. (23).

$$\overline{R}_j^z = \mathcal{D}\eta'^* - \sum_{d=1}^{\mathcal{D}} \mathbb{E}(\eta'_{W_d}) \tag{23}$$

where η_w' denotes the mean of χ_w' and

$$\eta'^* = \max_{w=0,\dots,N_M^j} \eta_w' \tag{24}$$

4.2. Upper confidence bound strategy

To demonstrate the UCB strategy, we define that ψ is a convex function such that, $\forall\lambda \geq 0$,

$$\ln \mathbb{E}e^{\lambda(X-\mathbb{E}[X])} \leqslant \psi(\lambda) \tag{25}$$

$$\ln \mathbb{E}e^{\lambda(\mathbb{E}[X]-X)} \leqslant \psi(\lambda) \tag{26}$$

where X is the normalized reward of the operator's offloading strategy such that $X \in [0, 1]$. Then we can take $\psi(\lambda) = \lambda^2/8$ (generated from Hoeffding's lemma).

Based on Eqs. (25) and (26), we can estimate the upper bound of the mean of each choice on some fixed level of confidence. Then under this estimate, we can choose the current best choice. The Legendre-Fenchel transform of ψ is defined by Eq. (27).

$$\psi^*(\varepsilon) = \sup_{\lambda\in\mathcal{R}}(\lambda\varepsilon - \psi(\lambda)) \tag{27}$$

where ε is the dual space to λ.

Then we can define the upper confidence strategy as follows.

Definition 9. (ξ, ψ)-UCB is a resource allocation decision strategy where ξ is an input parameter. According to (ξ, ψ)-UCB, during round d, select

$$W_d \in \underset{w=0,\ldots,N_M^j}{\arg\max}\left[\widehat{\eta}_{w,T_w(d-1)} + (\psi^*)^{-1}\left(\frac{\xi \ln d}{T_w(d-1)}\right)\right] \tag{28}$$

where $T_w(d) = \sum_{z=1}^{d} \delta_{W_z=w}$ denotes the number of times that the operator chooses w during the first d rounds, and $\widehat{\eta}_{w,d}$ denotes the sample mean of rewards by choosing w for d times.

The resource allocation strategy is able to guarantee the bound of pseudo-regret if certain requirements are satisfied. To better illustrate the bound of pseudo regret, we define that $\Delta_w = \eta^* - \eta_w$ is the suboptimality parameter of choice w. Then we have the following conclusion.

Theorem 4. *(ξ, ψ) **-UCB** with $\xi > 2$ satisfies*

$$\overline{R}_j^z \leqslant \sum_{i:\Delta_i>0}\left(\frac{\xi\Delta_i}{\psi^*(\Delta_i/2)}\ln D + \frac{\xi}{\xi-2}\right) \tag{29}$$

Proof of Theorem 4. The proof can be derived from that in [50]. □

Then based on Definition 9 and Theorem 4, we can design resource allocation strategies for operators. To guarantee a limited bound between the optimal operator profit and the actual profit, we propose the mechanism *HRA-UCB-Profit*. Similarly, *HRA-UCB-Utility* is proposed for operators to allocate heterogeneous wireless resources, so as to generate a near-optimal social utility.

1) HRA-UCB-Profit: The winner determination processes of *HRA-Profit* and *HRA-Utility*, i.e., those with complete information, focus on a time scale of one day. In contrast, the winner determination algorithms of *HRA-UCB-Profit* and *HRA-UCB-Utility* consider a time scale of D days, though only a specific time-slot T_z of each day is considered in SMAB problem z, as demonstrated in Fig. 4.

Algorithm 5 shows the winner determination process of operators during time-slot T_z on the d-th day, which will generate a near-optimal operator profit with incomplete user information according to Theorem 4.

2) HRA-UCB-Utility: Similar to *HRA-UCB-Profit*, when the operator's goal is to achieve a near-optimal social utility, the algorithm illustrated in Algorithm 6 can be used to determine the set of winning bidders, who will be offloaded to WiFi networks. Theorem 4 guarantees that the social utility loss will remain in a limited bound.

Based on Theorem 1 and Theorem 2, it is easy to prove that *HRA-UCB-Profit* and *HRA-UCB-Utility* also have the properties of *truthfulness* and *individual rationality*.

Algorithm 5: Winner Determination - *HRA-UCB-Profit*.

Input: $\mathbf{f}^z$, B_j, $\widehat{C}_j$, $\widehat{L}_j^z$, $\widetilde{C}_k^j$, $\widetilde{L}_k^{j,z}$, and the winner sets of rounds $1 \sim d-1$ ($\widetilde{\mathcal{I}}_{1\text{th}}, \widetilde{\mathcal{I}}_{2\text{th}}, \ldots, \widetilde{\mathcal{I}}_{(d-1)\text{th}}$)

if $(d > 1)$ **then**

  Calculate $\pi_j^z(w,1), \pi_j^z(w,2), \ldots, \pi_j^z(w,d-1)$ based on $\widetilde{\mathcal{I}}_{1\text{th}}, \widetilde{\mathcal{I}}_{2\text{th}}, \ldots, \widetilde{\mathcal{I}}_{(d-1)\text{th}}$ according to Eq. (18);

  Sort the bidders (bidding profile $\mathbf{f}^z$) according to Algorithm 2;

  Solve the optimal W_d according to Eq. (28), where $\widehat{\eta}_{w,T_w(d-1)}$ can be derived based on $\pi_j^z(w,1), \pi_j^z(w,2), \ldots, \pi_j^z(w,d-1)$. Note that if there exist multiple optimal W_d, choose the smallest one;

  $\widetilde{\mathcal{I}}_{d\text{th}} \leftarrow \emptyset$;

  for $(N_W^z \leftarrow 0; N_W^z \leq W_d; N_W^z \leftarrow N_W^z + 1)$ **do**

    Bidder N_W^z in the sorted bidder list is added to $\widetilde{\mathcal{I}}_{d\text{th}}$;

else

  Determine $\widetilde{\mathcal{I}}_{d\text{th}}$ according to Algorithm 3;

return $\widetilde{\mathcal{I}}_{d\text{th}}$, i.e., the winner set of round d;

Algorithm 6: Winner Determination - *HRA-UCB-Utility*.

Input: $\mathbf{f}^z$, B_j, $\widehat{C}_j$, $\widehat{L}_j^z$, $\widetilde{C}_k^j$, $\widetilde{L}_k^{j,z}$, and the winner sets of rounds $1 \sim d-1$ ($\widetilde{\mathcal{I}}_{1\text{th}}, \widetilde{\mathcal{I}}_{2\text{th}}, \ldots, \widetilde{\mathcal{I}}_{(d-1)\text{th}}$)

if $(d > 1)$ **then**

  Calculate $\theta_j^z(w,1), \theta_j^z(w,2), \ldots, \theta_j^z(w,d-1)$ based on $\widehat{\mathcal{I}}_1, \widehat{\mathcal{I}}_2, \ldots, \widehat{\mathcal{I}}_{(d-1)\text{th}}$ according to Eq. (19);

  Sort the bidders (bidding profile $\mathbf{f}^z$) according to Algorithm 2;

  Solve the optimal W_d according to.(28), where $\widehat{\eta}_{w,T_w(d-1)}$ can be derived based on $\theta_j^z(w,1), \theta_j^z(w,2), \ldots, \theta_j^z(w,d-1)$. Note that if there exist multiple optimal W_d, choose the smallest one;

  $\widetilde{\mathcal{I}}_{d\text{th}} \leftarrow \emptyset$;

  for $(N_W^z \leftarrow 0; N_W^z \leq W_d; N_W^z \leftarrow N_W^z + 1)$ **do**

    Bidder N_W^z in the sorted bidder list is added to $\widetilde{\mathcal{I}}_{d\text{th}}$;

else

  Determine $\widetilde{\mathcal{I}}_{d\text{th}}$ according to Algorithm 4;

return $\widetilde{\mathcal{I}}_{d\text{th}}$, i.e., the winner set of round d;

---

5. Simulation and evaluation

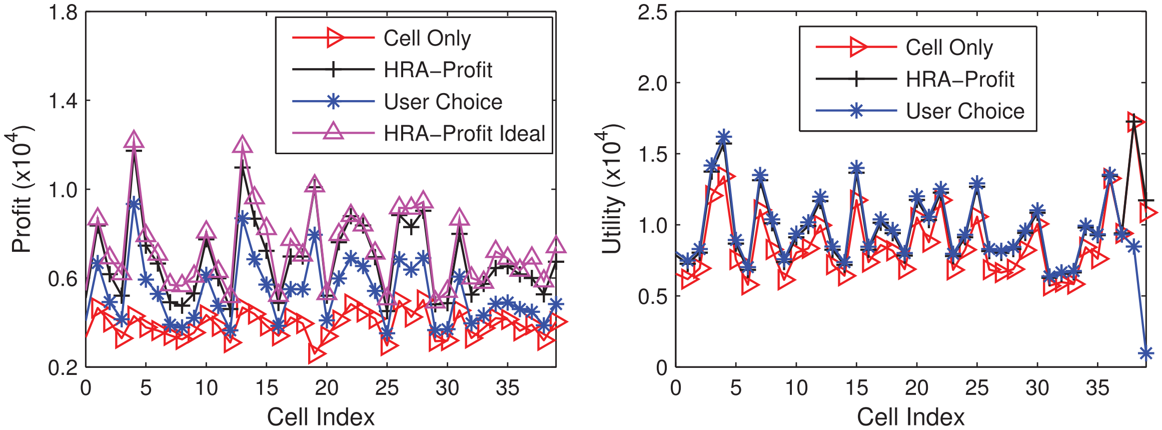
In this section, we simulate the proposed mechanisms based on real trace data and evaluate their performances compared with that of benchmark resource allocation methods.

5.1. Dataset

The two datasets used in our simulations are public datasets from CRAWDAD [51]. The first dataset includes fine-grained mobility data from commercial mobile phones over two months collected by a mobility monitoring system called *LifeMap*. The second dataset contains mobile phone records of mobile traffic consumption behaviors over six months. Table 2 shows some details of the two datasets.

5.2. Simulation setup

Based on the trace data, we simulate the dynamic heterogeneous wireless resources allocation under different mechanisms. We generate user instance data from the dataset within 156 valid cells, including the movement traces and the real-time available BSs and APs. Among the 156 valid cells, we select 40 valid cells, within which there are plenty of users for the simulation of busy regions during peak hours. To configure



(a) The Operator's Profit (b) The Social Utility

Fig. 5. Comparison of *HRA-Profit* with Benchmarks.

Table 2
Datasets.

Dataset	Data Type	Number/Description
Dataset 1	Nodes (User Instances)	9681
	Meaningful Places	651
	Paths	1717
	Valid Cells	156
	WiFi APs	52,510
	Duration	Over 2 Months
Dataset 2	Duration	Over 6 Months
	User Behavior	Call/SMS/Data

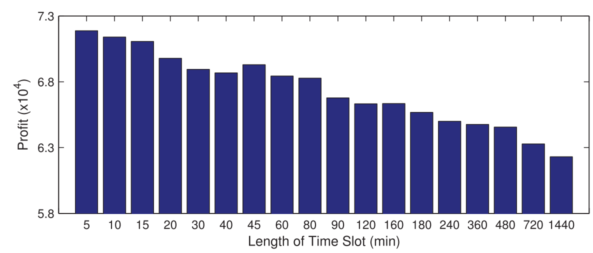


Fig. 6. Profit with Different Lengths of Time-slots.

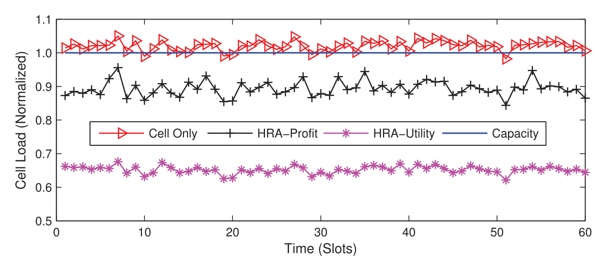


Fig. 7. Comparison of Cellular Utilization Rate between *HRA-Profit* and *HRA-Utility*.

the data consumption behavior of each user instance, we extract mobile phone data behaviors from the second dataset and match them with user instances.

It is assumed that user bids and utilities follow specific distributions. We take the Gaussian distribution for both of them in the simulation. The auction is triggered by the hybrid policy introduced in Section 3.2.

5.3. Evaluation results

1) Mechanisms with Complete Information: Four resource allocation mechanisms, *Cell Only, HRA-Profit, HRA-Utility* and *User Choice*, are considered in the evaluation. *Cell Only* means that no idle WiFi resources are utilized, and *User Choice* indicates that users will choose to connect WiFi only if they can gain higher surpluses than connecting to cellular networks.

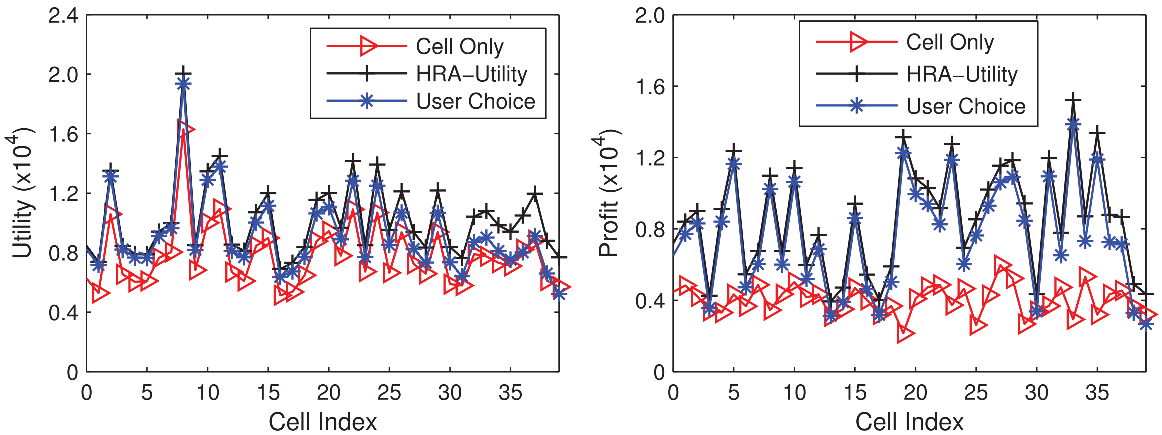
The comparison of *HRA-Profit* with benchmarks is shown in Fig. 5. Operator's profit increase by 25%-40% compared with that under *User Choice*. However, user utilities within most cells are lower than that under *User Choice*. Note that the operator's profit under *HRA-Profit* are very close to the theoretically maximal profit (*HRA-Profit Ideal*), and their bounded difference has been proven in Theorem 3.

To investigate the performance of *HRA-Profit* with different lengths of time-slots, we plot the relation between profit and time-slot lengths in Fig. 6. We can see that shorter time-slots (i.e., smaller $\overline{T}$) generate higher profit because they can better capture the dynamic of user demands and traffic loads. It should be noted that exceptions still exist, such as the profit with 45 *min* and 40 *min*, because the profit are also closely related to the dynamic bids of users.

Fig. 7 shows the dynamic utilization rate of a BS under different allocation mechanisms. We can see from the figure that both *HRA-Profit* and *HRA-Utility* can effectively relieve the overload of the BS, which means that the offloading framework can help improve the QoS in cellular networks when congestions happen. With *HRA-Utility*, the BS load is maintained between 60%-70% of the capacity, indicating that the cellular capacity is underutilized. In comparison, *HRA-Profit* achieves a better cellular utilization rate of 85%-95%.

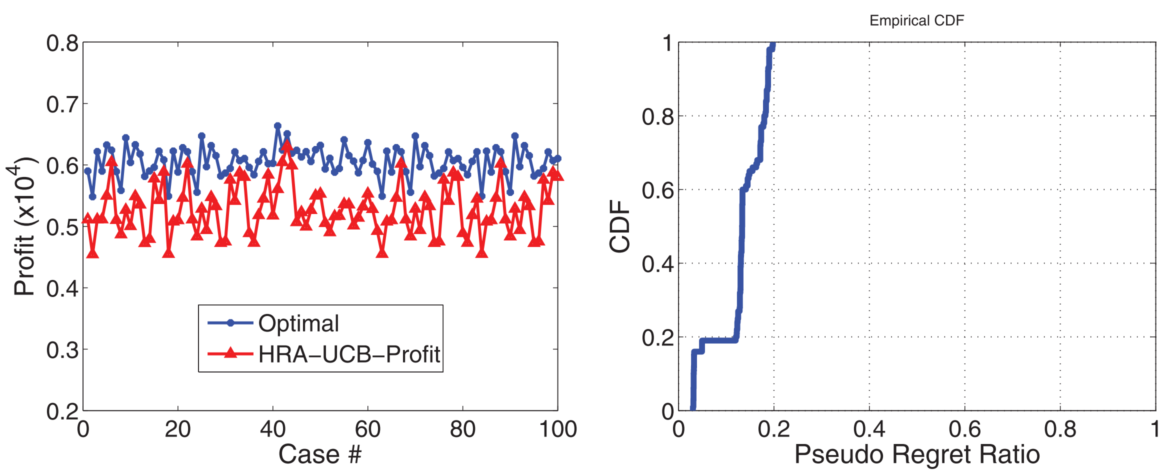
The evaluation of *HRA-Utility* is shown in Fig. 8. Social utility under *HRA-Utility* increases by up to 47% compared with that under *User Choice*, while the profit of *HRA-Utility* and *User Choice* is quite close. Both *HRA-Utility* and *User Choice* significantly increase the profit and social utility compared with that when only cellular resources are utilized.

Combining our motivations and experimental results, the gained insights are mainly divided into three aspects. First, in addition to alleviating network congestion, offloading can further optimize different economic targets with an appropriate economic framework. Secondly, the willingness of users is a non-negligible factor in the market's resource allocation. And encouraging users to participate honestly in resource allocation can help the operator achieve approximate theoretical optimality. In the end, the effectiveness of individual user decisions is limited, and it is necessary to cooperate with the operator, who has the access to the global network information. In summary, the improvement of



(a) The Social Utility (b) The Operator's Profit

Fig. 8. Comparison of *HRA-Utility* with Benchmarks.



(a) Profit (b) Pseudo Regret Ratio

Fig. 9. Performance of *HRA-UCB-Profit*.

economic targets in the market require participants (i.e., the MNO and users) to optimize together.

2) Mechanisms with Incomplete Information: According to Definition 7, 100 SMAB problems are selected randomly from all the SMAB problems within the 40 valid cells for evaluation. We consider a 1000-day duration when evaluating the performance of *HRA-UCB-Profit* and *HRA-UCB-Utility*. It is assumed that the data consumption volumes of all users within the coverage of each cell follow normal distribution.

Fig. 9 illustrates the performance of mechanism *HRA-UCB-Profit*. We can see from Fig. 9(a) that the profit gained by *HRA-UCB-Profit* are close to that gained by the optimal choice. Fig. 9(b) indicates that the pseudo regret ratios (the ratio between pseudo regret and the optimal profit) are under about 20%. Similarly, Fig. 10 shows the performance of *HRA-UCB-Utility* according to the pseudo regret, i.e., the difference between the utility gained by the optimal choice and that gained by *HRA-UCB-Utility*. The pseudo regret ratios are within the range of around 2% ∼ 14%.

6. Implementation issues

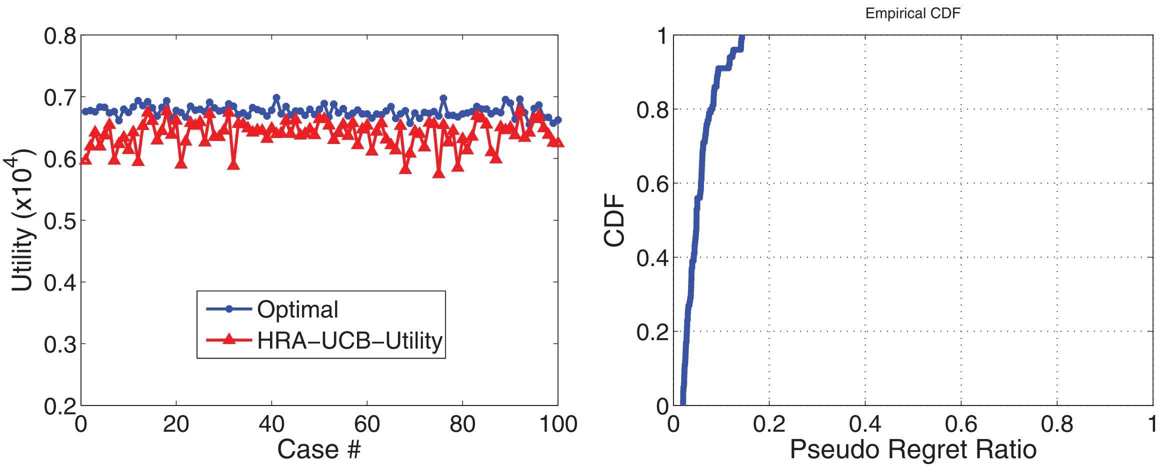
In this section, we discuss the implementation issues of the proposed framework from multiple perspectives, which may provide some useful suggestions for framework deployment.

1) Controller: The controller involves three function modules: *i*) *Information module* obtains cellular load information from the Base Station Controller (BSC), user's available networks from BSs and APs, user's bids from APs, and *etc.; ii*) *Computation module* implements the auction mechanism and the **WiFi Pricing** algorithm; *iii*) *Scheduler* controls the pace of dynamic resource allocation decisions, which is based on the cellular load information and the configuration of MNOs.

Existing protocols, like ANDSF [26], provide network discovery and selection functions based on the network status information. Therefore, the logical controllers for the mechanism in this work can be built on and supplement these protocols considering users' valuations.

The two types of heterogeneous networks and the deployment of Offloading Controllers (OCs) are illustrated in Fig. 11. The OC and Access Point Controller (APC) are deployed on the switch of the WiFi network. OC is connected with the serving gateway (MME/S-GW) to dynamically receive cellular network information and user bids. OC consists of information processing function module and resource allocation decision-maker, which are shown in Fig. 3. APC is connected with APs to receive the WiFi connection states of users and send certification signals based on offloading decisions.

The interaction between OC and APC can be illustrated via the bilateral information flows. OC informs APC the auction results, according to which APC will send certification signals to APs. And APC pro-



(a) Utility (b) Pseudo Regret Ratio

Fig. 10. Performance of *HRA-UCB-Utility*.

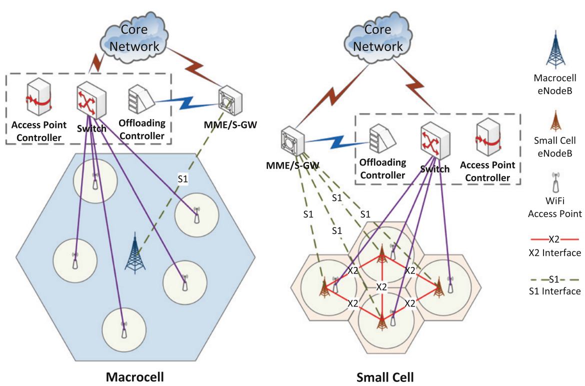


Fig. 11. Controller Deployment in Macrocell and Small Cell.

vides OC with user connection information for the next-round auction process.

2) User-side Management: With the wide spread of intelligent mobile devices, application-level solution (*e.g.*, mobile application) becomes a feasible way to achieve user-side management. MNOs like AT&T have already developed applications with smart WiFi management functions. These applications should allow users to set configuration information and customize conditional options, *e.g.*, automatically tuning their bids according to different battery levels, and making application-level connection constraints.

3) User Experience: The handoffs among different networks are assumed to be transparent because they are beyond the scope of this paper. In reality, the handoffs will affect user experience due to handoff delays, disconnections and so on. But these problems will be relieved with the development of carrier-grade WiFi and seamless handoffs.

7. Related work

To solve the conflicts between the shortage of cellular resources and the increasing mobile data demands, both industry and academia have proposed various solutions.

Temporal Dynamics: From operator's perspective, cellular traffic obeys obvious diurnal and weekly patterns [24,25], allowing researchers to propose dynamic time-dependent pricing strategies [4,5,25,52], which encourage users to shift their delay-tolerant demands during peak hours to off-peak periods. With time-dependent pricing, operator's service capacity remains unchanged, while the carrier WiFi is not fully utilized, which actually leads to a waste of resources.

From user's perspective, unlike the proposed HRA framework in this paper, information about user's delay-tolerance is involved in the resource allocation in some work [22,53], which imposes extra decision cost on users.

Third-party Resources: Many researchers have studied cellular data offloading utilizing third-party WiFi from economic or quantitative perspectives [16,19]. Zhuo et al. [54] study a coupon-based incentive mechanism to encourage delay-tolerant users to offload their traffic demand. However, the offloaded traffic amount is assumed to be predetermined, without considering the dynamic load of cellular networks. J. Lee et al. [22] study the economic benefits of operators and users brought by delayed data offloading based on a two-stage sequential game. Lu et al. [8] propose a bid framework that allows third-party sellers to submit imprecise valuations in offloading. Apostolaras et al. [2] design a new mechanism for offloading to wireless mesh networks, which can significant save power consumption. Yu et al. [11] give out a detailed discussion of various economic challenges and benefits for data offloading.

However, this type of method transfers user demands on MNOs to third-party WiFi or other users, rather than improves the operator's service capacity. Actually, most literatures study the supplies and demands between MNOs and third-party resource owners, without considering dynamic demands of users. In our work, we do not care about how MNOs get third-party resources. Both the resources of MNOs and that of third-party are regarded as the resources of MNOs, with the assumption that MNOs have succeed in getting third-party resources. In other words, the WiFi resources in this paper refers only to the MNOs' own resources, i.e., carrier WiFi resources. What we really care about is the relationship between MONs and mobile users, enabling MNOs to achieve offloading with considering users' valuations on resources.

HetNet and Carrier WiFi: HetNet is a promising way to enlarge serving capacity and improve mobile communication performance by making full use of heterogeneous network infrastructures, such as WiFi [53]. For example, due to the numerous benefits (*e.g.*, enhancing throughput and improving coverage) brought by small cells, heterogeneous small cells (*e.g.*, femtocell and carrier WiFi) have achieve massive deployments, raising excessive energy consumption issues. To provide possible solutions, Wu et al. [55] design the green-oriented traffic offloading with small cells, which exploits multiple advanced energy technologies and clarifies valuable challenges. Moreover, the related studies on heterogeneous resource allocation can be divided into the technical perspective [10] and the economic perspective [56,57]. For example, Zhou et al. for the first time consider different queuing models to distinguish the characteristics of licensed and unlicensed bands, which is from a technical optimization perspective, while the proposed framework in this paper investigates heterogeneous resource allocation from the perspective of economic optimization. Joe-Wong et al. [56] study user's adoption behaviors for supplementary wireless technologies. In contrast, we study the operator-dominant integrated resource utilization, which can avoid anarchy brought by user's selfishness and lack of information.

Communication industries like Cisco and Ericsson have provided solutions for involving carrier WiFi to enlarge mobile service capacities [58,59]. However, they only consider technical issues. Poularakis et al. [60] analyze whether carrier WiFi can help reduce the costs of MNO. But the differentiated QoS and various users' valuations are not captured. To capture the differentiated QoS and various users' valuations, economic issues like pricing should also be considered.

Auction-based Pricing: Pricing mechanisms are preferred to deal with the allocation of scarce resources. For example, Zhou et al. [13] develop a pricing-based stable matching algorithm to match users with resources, effectively improving the transmission rate. But it emphasizes the allocation of resources and cannot stimulate the increase of resource value in the context of scarce resources. Compared with other pricing mechanisms, auctions can better utilize users valuations on resources to increase profit and social utility [61,62]. Thus, auctions are widely used in the studies of resource allocation in wireless communications [19,63–66]. To deal with the complicated process of auction, we design a simple and feasible bidding manner for mobile communication circumstances, which could satisfy delay requirements.

8. Conclusion

In this paper, we propose a novel bid-based operator-dominant offloading framework for the dynamic allocation of MNO's heterogeneous wireless resources. The HRA framework not only enables operators to efficiently utilize both cellular and carrier WiFi simultaneously, but also encourages users to reveal their valuations on resources through auctions, without increasing users' decision cost. Thus, the operator-dominant offloading can avoid anarchy brought by users selfishness and lack of information. In detail, two auction mechanisms, *HRA-Profit* and *HRA-Utility*, are designed to achieve the maximal profit and social utility, respectively. Both of them have been proven to be truthful and satisfy individual rationality, while the trace-based simulations and evaluations have proven their efficiency. To enable the newly proposed framework to be applied to more complex scenarios with incomplete information, *HRA-UCB-Profit* and *HRA-UCB-Utility* are proposed to optimize operator profit and social utility. In addition, the proposed allocation framework can also be applied to other scenarios where two types of limited heterogeneous resources (substitutes) are required to be allocated among requesters.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Yi Zhao: Writing - original draft, Data curation, Software, Methodology, Conceptualization. **Ke Xu:** Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Yifeng Zhong:** Conceptualization, Methodology, Software. **Xiang-Yang Li:** Conceptualization, Writing - review & editing. **Ning Wang:** Conceptualization, Writing - review & editing. **Hui Su:** Writing - review & editing. **Meng Shen:** Writing - review & editing. **Ziwei Li:** Writing - review & editing.

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Appendix A

Proof of Theorem 1. If U_i fails to change the result set of winners by telling a lie, the WiFi price and U_i's surplus will not change either according to Algorithm 1. So we discuss the circumstances where the auction result on U_i is affected by his/her lies. The effect can be divided into two categories, from winner to loser and from loser to winner.

(1) If U_i becomes a loser from a winner because of lying, we first derive the surplus when U_i tells the truth according to $\widetilde{p}^z \le b_i^z \cdot \widehat{p}_i$ (from Algorithm 1) and Eq. (6), shown as Eq. (30).

$$\begin{aligned} s^z_{i(truth)} &= {\varphi'}^z_i|_{\delta^z_i=0} - \widetilde{p}^z \ge \varphi^z_i|_{\delta^z_i=0} - b^z_i \cdot \widehat{p}_i \\ &= \varphi^z_i|_{\delta^z_i=0} - (\widehat{p}_i + \varphi^z_i|_{\delta^z_i=0} - \varphi^z_i|_{\delta^z_i=1}) = \varphi^z_i|_{\delta^z_i=1} - \widehat{p}_i \end{aligned} \tag{30}$$

The surplus of U_i when he/she lies is Eq. (31).

$$s^z_{i(lie)} = {\varphi'}^z_i|_{\delta^z_i=1} - \widehat{p}_i = \varphi^z_i|_{\delta^z_i=1} \cdot (\min\{\widehat{p}_i, 1\})^\alpha - \widehat{p}_i \tag{31}$$

Then according to Eq. (30) and Eq. (31), we have

$$s^z_{i(truth)} - s^z_{i(lie)} \ge \varphi^z_i|_{\delta^z_i=1} \cdot \left[1 - \left(\min\left\{\frac{\widehat{C}_j}{\widehat{L}^z_{j(lie)}}, 1\right\}\right)^\alpha\right] \ge 0$$

(2) Assume U_i becomes a winner from a loser by lying, then $\widetilde{p}^z_{(lie)} = \widetilde{p}^z_{(truth)}$ if no one loses the auction due to U_i's lies and $\widetilde{p}^z_{(lie)} \ge \widetilde{p}^z_{(truth)}$ otherwise. According to the fact that U_i will lose if he/she tell the truth, we know $\widetilde{p}^z_{(truth)} \ge b^z_i \cdot \widehat{p}_i$. In conclusion, we can derive that $\widetilde{p}^z_{(lie)} \ge b^z_i \cdot \widehat{p}_i$, which means U_i will gain a negative surplus by lying.

Overall, users will gain an equal or higher surplus by telling the truth rather than lying, i.e., submitting the truthful bid is a weakly dominant strategy. □

Proof of Theorem 2. The users may win or lose when participating the auction. Therefore, we discuss their surplus variation in these two situations.

(1) If U_i loses the auction, the change in his/her surplus is denoted by Eq. (32).

$$\Delta s^z_i = {\varphi'}^z_i|^{(after)}_{\delta^z_i=1} - \widehat{p}_i - ({\varphi'}^z_i|^{(before)}_{\delta^z_i=1} - \widehat{p}_i) = {\varphi'}^z_i|^{(after)}_{\delta^z_i=1} - {\varphi'}^z_i|^{(before)}_{\delta^z_i=1} \tag{32}$$

It is obvious that $\widehat{L}^z_{j(after)} \le \widehat{L}^z_{j(before)}$ because some users may be offloaded to WiFi. Then according to Eq. (2), we have ${\varphi'}^z_i|^{(after)}_{\delta^z_i=1} \ge {\varphi'}^z_i|^{(before)}_{\delta^z_i=1}$, and $\Delta s^z_i \ge 0$.

(2) If U_i wins the auction, then he/she will be offloaded to WiFi.

$$\begin{aligned} \Delta s^z_i &= {\varphi'}^z_i|^{(after)}_{\delta^z_i=0} - \widetilde{p}^z - \left({\varphi'}^z_i|^{(before)}_{\delta^z_i=1} - \widehat{p}_i\right) \\ &= {\varphi'}^z_i|^{(after)}_{\delta^z_i=0} - {\varphi'}^z_i|^{(before)}_{\delta^z_i=1} - (\widetilde{p}^z - \widehat{p}_i) \end{aligned} \tag{33}$$

From Algorithm 1 and Theorem 1, we know that the WiFi price $\widetilde{p}^z \le b^z_i \cdot \widehat{p}_i$. Therefore,

$$\Delta s^z_i \ge {\varphi'}^z_i|^{(after)}_{\delta^z_i=0} - {\varphi'}^z_i|^{(before)}_{\delta^z_i=1} - \widehat{p}_i \cdot (b^z_i - 1) \tag{34}$$

Combined with Eq. (2) and Eq. (6), we have

$$\Delta s_i^z \geq \varphi'^z_i|^{(after)}_{\delta_i^z=0} - \varphi'^z_i|^{(before)}_{\delta_i^z=1} - \left(\varphi_i^z|_{\delta_i^z=0} - \varphi_i^z|_{\delta_i^z=1}\right)$$
$$= \varphi'^z_i|^{(after)}_{\delta_i^z=0} - \varphi_i^z|_{\delta_i^z=0} + \left(\varphi_i^z|_{\delta_i^z=1} - \varphi'^z_i|^{(before)}_{\delta_i^z=1}\right)$$
$$= \varphi'^z_i|^{(after)}_{\delta_i^z=0} - \varphi_i^z|_{\delta_i^z=0} + \varphi_i^z|_{\delta_i^z=1} \cdot [1 - (\min\{\hat{p}_i, 1\})^\alpha]$$
$$\geq \varphi'^z_i|^{(after)}_{\delta_i^z=0} - \varphi_i^z|_{\delta_i^z=0}$$

Algorithm 3 avoids congestions in WiFi networks, so $\varphi'^z_i|^{(after)}_{\delta_i^z=0} = \varphi_i^z|_{\delta_i^z=0}$. Therefore, $\Delta s_i^z \geq 0$. □

Proof of Theorem 3. Assume that π^{*z} is achieved when $\Delta L = \Delta L^* \in [0, \hat{L}_j^z]$. The actual profit π^z is satisfied when $\Delta L = \sum_{i=1}^{N_W^z} \bar{v}_i^x$ ($N_W^z \in \{1, 2, \ldots, N^{j,z}\}$). Note that $\hat{L}_j^z = \sum_{i=1}^{N^{j,z}} \bar{v}_i^z$. From Algorithm 3, we know that

(1) If $\sum_{i=1}^{N_W^z} \bar{v}_i^z < \Delta L^* < \sum_{i=1}^{N_W^z+1} \bar{v}_i^z$ ($N_W^z < N^{j,z}$),

$$\pi^{*z} - \pi^z = \int_{\sum_{i=1}^{N_W^z} \bar{v}_i^z}^{\Delta L^*} \frac{\partial \pi(\hat{L}_j^z, \Delta L)}{\partial \Delta L} \mathbf{d}\Delta L$$
$$< |\frac{\partial \pi(\hat{L}_j^z, \Delta L)}{\partial \Delta L}|_{\max} \cdot \bar{v}^z_{N_W^z+1} < |\frac{\partial \pi(\hat{L}_j^z, \Delta L)}{\partial \Delta L}|_{\max} \cdot V$$

(2) If $\sum_{i=1}^{N_W^z} \bar{v}_i^z \geq \Delta L^*$,

$$\pi^{*z} - \pi^z = -\int_{\Delta L^*}^{\sum_{i=1}^{N_W^z} \bar{v}_i^z} \frac{\partial \pi(\hat{L}_j^z, \Delta L)}{\partial \Delta L} \mathbf{d}\Delta L$$
$$< |\frac{\partial \pi(L_j^z, \Delta L)}{\partial \Delta L}|_{\max} \cdot \bar{v}^z_{N_W^z} < |\frac{\partial \pi(\hat{L}_j^z, \Delta L)}{\partial \Delta L}|_{\max} \cdot V \quad \square$$

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