

On Contract Design for Incentivizing Users in Cooperative Content Delivery With Adverse Selection

Bidushi Barua, Marja Matinmikko-Blue, Yanru Zhang, Alhussein A. Abouzeid, and Matti Latva-aho

Abstract—Cooperative content delivery using multiple air interfaces (CCDMI) is a powerful solution to mitigate congestion in cellular networks. In CCDMI, the operator distributes content to selected users that further distribute it locally among its nearby users. However, a user that is capable of contributing to CCDMI might act selfishly and refuse to participate. Although the operator can encourage user participation by offering incentives, it has incomplete information about users' willingness to participate. In order to overcome this problem of adverse selection in CCDMI, we propose two contract-based methods under information asymmetry. In both methods, the operator designs a performance based contract set for the users that are capable of local content distribution. Using mathematical analysis, we show that the optimal contract under information asymmetry achieves close to optimal utility for the users and the operator, compared to the information symmetry case. Moreover, the users with high willingness to participate get positive utility and the users with low willingness get zero utility. Hence, by assigning contracts, the operator can motivate user participation, despite the information asymmetry between them. Our results verify that the proposed methods improve the system performance in terms of the utility of the operator and the users.

Index Terms—Adverse selection, cooperative content delivery, contract theory, game theory, incentive mechanism, cellular networks, WLAN.

I. INTRODUCTION

Over the last decade the surge in new smart device users and the high demand services they consume has led to a phenomenal growth in mobile data traffic, which is expected to continue. To address this challenge, the wireless industry is preparing for a long term 1000 times more data traffic in cellular networks through the development of 5G networks [1].

In the current cellular networks, the default method of acquiring access to the desired content is through independent downloading of the content by every user through their own cellular links. This can lead to cellular traffic congestion in scenarios where many users are in close proximity of one another, and they demand rich content. Moreover, when many users demand the same rich content the cellular congestion problem can worsen. Although alternative technologies such as Long-Term Evolution (LTE) Broadcast with Evolved Multimedia Broadcast Multicast Services (eMBMS) [2] is efficient

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in delivering the same content to multiple users through multicasting, the absence of feedback and the limitation in performance, due to the worst performing link among all links between the Base Station (BS) and users [3], restricts its applicability. Moreover, many application scenarios include both synchronous and asynchronous content delivery to a group of users. As a result, the synchronous technology of eMBMS is only applicable to a subset of all such possible scenarios.

Another approach of efficient content delivery in wireless networks is to utilize complementary and revolutionary networking techniques to deliver mobile data that were originally planned for transmissions over cellular networks [4]. These content delivery techniques are helpful in addressing the challenges of increased mobile data traffic in the future wireless networks and so they are called mobile/data offloading techniques. These techniques can be classified into three types, based on (a) offloading through small cell networks (SCNs), (b) offloading through WiFi networks, and (c) offloading through devices [5]–[7]. In the work [5], offloading benefits resulting from femto-cell deployments were investigated and the joint macro-femto-cell mobile network was shown to have potential offloading gains. However, since the femto-cells utilize the same spectrum as the cellular network, interference management becomes a critical issue in these networks [8]. More advanced technologies such as LTE-U (LTE-Advanced in the unlicensed band) [6] offers operators a way to offload traffic onto the unlicensed spectrum which involves leveraging the small cells and aggregating unlicensed spectrum with the licensed spectrum for LTE-Advanced.

WiFi offloading can be considered to be another promising solution to utilize the various benefits of cellular and WiFi networks, given the fact that WiFi access points (APs) are currently widely deployed by operators and residents [7]. However, issues such as the possibility of cellular/WiFi network congestion [9], limited coverage and constrained mobility within the cell, need to be addressed in these networks.

Smart devices although are content hungry, these devices have exhibited advanced features, such as support for large memory space, increasing processing capabilities, and also support for using multiple interfaces. This makes it possible to deploy a device based network such as a device-to-device (D2D) network that relies on direct communication between smart devices without any need for an infrastructure backbone for cellular offloading [10]. However, critical issues such as neighbor discovery, transmission scheduling, resource allocation and interference management still need to be considered for the effective integration of D2D in future cellular architectures. An alternative device based approach

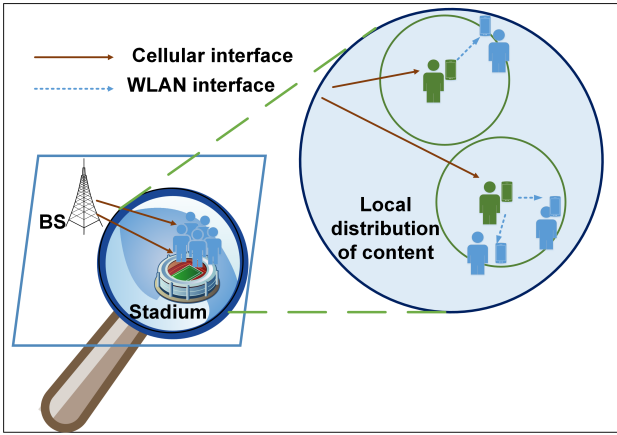


Fig. 1: CCDMI for distributing common rich content in high traffic demand areas, for e.g., in a stadium.

is the method of cooperative content delivery using multiple interfaces (CCDMI) that offers a powerful solution to overcome several limitations of the traditional use of a single wireless interface on a smart device for the purpose of content downloading. For instance, the works in [11]–[13], have shown that the available multiple interfaces on smart devices can be utilized locally to disseminate data content among a group of users, thereby reducing congestion in cellular networks (as illustrated in Fig. 1).

In our previous work [3], we proposed a method of CCDMI in which the users with smart devices cooperatively participated to deliver content to a group of users using cellular and WLAN interfaces. On the basis of cellular and WLAN links of the users, the BS selected a subset of users, called *selected* users, who were given the content directly via cellular connection. The proposed method incurred little overhead as the information it utilizes for user selection already exists in the network. We use the same method of CCDMI in our current work and throughout the rest of the paper, we refer to these selected potential relay users as *relay* users. Thereafter, the relay users distributed the content to other users within their vicinity using their WLAN interfaces. Such a selection of users by the operator made the process of CCDMI efficient in terms of radio resource consumption and energy savings.

Once the BS chooses the relay users for CCDMI, every relay user is assumed to be willing to participate in CCDMI. However, this is not always true, since the users might suffer significant costs in terms of battery consumption, mobile data usage, effort etc. [14], [15] for participation in CCDMI. An independent relay user therefore, might act selfishly and refuse to participate to maximize its own benefit. A similar instance of user selfishness was also evident in [16], where the authors considered offloading social data traffic through a delay tolerant network of D2D devices. This kind of selfish behavior creates the challenge of insufficient participation of users in CCDMI which necessitates the introduction of an incentive mechanism design. Incentives are rewards the operator can offer the mobile users in return for participating in CCDMI. Among different incentive mechanisms for inducing cooperation that have been studied in the literature, the most common mechanisms are the ones based on auctions [17], [18] and games [19]. Although auction methods guarantee system

efficiency and truthfulness of the users, they are not suitable for tasks where massive participation is required to achieve the desired geographical coverage. Stackelberg game is an alternative incentive mechanism that can be used to encourage entities to offload cellular traffic [19] and this method is ideal to model perfect information games.

In this paper, we assume that the operator does not have the exact information about the relay user's preferences/willingness to participate. As a consequence, there arises the possibility of an unwilling relay user to dishonestly report its preferences to be high instead of low to the operator in order to reap incentives. This can be detrimental to the process of CCDMI, where the operator would not be able to offer the right incentives to the relay users according to their preferences. Thus, the operator would face the adverse selection problem¹ in CCDMI. In the adverse selection problem (e.g. see [20]), the principal, which here is the operator, is not informed about a certain characteristic of the agent, which here is the device/user/relay, at the time when the contract is designed. The adverse selection problem in CCDMI would further encourage relay users to be dishonest about their preferences, leading to a reduction in the network payoff. Therefore, to avoid such an undesirable situation, we use the tools of contract theory that provides effective tools to provide incentives under adverse selection [21], [22]. This leads to the design of contract-based incentive mechanisms that reveals the true preferences of relay users and rewards relay users who are willing to participate. The main contributions of this paper are:

- Firstly, we utilize the framework of normal form games to model the interactions between the BS and a relay user, as a *one stage game*. We show that the dominant strategy of the relay user is to act selfishly and to refuse participation in CCDMI, that causes the BS utility and the utility of other users to suffer loss.
- We address the adverse selection problem in CCDMI, and propose two novel *contract-based incentive methods* that motivates the relay users to reveal their true preferences. As a result, the operator can incentivize these users in accordance with their preferences, that will maximize its own and the overall network's utility. The two proposed methods are (a) Multiple-User Single-Contract (MUSC) method and (b) Multiple-User Multiple-Contract (MUMC) method and they are designed for different application scenarios depending on the nature of incentives demanded by a relay user that prefers to participate in CCDMI.
- We compare each proposed method with a benchmark adverse selection-free method and using numerical evaluations and simulation results, show that the optimal contracts obtained using the proposed method under adverse selection, achieve close performance to optimal contracts

¹This is similar to adverse selection in health insurance [20] where the type of the patient (healthy versus unhealthy) is hidden from the service provider. One type of insurance that is designed for average customer might be too expensive for healthy patients and too cheap to cover the costs for unhealthy patients on average. The insurance company in this scenario does not know the health of the customer, so it is subject to *adverse* selection by the more informed customer.

which are adverse selection-free.

- Finally, using simulation results, we show the impact of different parameters of the contract on the utility of the relay user and the BS, and compare the performance of the two proposed methods in terms of the utility of the relay user with an increase in number of users the relay user serves through WLAN.

The rest of the paper is structured as follows. We review the related work in Section II. In Section III we present the system setup. Section IV presents the mathematical formulation of the adverse selection problem in CCDMI which is followed by a game theoretic model that studies the interactions between the BS and a user capable of distributing content to other users locally. Then the proposed method of offering contracts under adverse selection in CCDMI is described in Section V, and the simulation results are described in Section VI. Finally, Section VII draws conclusions and outlines possible avenues for future work.

II. RELATED WORK

In heterogenous cooperative wireless networks, the proper design of incentive mechanisms is crucial in order to motivate users to participate in collaborations such as for offloading traffic. Broadly speaking, the different forms of incentives that can be used to encourage users in a network to cooperate can be classified as (a) monetary [1], [23] and (b) non-monetary incentives [24], [25] which we review next.

A. Monetary Incentives

Monetary incentives refer to rewards in the form of money which the operator/service provider or the platform directly pays to the users for their successful contribution in completing a task. The monetary incentive mechanisms in mobile networks, studied in the literature, are mostly based on reverse auctions. In the content delivery method proposed in [18], edge nodes are incentivized using a reverse auction model to encourage cooperation in providing caching services. Based on the interaction between mobile users and edge nodes, candidates of edge node are selected by the users to cache content with the bid containing the caching price and the caching size. Although auction methods are simple, risk-free of bid non-fulfilment and oblivious to truthfulness, the main drawback of these methods is that they are not suitable for tasks where massive participation is required to achieve a required geographic coverage. In those cases, lottery or Tullock contest [26] can be a good alternative monetary incentive mechanism where the winner is determined by a winning probability, therefore, every user has a chance to win.

Game-theoretic model can be used to design an incentive mechanism to encourage different entities to offload cellular traffic. In [19] a two-stage non-cooperative Stackelberg game theory is applied for a data offloading scheme to determine the optimal amount of monetary incentives a macro-cell should offer to small-cells. Offering of contract is another effective tool used to provide monetary incentives when the provider has limited information of the users valuation of the resources [21], [27]. In [21], the authors proposed a quality-price contract for

spectrum trading in a monopoly spectrum market. The work in [27] proposed a contract-based incentive mechanism in a cognitive radio (CR) network where the primary users are provided with payments to share their spectrum and suffer some degradation in performance. On the other hand, unlike contracts, the incentive method of pricing can be used when the service provider has knowledge about the value of the resource that is being allocated to the users. In the pricing framework proposed in [28], each cellular data flow corresponding to a mobile source-destination pair offers payment to incentivize APs to participate in offloading, and then payment is shared in proportion to the amount of data offloaded to each AP.

B. Non-monetary Incentives

The non-monetary incentives can be classified as (a) performance-based incentives, e.g., capacity, cost, and rate, (b) ranking incentives, e.g., trust and reputation, and (c) contract-based incentives. Improved capacity or throughput per user for the mobile user is the most basic performance-based incentive to meet the explosion of data traffic. In [29], the authors discuss a network assisted WLAN offloading model to maximize per user throughput in a heterogenous network. Another performance-based incentive is cost minimization in cellular networks. In [30], the authors propose a novel mobile tethering based cooperative network system where tethering markets are opened and cellular traffic is traded in order to minimize the overall cellular traffic cost of the system. The rate in the form of the average completion time of demanded data transmissions, can be a significant performance parameter too, in order to incentivize users. For instance, in [31], the authors proposed a method to find optimum fraction of traffic to be offloaded for maximizing probability that a randomly located user has a rate greater than arbitrary threshold.

Trust and reputation system is another non-monetary incentive method where trust refers to local and subjective measure of the relationship between two persons/agents, and can be derived from direct or indirect past interactions whereas, reputation is a global and a rather objective measure by aggregating all other people's trust with respect to a certain person [32]. This mechanism is more sustainable than monetary incentive mechanisms due to the lack of financial burden and the long-term social influence. In [24], [33], the authors propose an inference system to determine the trust of contribution, given quality of the contributed data and the trust of participant. The consequent reputation of the participant determines the reward of the participant user, that incentivizes the user to contribute more and improve the quality of its contribution.

The tool of contracts discussed before for providing monetary incentives, has also proven to be successful in providing non-monetary incentives to users in order to encourage them to participate in cooperation under conditions of information asymmetry [22], [34], [35]. In [34], the authors proposed a contract-based cooperative spectrum sharing mechanism under different information cases. The two main problems that arises due to information asymmetry are, (a) adverse selection, where the users have certain information hidden

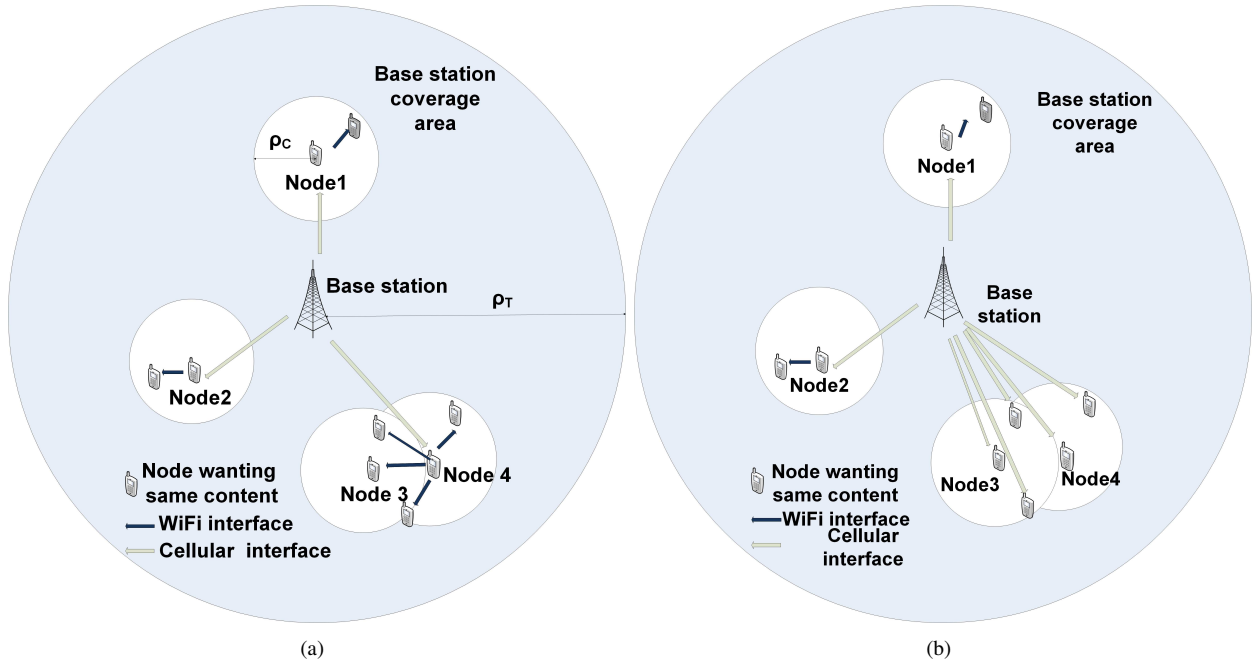


Fig. 2: An example scenario of the task of CCDMI with $N_c = 3$; (a) all capable users are of high preference type, (b) all capable users except node 4 are of high preference type.

from the operator and (b) moral hazard [36], [37], where the user can exert some hidden effort which will also have an impact on the performance of the operator. In [22], the authors propose an contract-based incentive method to encourage users to participate in device-to-device (D2D) mechanism under adverse selection. The BS offers users with free data as non-monetary incentives in return for rate offered due to the users participation in D2D. In [35], the authors propose a contract-based incentive method for an adverse selection situation in a relay-assisted cooperative communication between a source node and a destination node. By using this method, the source can provide incentives to the relay nodes to reveal the relay's channel conditions with the destination node. In this paper, we address the adverse selection problem in CCDMI and propose methods of designing contracts to overcome the limitation of information asymmetry between the operator and the set of relay users.

III. SYSTEM MODEL

In this section, we describe the system model in order to formulate the problem of adverse selection that arises during the process of distributing content to a group of users at the vicinity of each other using the method of CCDMI. Consider a generic circular cell of radius ρ_T in which a BS is located at the cell center, as illustrated in Fig. 2. There are n_c number of hotspot clusters of *users*² located in the cell of interest where $\rho_C (< \rho_T)$ represents the radius of the hotspot cluster. Each cluster has n_i users. Let $\mathcal{N} = \{1, 2, 3, \dots, (n_c n_i)\}$ be the set of N users that are distributed in clusters around the BS. The number of users in an instant is modeled as a Poisson

distribution of mean λ .

From the set of N users interested in receiving the same content, the BS selects a subset N_c of users known as the relay users for distributing the content through CCDMI. This set of users is selected by the BS by employing *mobile crowdsourcing*. As a result of the crowdsourcing process, a user operates in one of the possible modes namely, the *relay*, the *recipient* or the *isolated* mode. The relay mode user receives the content from the BS via a cellular link and then potentially may distribute the same content via WLAN to other users within its vicinity. The recipient mode user receives the content via WLAN, from a relay user. The isolated mode user receives the content directly from the BS via a cellular link. The users that are in relay mode are assumed by the BS to be potentially good enough for distributing content to other users that are in close proximity through their WLAN interfaces and thus, we refer to these users as *capable* users. Such users usually have a good quality cellular link with the BS and good WLAN coverage with other users in its vicinity. However, a capable user may be willing or unwilling to participate, that also influences the BS's utility. We assume that a capable user is of *high (H) preference type* if it is willing to participate and it is of *low (L) preference type* if it is unwilling to participate. Thus, the set of preference types for the capable user $i \in \mathcal{N}_c$, is given by $\Theta_i = \{H, L\}$. Naturally, the capable users of high preference type are more preferred by the BS and will be promised a greater reward for participating.

We consider the problem of overcoming adverse selection in CCDMI where the BS needs to incentivize capable users of high preference type when the BS has incomplete information

²The term 'user' is used to represent 'node' and/or 'access point' interchangeably with relevance to the context

about the true preference types of the capable users. In order to overcome such a situation of information asymmetry between the BS and the set of capable users, we adopt the tools of contract theory [36] so that the BS can offer incentives to capable users of high preference type even when their preference types of users are not known to the BS with absolute certainty.

Fig. 2 provides an illustrative example showing the impact of the preference type of a capable user on the utility of the BS and the other users which the capable user can potentially serve. Four hot spot clusters of users (nodes/access points) are distributed across the cellular coverage area of the BS and each of these users is interested in receiving the same content. Through crowdsourcing, the BS selects users 1, 2 and 4 as capable users. In Fig. 2(a), the capable users 1, 2 and 4 are of high preference type. Hence, CCDMI is successfully implemented by the BS. However, a high preference type capable user consumes its own resources in order to distribute content to other users within its vicinity. Therefore, a capable user might be reluctant to participate in CCDMI and act instead as a low preference type user. In Fig. 2(b) the capable user 4 acts as a low preference type user and does not distribute the content to the other users in its vicinity. In this case, the BS has to distribute the content directly via cellular links to the other users. Therefore, user 4, by acting as a low preference type user, saves its own resources which it would have used in order to distribute content to other users via WLAN. On the other hand, due to user 4's unwillingness to participate, the BS and other users within its vicinity suffer and end up with lower utility values as compared to the case when all capable users are of high preference type. Moreover, since the BS does not have the complete information about the preference types of the capable users, the BS cannot incentivize the users according to their preference types. This leads to the adverse selection problem in CCDMI which occurs when one of the parties has some private information which is hidden from the other party. In this case, the BS is the uninformed party that is suffering from the adverse selection problem [36].

IV. MATHEMATICAL FORMULATION OF THE ADVERSE SELECTION PROBLEM IN CCDMI

In this section, we mathematically model the adverse selection problem [20] in CCDMI. Firstly, we define the utility functions of the BS and the capable users. Thereafter, we model the interactions between the BS and the capable users as a one-stage game.

A. BS's Utility Function

The objective of the BS is to maximize the number of carriers saved due to the participation of capable users in CCD. When a capable user participates in CCD and serves the users within its vicinity, the BS saves the cellular carriers which would have otherwise served those users. Therefore, the BS's utility is modelled as follows. The BS's utility is denoted by W and the number of users that a capable user i can potentially serve locally is denoted by T_i . Therefore, T_i is also the number of carriers saved if capable user i participated in CCD. P_i

denotes cost in terms of effort exerted by capable user i to serve the other users locally. For simplicity, it is assumed that

$$P_i = \begin{cases} 0, & \text{if capable user } i \text{ is of low preference type} \\ P, & \text{if capable user } i \text{ is of high preference type} \end{cases} \quad (1)$$

where P is a constant and $P > 0$. And b denotes the number of resource carriers the BS provides to capable users as incentives. Then the utility of the BS is defined as

$$W \triangleq \sum_{i \in \mathcal{N}_c} T_i P_i - b, \quad (2)$$

where the first term of (2) represents the BS's gain in terms of number of carriers saved due to CCD and the second term of (2) represents the BS's cost for offering carriers as incentives to the capable users who participate in CCD. Moreover, it is assumed that $\sum_{i \in \mathcal{N}_c} T_i P_i > b$.

B. User's Utility Function

A capable user's objective is to maximize the net benefit it receives due to participation in CCD. Therefore, a capable user's utility is modelled as follows. The utility function of the capable user i is denoted by U_i and, the general amount of resources allocated by the BS to the capable user i is R_i . $v(R_i)$ is a valuation function that depends on R_i . Let $R_i = \bar{R}_i + r_i$, where \bar{R}_i and r_i denote the basic amount of resources and the additional incentive resources the BS allocates to capable user i , respectively. If the resources allocated to user i is less than the basic resource \bar{R}_i which is required to serve user i successfully, the valuation function is equal to zero. If $r_i \geq 0$, then the valuation function $v(R_i)$ is modelled as an exponential function in order to represent the defining feature of diminishing marginal returns. The valuation function $v(R_i)$ is therefore, denoted as

$$v(R_i) = \begin{cases} 0, & \text{if } R_i < \bar{R}_i \\ 2 - \exp\{-(R_i - \bar{R}_i)\}, & \text{if } R_i \geq \bar{R}_i \end{cases} \quad (3)$$

Further, we denote c as the capable user's unit cost per effort exerted for providing the content to other user within its reach using its WLAN interface. For simplicity we assume that $c = 1$. Then we define the utility function of a capable user i as

$$U_i \triangleq v(R_i) - cP_i, \quad (4)$$

where the first term represents the amount of benefit the capable user i receives due to the amount of resources it is allocated by the BS, and the second term represents the loss it suffers in order to serve the other users, locally.

C. Adverse Selection in CCDMI as a One-stage Game

In this section, we model the interactions between the BS and a capable user, that can strategically choose between being of high and low preference types, as a one stage game. We show that a capable user's dominant strategy is to be of low preference type. This motivates the design of contracts in the next section, since the result here shows that the user chooses to be of low preference type even in the presence of incentives by the BS.

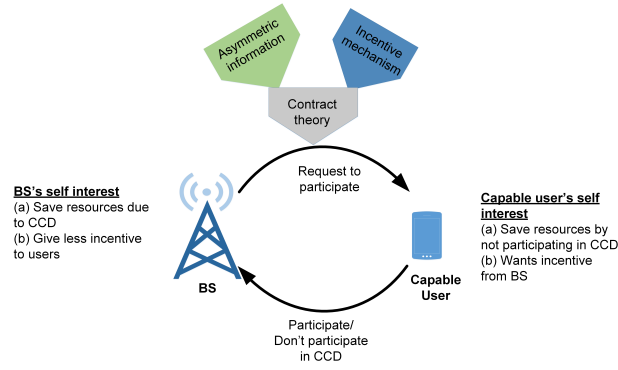


Fig. 3: Contract theory for adverse selection in CCDMI.

TABLE I: Payoff table for the one-stage adverse selection game. (Low Preference, Basic Service) is a unique Nash equilibrium.

User i \ BS	Basic	Basic with incentives
Low preference type	$v(\bar{R}_i),$ $\{T_i * 0 + \sum_{j \in \mathcal{N}_C, j \neq i} T_j * P\}$	$v(\bar{R}_i + r_i),$ $\{T_i * 0 + \sum_{j \in \mathcal{N}_C, j \neq i} T_j * P\} - b$
High preference type	$v(\bar{R}_i) - c * P,$ $\{T_i * P + \sum_{j \in \mathcal{N}_C, j \neq i} T_j * P\}$	$v(\bar{R}_i + r_i) - c * P,$ $\{T_i * P + \sum_{j \in \mathcal{N}_C, j \neq i} T_j * P\} - b$

We consider a capable user $i \in \mathcal{N}_C$ whose preference type is unknown to the BS. The BS therefore, has the choice of offering the capable user i a basic amount of resource (\bar{R}_i) or the basic amount of resources with some incentives ($\bar{R}_i + r_i$).

The payoff table for this one stage game is represented in Table I. A unique Nash equilibrium exists for this game: user i chooses to be of low preference type, and BS offers basic service. Therefore, the capable user i 's dominant strategy is to be of low preference type. From the utility definition of the BS from (2), however, it can be said that the BS cannot maximize its utility when a capable user is of low preference type. To overcome this problem, it is important for the BS to incentivize the capable user to be of high preference type by offering the right incentives. However, since the BS has incomplete information about the preference types of the capable users, this adverse selection problem can be resolved by offering contracts in such a way that the capable users are rewarded according to their preference types and the BS gets optimal utility. In the next section, we propose incentive methods based on contracts through which the BS can incentivize the capable users according to their preference types.

V. PROPOSED METHODS OF INCENTIVIZING CAPABLE USERS BY OFFERING CONTRACTS

In this section, we describe the utility functions for the BS and capable users, the feasibility conditions to define contracts for capable users, and finally define the optimization problem representing the optimal contract so that the adverse selection problem is overcome. Before designing the contract, we observe the main objectives of both the BS and every capable user (see Fig. 3). Firstly, the BS wants to maximize the outcome due to the participation of the capable users, and at the same time, minimize the rewards given to the capable users for their participation. On the other hand, a capable user wants to maximize the additional resources it obtains from the

BS as rewards, and minimize the cost required to distribute the content to other users through its WLAN interface. Both the BS and the capable users have conflicting objectives in this interaction. Therefore, both the BS and the capable users need to evaluate the trade-off between their costs and rewards. We propose a contract-based framework because it brings the BS and the capable users together and helps to resolve the conflict.

A. Contract Formulation

According to the *revelation principle* [36] in contract theory, to determine the optimal contracts under asymmetric information, it suffices to consider one *contract item* for each preference type, but it has to be ensured that a capable user of a certain preference type has incentive to select only the contract item that is designed for it. In our problem, a capable user can opt to be of high or low preference type. Thus, for designing a contract for capable users in CCDMI, it is enough to design a contract that consists of two contract items i.e., for high and low preference type of a capable user. For modelling the contract, we represent the preference type of a capable user by coefficient parameter θ_k . The values taken by θ_k where $k = \{H, L\}$ represent the extent to which a capable user is willing/not willing to participate in CCDMI. Without loss of generality, we assume that $\theta_L < \theta_H$. Since there are only two possible preference types, the BS needs to design contract items for high and low preference type users.

The BS determines the contract which specifies the relationship between the capable user's performance in terms of the effort for participating in CCDMI and the corresponding reward to be given to the capable user by the BS for that performance. Let P^H and P^L denote the costs suffered by a high and low preference type capable user, respectively, to participate in CCDMI, $\mathcal{P} \triangleq \{P^H, P^L\}$ and $P^H > P^L$. Let r^L and r^H represent extra resources that the capable user receives when it accepts the contract designed for low and high preference type users respectively and $\nabla \triangleq \{r^L, r^H\}$. Intuitively, a high preference type user should be rewarded more than a low preference type user. Moreover, the reward received by a capable user r is a strictly increasing function of P . Therefore, $r^L < r^H$. The set of contract items $\Phi = \{(P^k, r^k), \forall k = \{H, L\}\}$ is a contract set and fully defines the contract. Each such distinct cost-reward (P^k, r^k) pair association becomes a contract item. The contract

specifies a reward $r^k \in \nabla$ for every effort $P^k \in \mathcal{P}$. Once a contract is designed and offered, each capable user will choose the contract item that maximizes its payoff. As we now look at the problem of adverse selection using the concepts of contract theory, it is necessary to generalize the definitions of the BS utility and capable user's utility functions from the previous sections as defined next. We will discuss these new definitions of utility functions in the next section.

B. Utility Functions for Defining Contract in Adverse Selection

In this subsection, we model the adverse selection problem between the BS and the capable users as a principal-agent model in contract theory [36], and then define the utility functions of the BS and the capable users. We consider the BS as the risk neutral principal of an adverse selection problem, where the capable users act as the agents. A risk neutral entity is indifferent between the two options of taking risks to achieve an outcome and accepting a guaranteed outcome. On the other hand, we assume that a capable user is risk adverse agent which means that in the event of being exposed to an uncertainty, the agent attempts to reduce that uncertainty.

(1) BS's utility function with contract: The utility of the BS W_i due to a capable user i , $i \in \mathcal{N}_c$, of type k is defined as

$$W_i \triangleq T_i P^k - c r^k, \quad (5)$$

where r^k is the additional resource blocks which the capable user i is rewarded according to the contract provided the user's performance is P^k . Here, each capable user i chooses a contract item (P^k, r^k) that maximizes its utility, where $(P^k, r^k) \in \{(P^H, r^H), (P^L, r^L)\}$. The term c is the BS's unit cost of providing incentives to a capable user. Hence, the utility of the BS due to all the capable users, is given by

$$\sum_{i \in \mathcal{N}_c} W_i = \sum_{i \in \mathcal{N}_c} T_i P^k - c r^k. \quad (6)$$

(2) User's utility function with contract: In this case, a capable user tries to maximize rewards it receives in the form of resources allocated by the BS minus the cost of acting as a high/low preference type user. The utility of a capable user i , $i \in \mathcal{N}_c$, of type k is defined as

$$U_i^k \triangleq \theta_k v(r^k) - c P^k. \quad (7)$$

where $v(r^k)$ is a strictly increasing and concave function ($v(0) = 0, v'(r^k) > 0, v''(r^k) < 0$ for all r^k) which models capable users as risk-averse agents. The parameter θ_k represents the preference type of a capable user and this information is private to this user.

C. Feasibility Conditions for Contracts

In this subsection, we consider the necessary and sufficient conditions for a feasible contract [36] in order to solve the adverse selection problem that arises in CCDMI. We will then use these conditions to derive the optimal contracts in the next section. These conditions defined for the capable users, ensure that they are incentivized sufficiently to participate in CCDMI.

Definition 1. *Individual rationality constraint (IR-constraint): A contract item which a capable user accepts should guarantee a non-negative payoff, i.e.,*

$$\theta_k v(r^k) - P^k \geq 0, \quad k = H, L. \quad (8)$$

In CCDMI, if a capable user refuses the contract, it will still receive the content directly from the BS by default cellular method. In this case, the capable user is not allocated any reward by the BS and the capable user faces no expense because it does not participate in CCDMI. Then the utility of the capable user is called its *reservation utility* and its value is zero (by using (7)). Therefore, a capable user will accept a contract item only if its utility is at least equal to zero.

Definition 2. *Incentive compatibility constraint (IC-constraint): Each capable user must choose a contract item designed specifically for its own preference type, i.e.,*

$$\theta_k v(r^k) - P^k \geq \theta_k v(r^l) - P^l, \quad k, l = H, L, k \neq l. \quad (9)$$

We need to define this constraint to make sure that a capable user accepts the contract item according to its preference type, and thus to make the contract incentive compatible. This constraint ensures that a capable user of type k gets maximum utility by accepting the contract designed for a type k capable user. Therefore, by accepting the contract which maximizes its utility, the capable user is indirectly revealing its preference type. So the contract that satisfies this constraint can also be called a *self-revealing contract*. It is necessary to define this constraint for the contract, or else it is possible for example, that a capable user of low preference type would reap higher benefits by accepting the contract item designed for high preference type user. Next, we discuss the other conditions that are needed for contract feasibility.

Lemma V.1. *For any feasible contract $\Phi = \{(P^k, r^k), \forall k \in \{H, L\}\}$, $r^H > r^L$ if and only if $\theta_H > \theta_L$, and $r^H = r^L$ if and only if $\theta_H = \theta_L$.*

Proof: Firstly, we prove the sufficiency, i.e., if $\theta_H > \theta_L$, then $r^H > r^L$. We begin by assuming that $\theta_H > \theta_L$. Using the IC-constraint for high and low preference type capable users, we get

$$\begin{aligned} \theta_H v(r^H) - P^H &\geq \theta_H v(r^L) - P^L, & \text{(ICH)} \\ \theta_L v(r^L) - P^L &\geq \theta_L v(r^H) - P^H. & \text{(ICL)} \end{aligned} \quad (10)$$

Adding the inequalities of (10), we get

$$\begin{aligned} \theta_H v(r^H) + \theta_L v(r^L) &\geq \theta_H v(r^L) + \theta_L v(r^H) \\ \Rightarrow v(r^H)(\theta_H - \theta_L) &\geq v(r^L)(\theta_H - \theta_L). \end{aligned} \quad (11)$$

As $\theta_H > \theta_L$, hence $\theta_H - \theta_L \geq 0$. Dividing both sides of the inequality (11) by $\theta_H - \theta_L$, we have $v(r^H) > v(r^L)$. Since $v(r^k)$ is a strictly increasing function of r^k , we can conclude that $r^H > r^L$.

Next, we prove the necessity, i.e., if $r^H > r^L$, then $\theta_H > \theta_L$. We consider the inequalities of (10) and in the same way as

above, add these inequalities to get

$$\begin{aligned} \theta_H v(r^H) + \theta_L v(r^L) &\geq \theta_H v(r^L) + \theta_L v(r^H) \\ \Rightarrow \theta_H \{v(r^H) - v(r^L)\} &\geq \theta_L \{v(r^H) - v(r^L)\}. \end{aligned} \quad (12)$$

Since $r^H > r^L$ and $v(r^k)$ is a strictly increasing function of r^k , $v(r^H) > v(r^L)$ and $v(r^H) - v(r^L) > 0$. Dividing both sides of the inequality (12) by $v(r^H) - v(r^L)$, we get $\theta_H > \theta_L$. By using the same procedure, we can prove that $r^H = r^L$ if and only if $\theta_H = \theta_L$. ■

Lemma V.1 shows that if a capable user is of high preference type, then it should receive more incentives from the BS and vice versa. And if two capable users receive the same reward, then they are of the same preference type. From here, we can deduce the next condition for contract feasibility which is defined below.

Definition 3. *Monotonicity condition (M-condition): For any feasible contract $\Phi = \{(P^k, r^k), \forall k \in \{H, L\}\}$, the reward r^k follows $0 \leq r^L < r^H$.*

Monotonicity condition (M-condition) implies that capable users of high preference type get higher rewards. From this condition, we can have the following proposition.

Proposition V.2. *As r is a strictly increasing function of P , P satisfies the following condition intuitively $0 \leq P^L < P^H$.*

Proposition V.2 implies that incentive compatible contracts requires a high cost of participation from a capable user if it receives a high reward and vice versa.

Lemma V.3. *For any feasible contract $\Phi = \{(P^k, r^k), \forall k \in \{H, L\}\}$, the utility of a capable user of different preference types should satisfy $0 \leq U^L < U^H$*

Proof: Using Definition 3, Proposition V.2 and if $\theta_H > \theta_L$, we have

$$\begin{aligned} U^H = \theta_H v(r^H) - P^H &\geq \theta_H v(r^L) - P^L \quad (\text{IC}) \\ &> \theta_L v(r^L) - P^L = U^L. \end{aligned} \quad (13)$$

Therefore, $0 \leq U^L < U^H$ i.e., a capable user of high preference type gets higher utility than being of low preference type. In the next section we will use these constraints for finding optimal contracts for the adverse selection problem in CCDMI.

D. Optimal Contract Methods for Adverse Selection Problem in CCDMI

Next, we describe two different kinds of contract methods to incentivize capable users to participate in CCDMI. As the BS does not know about their exact preference type, it offers each capable user, contract items for both high and low preference type user. The capable user is assumed to accept the contract that would maximize its utility. The BS only knows the ex-ante probabilities of each capable user's type. The BS assumes that q_i^H is the probability that a capable user i is of preference type high and $(1 - q_i^H)$ is the probability that the capable user i is of preference type low. Next we define the two different kinds of optimal contract methods Multiple-User Single-Contract (MUSC) and Multiple-User Multiple-

Contract (MUMC) method based on the nature of demand of incentives by the high preference capable user. In the MUSC method, every high preference type capable user gets a common utility, irrespective of its contribution to the CCDMI saving of resources by serving other users. Hence, the MUSC method is particularly suited when a capable user cooperates for the overall welfare of the network and is satisfied with a common reward for its participation. On the other hand, the MUMC method is proposed to solve the adverse selection problem where a high preference type capable user enjoys utility that is proportional to the amount of CCDMI saving of resources it contributes. Thus, the MUMC method is used for those cases when the amount of incentives rewarded to a capable user justifies that user's amount of contribution to the process of CCDMI saving of resources.

1) *Multiple-User Single-Contract (MUSC) method:* We propose an incentive method of offering contracts, where we assume that irrespective of the amount of contribution of a capable user i in terms of the number of other users it can serve, T_i , the capable user is satisfied with a common reward that gives it an incentive to participate in CCDMI and result in the overall welfare of the BS and all capable users. Therefore, the optimal contract defined in this method results in a common contract set for all N_c capable users, irrespective of their T_i values. Since all capable users are provided with one common contract, this method is called the Multiple-User Single-Contract (MUSC) method. The advantage of this method lies in the fact that the optimal contract is obtained by solving a single optimization problem. It is clear that in this situation, the capable user i is not too selfish and greedy regarding the incentives and is not concerned about getting greater share of rewards in proportion to the amount of its contribution, T_i . Rather, the capable user is satisfied enough to cooperate and contribute to the overall welfare given any fixed amount of reward and for a reasonable cost of participation demanded of it from the BS.

The BS finds the optimal contract by solving the optimization problem given by

$$\begin{aligned} &\underset{P^k, r^k}{\text{maximize}} \sum_{i \in \mathcal{N}_c} q_i^H \{T_i P^H - c r^H\} + (1 - q_i^H) \{T_i P^L - c r^L\} \\ \text{subject to} \quad &\theta_k v(r^k) - P^k \geq 0, \quad k = H, L \quad (\text{IR}), \\ &\theta_k v(r^k) - P^k \geq \theta_k v(r^j) - P^j, \\ &\quad k, j = H, L, k \neq j \quad (\text{IC}), \\ &0 \leq r^L < r^H \quad (\text{M}). \end{aligned} \quad (14)$$

The IC constraint can be re-written as,

$$\theta_k (v(r^j) - v(r^k)) - (P^j - P^k) \leq 0 \quad (15)$$

It can be clearly observed that the convexity of the constraint cannot be clearly proved for all cases. Hence, this optimization problem defined by (14) is non-convex. In order to solve this problem, we firstly formulate a relaxed problem without the M-condition, by reducing the remaining constraints. The

relaxed problem with the M-condition becomes

$$\begin{aligned}
& \underset{P^k, r^k}{\text{maximize}} && \sum_{i \in \mathcal{N}_c} q_i^H \{T_i P^H - c r^H\} + (1 - q_i^H) \{T_i P^L - c r^L\} \\
& \text{subject to} && \theta_L v(r^L) - P^L = 0, \\
& && \theta_H v(r^H) - P^H = \theta_H v(r^L) - P^L, \\
& && 0 \leq r^L < r^H.
\end{aligned} \tag{16}$$

Further, we solve the relaxed optimization problem by using the standard procedure of Lagrangian multiplier method and check if this solution also satisfies the M-condition. By solving this optimization problem the BS finds the optimal contract and it is found that the low preference type capable user obtains zero utility whereas a high preference type capable user achieves a strictly positive utility.

2) *Multiple-User Multiple-Contract (MUMC) method:* We propose another method of incentivizing capable users where the contracts that are offered reflect every capable user's amount of contribution to the BS's utility. The BS can design a different and unique contract set for each capable user in order to ensure that this user gets a utility proportional to the amount of its contribution in terms of the number of other users it can serve. In this case, the performance-reward contract set is uniquely defined for each capable user and hence this method is called the Multiple-User Multiple-Contract (MUMC) method. The capable users in this method are greedy and they expect the right amount of reward and is satisfied only if they get that amount of reward as incentive to participate in CCDMI. Unlike the case in the MUSC method, the contract sets are obtained here by solving N_c number of optimization problems.

In this method, two capable users of the same preference type are offered different contracts. As a result, they will get different rewards and the amount of reward is proportional to the value of T_i . Similarly, the cost of participation required from any two capable users may vary according to their respective values of T_i . The only disadvantage of this method is that the complexity of the solution will increase with an increase in the number of capable users in the system. The BS finds the optimal contract for user $i \in \mathcal{N}_c$ by solving the optimization problem given by

$$\begin{aligned}
& \underset{P_i^k, r_i^k}{\text{maximize}} && q_i^H \{T_i P_i^H - c r_i^H\} + (1 - q_i^H) \{T_i P_i^L - c r_i^L\} \\
& \text{subject to} && \theta_k v(r_i^k) - P_i^k \geq 0, \quad k = H, L \quad (\text{IR}), \\
& && \theta_k v(r_i^k) - P_i^k \geq \theta_k v(r_i^l) - P_i^l, \\
& && \quad k, l = H, L, \quad k \neq l \quad (\text{IC}), \\
& && 0 \leq r_i^L < r_i^H \quad (\text{M}).
\end{aligned} \tag{17}$$

We adopt the same procedure to solve the optimization problem as used in MUSC method. The optimal contract obtained by solving this optimization problem for each capable user results in the capable users of low preference type getting zero utility and the capable users of high preference type getting a strictly positive utility.

For implementing the proposed contract-based methods for a practical network the following signalling information are

TABLE II: Physical layer parameter

Parameter	Value
Cellular area radius	1000 meters
WLAN area radius	75 meters
Noise power	BS: -100 dBm; user: -40 dBm
WLAN rate range	5-40 Mbps
Cellular rate range	600 kbps-2 Mbps
Path loss constant and path loss exponent	k : 1; α : 3
Transmit power	BS: 46 dBm; device: 20 dBm

exchanged between the BS and the capable users. On the basis of the information available at the BS end, such as the cellular network radius, cellular user's transmit power, the number of users, and the initial probability with which a capable users is of high preference type, the BS finds the optimal contract for each capable user. Then the BS acts in the following way. The BS broadcasts the menu of contract items to the capable user. By evaluating the contract, the capable user sends feedback signals indicating their willingness to accept or reject the contract. If the capable user accepts the contract, the BS signs the contract with the user. If any capable user rejects the contract, it will serve that capable user and all the users it could serve, directly. After signing the contract, the capable user of high preference will distribute the content to other users. In order to watch the ongoing communication between the capable user and the other users it could serve, the BS sends control signals and receives feedback signals from the recipient users. If the transmission is successful the BS rewards the capable user with incentives as mentioned in the contract. If the transmission fails, the BS serves the user directly and the capable user will not receive any reward.

VI. RESULTS

In this section, we evaluate the performance of the proposed methods by performing a set of numerical evaluations and further, by performing a set of MATLAB simulations on the current system setup. Firstly, in Section VI-A, we investigate the impact of the preference type of a capable user on its own performance and on the performance of the BS in CCDMI. Then in Section VI-B, we perform numerical evaluations to confirm if the feasibility conditions of the proposed MUSC and MUMC incentive mechanisms are satisfied. After that, in Section VI-C, we analyze the performance of the proposed contract methods for different parameters of the contract by performing a set of simulations and finally in Section VI-D, we compare the performance of capable users for the two proposed methods on the basis of each capable user's contribution to CCDMI in terms of the number of other users it can potentially serve. The main parameters of the cellular network are shown in Table II.

A. Impact of the Preference Type of a Capable User on the Performances of the BS and the Capable Users in CCDMI

Firstly, we show how a single capable user's preference type influences (a) the utility of the BS and (b) the utility of the capable user i itself.

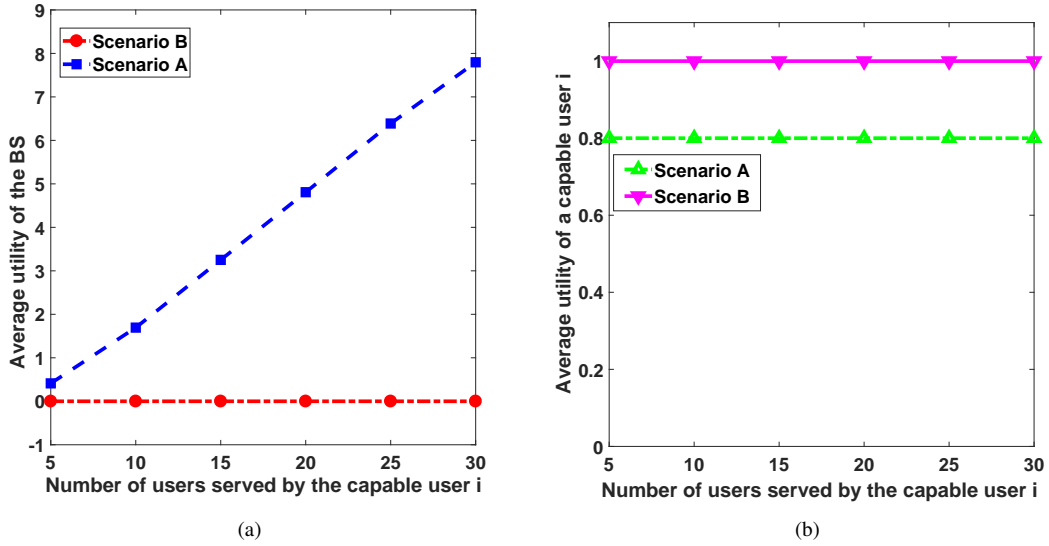


Fig. 4: Comparison of BS and user utilities for two scenarios representing different combinations of preference types: (a) Average utility of the BS with increasing T_i , (b) average utility of capable user i with increasing T_i .

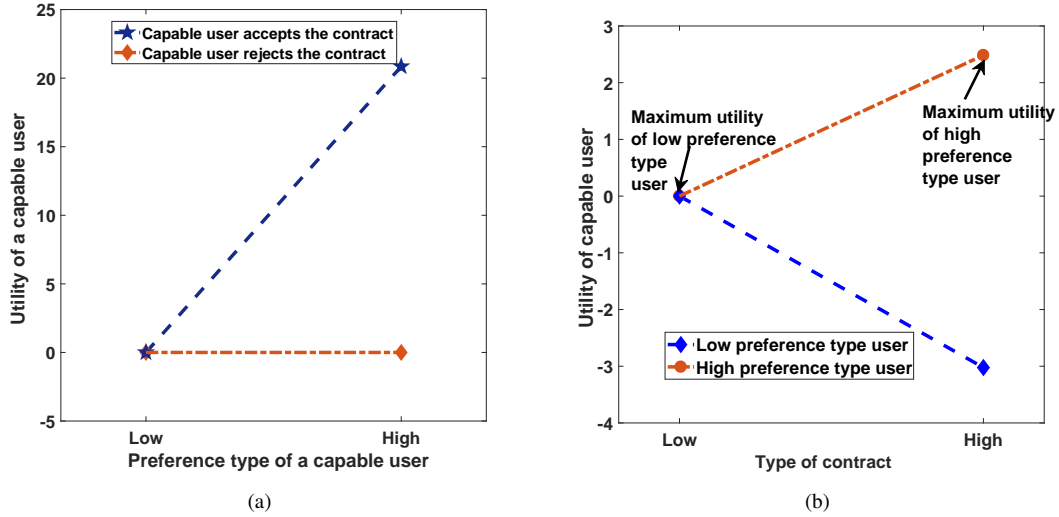


Fig. 5: Evaluation of (a) contract individual rationality, (b) contract incentive compatibility conditions, using the MUSC method.

To understand this, we consider that the user i ($i \in \mathcal{N}_c$) can be of high or low preference type. We consider two scenarios: (i) Scenario A: all the capable users including user i are of high preference type, and (ii) Scenario B: all the capable users except user i , are of high preference type. The utilities of the BS and the capable user i are calculated for both the scenarios. The same procedure is repeated for a different network configuration of the BS and the group of capable users. After multiple iterations, the average utility of the BS and the average utility of the capable user is obtained.

(1) *Average Utility Performance of the BS*: In Fig. 4(a), the graph shows the effect of a capable user's preference type on the average utility of the BS for the two scenarios described above. We observe that the average utility of the BS is always higher for Scenario A as compared to its average utility for

Scenario B. Moreover, for Scenario A, the average utility of the BS increases with the number of other users T_i that a capable user i can potentially serve. On the other hand, for Scenario B, the average utility of the BS is unaffected and constant, with increasing T_i .

(2) *Average Utility Performance of the Users*: Fig. 4(b) illustrates the effect of a capable user i 's preference type on its own average utility. We observe that the average utility of user i is always higher for Scenario B as compared to its average utility in Scenario A. Moreover, it can be shown that for both the scenarios, the average utility of user i remains unaffected by increasing T_i number of other users that it can potentially serve. Hence, when user i behaves as a low preference type user, it improves its own average utility but the BS suffers a loss in its average utility, in comparison to the case when i

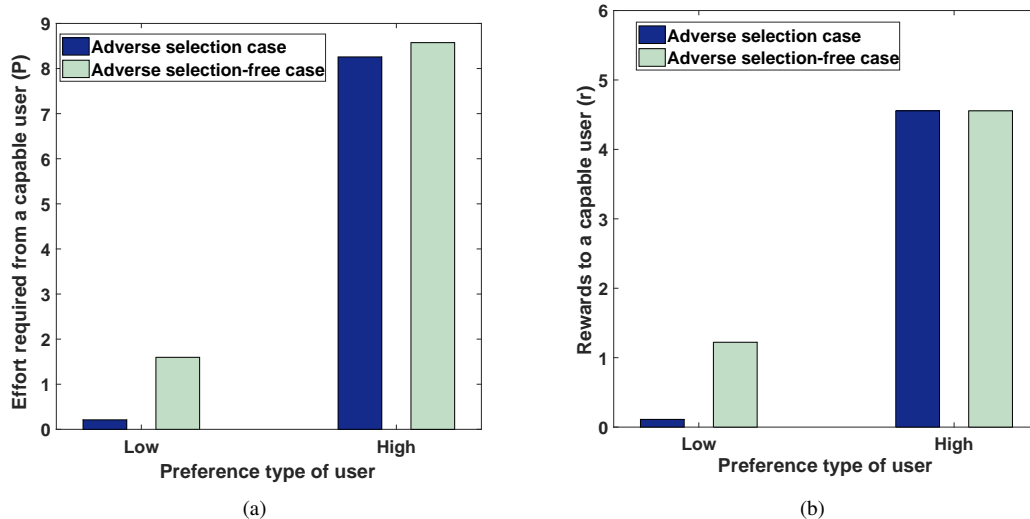


Fig. 6: Evaluation of contract monotonicity condition using the MUSC method by comparison of (a) effort required from a capable user of different preference types for different information cases. (b) reward of capable user of different preference types for different information cases.

behaves as a high preference type user.

B. Numerical evaluations of the Feasibility Conditions for the Contract-based Incentive Mechanism

In this subsection, we perform numerical evaluations to verify if the feasibility conditions of the proposed contract methods (as explained in Section V-C) are satisfied and then we perform simulations to analyze the system performance of CCDMI under adverse selection for different contract parameters. We show the following results for the MUSC method of offering contracts.

(a) **Individual Rationality Condition:** In Fig. 5(a), we compare the utility of a capable user when it does not accept the contract, to its utility when it accepts the contract item according to its preference type. Fig. 5(a) shows that the utility of a capable user is zero when it does not accept any contract irrespective of its preference type. On the other hand, utility of a capable user when it accepts a contract item according to its preference type, is at least equal to its utility when it rejected the contract. Therefore, the optimal solution for contracts under information asymmetry, which is obtained by applying the proposed MUSC method, satisfies the IR-constraint.

(b) **Incentive Compatibility Condition:** Fig. 5(b) compares the utility of a capable user when it accepts the contract item designed for its own preference type to its utility when it accepts the contract item designed for users of another preference type. We observe in Fig. 5(b) that the utility of a user of low preference type is maximum when it accepts the optimal contract item designed by the BS for low preference type users. On the other hand, the maximum utility of a high preference type user is achieved when it accepts the contract item designed for high preference type users. Therefore, by using the MUSC method, the optimal solution for contracts under information asymmetry satisfies the IC-constraint for contract feasibility.

(c) **Monotonicity Condition:** We perform numerical computations to further compare the performance of the proposed MUSC method under adverse selection for wireless content delivery against the adverse selection-free method in which the BS knows exactly about the preference types of the capable users and therefore offers contracts to them according to their preference types. This comparison with the adverse selection-free case is done because it can serve as an upper bound for the performance of the proposed MUSC method. In Fig. 6(a), we compare the optimal effort required of a high preference type capable user to the optimal effort required of a low preference type capable user for both the adverse selection and adverse selection-free cases. Fig. 6(a) shows that a high preference type user always has a higher required optimal effort as compared to low preference type user for both the information cases. Also, we observe that for a high preference type user, the optimal effort required for the contract in adverse selection case is very close to the optimal effort required for the contract in the adverse selection-free case. On the other hand, for a low preference type user, the optimal effort required for the contract in adverse selection case is much less as compared to the optimal effort required for the contract in adverse selection-free case. In Fig. 6(b), we compare the optimal incentives rewarded to a high preference type user to the optimal incentives rewarded to a low preference type capable user. This comparison is also made for both the adverse selection and adverse selection-free cases. From Fig. 6(b), we observe that the high preference type user is rewarded with higher optimal incentives by the BS and vice versa for both the information cases of finding optimal contract sets. Moreover, for a high preference type user, the optimal reward for contract in the adverse selection case is same as the optimal reward for contract in the adverse selection-free case. On the other hand, for a low preference type user, the optimal reward for contract in the adverse selection case is much less than as compared to the optimal reward for contract in the

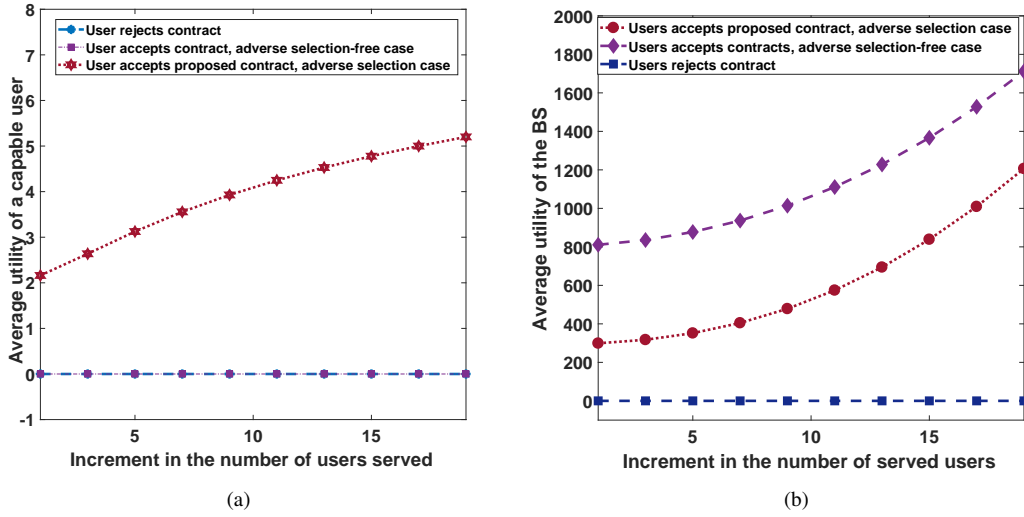


Fig. 7: (a) Average utility of a capable user with increasing ΔT_i , (b) Average utility of the BS with increasing ΔT_i .

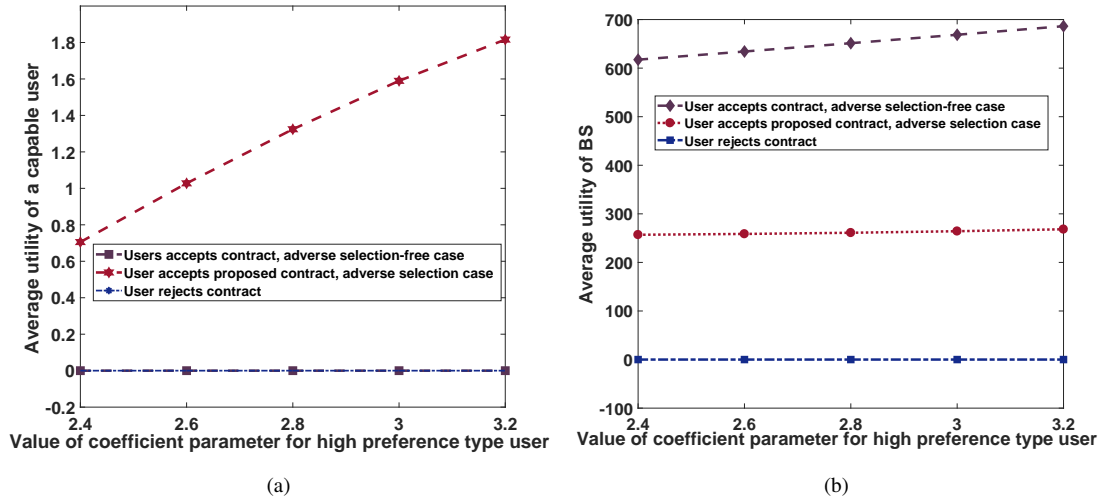


Fig. 8: (a) Average utility of a capable user with increasing θ_H , (b) Average utility of the BS with increasing θ_H .

adverse selection-free case. Therefore, we can conclude that the optimal effort required of the capable user by the BS and the optimal rewards given to the capable user as incentives by the BS, both satisfy the M-condition. Similarly, for the MUMC method, numerical evaluations can be performed to show that the contract feasibility conditions are satisfied.

C. Performance Analysis of the Incentive Mechanism for Different Contract Parameters, ΔT_i and θ_k

Now, we study the influence of different parameters of the contract on the performance of the system. We assume that the BS encounters a group of high and low preference type capable users such that the BS knows that a capable user i is of high preference type with a probability q_i^H . The BS applies the MUSC method to find the optimal contract and then offers the contract to all the capable users. We conduct multiple iterations over time so that probability distribution of

the preference type of the capable user i is different in every iteration and the distribution of high preference type capable users averages to q_i^H . At each instant, the capable users can choose to reject, or accept the contract item that maximizes its utility. Finally, the average utilities of the capable users and the BS are found. We use the same simulation parameters as shown in Table II. In addition, we assume $N_c = 30$ and the BS's unit cost of providing incentives to capable users, $c = 0.05$. We compare the performance of the proposed MUSC method under adverse selection with two benchmark methods, (a) the adverse selection-free method, where the BS knows exactly about the preferences of the capable users and (b) a content delivery method under adverse selection, without the contract-based incentive mechanism. The method of evaluating the optimal contracts for the adverse selection-free case represents the optimal outcome BS can achieve and can therefore serve as an upper bound for the proposed MUSC method under adverse

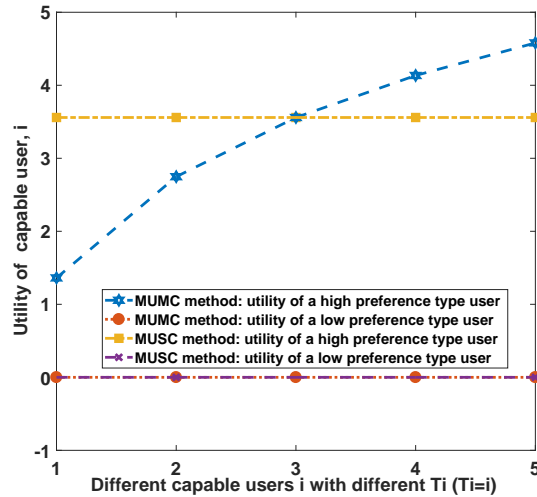


Fig. 9: Comparison of utilities of low and high preference type capable user for MUSC and MUMC methods for different contributions T_i .

selection. In case of the content delivery method under adverse selection, without the contract-based incentive mechanism, the capable users prefer not to participate and the BS delivers the content directly to all users. This method therefore, provides the lower bound on the outcome the BS can achieve under adverse selection.

(a) Impact of ΔT_i on the Performance of the BS and the Capable Users: We simulate the MUSC method in Fig. 7. We measure the average utility of the BS and the capable user i by conducting simulations for multiple iterations for a constant value of T and repeat the same procedure for each increment in the value of T , ΔT_i . We observe in Fig. 7(a) that for a constant ΔT_i , the average utility of a capable user is always higher for our proposed MUSC method as compared to its average utility in the adverse selection-free case or when the capable user rejects the contract. Moreover, the average utility of a capable user increases with an increment in T_i , ΔT_i for our proposed MUSC method, whereas the average utility of a capable user remains constant with ΔT_i for the other two methods. We also consider the effect of increasing ΔT_i on the average utility of the BS, in Fig. 7(b). The average utility of the BS is highest for the adverse selection-free case, as compared to its average utility for our proposed method under adverse selection. In both the information cases, average utility of the BS increases with ΔT_i . The least average utility of the BS is when the capable users don't accept the contract and in this case the average utility value remains unaffected by a change in ΔT_i .

(b) Impact of θ_k on the performance of the BS and the capable users: In order to study the effect of the value of coefficient parameter θ_k on the performance of the capable user and the BS, we keep the coefficient parameter of low preference type users, θ_L constant and increase the coefficient parameter of high preference type users θ_H . Then we see how the average utility of the BS and the average utility of the capable user changes with an increase in the value of θ_H . In Fig. 8, we conduct simulations for multiple iterations for a constant value

of θ_H and repeat the same procedure for each increasing value of θ_H . In Fig. 8(a), we see that the average utility of the capable user increases with an increasing θ_H for our proposed method under adverse selection. On the other hand, for the other two methods, the average utility of the capable user remains constant with increasing θ_H . Moreover, the average utility of the capable user for the proposed MUSC method under adverse selection is always higher as compared to its average utility when the capable users rejects the contract or when there is no adverse selection. In Fig. 8(b), we observe that the average utility of the BS increases with θ_H for both the adverse selection case and the adverse selection-free case. On the other hand, the average utility of the BS is constant and unchanging with θ_H when the capable user refuses the contract. It is clear that the BS has maximum average utility when it has complete information about the preference types of the capable users and offers contracts accordingly. For our proposed methods under conditions of adverse selection, we see that the BS's average utility is always higher than its average utility when the capable users reject the contract.

D. Performance Comparison of Incentive Mechanisms MUSC and MUMC

Here, using numerical evaluations, we analyze the effect of amount of contribution of a capable user i to CCDMI in terms of the number of users it can serve T_i , on the utility of the capable user for the two proposed incentive methods of offering contracts, called the MUSC and MUMC mechanisms. From Fig. 9, we observe that if the MUMC method is used to solve the adverse selection problem in CCDMI and if a capable user contributes more to the BS utility, in terms of T_i , then it ends up enjoying a greater utility value, but at the cost of a solution with higher complexity. Thus, the MUMC method of contracts is suitable for those cases when a capable user needs incentive to justify its amount of contribution to the process of CCDMI saving of resources in terms of the number of carriers it saves for the operator by participating. On the

other hand, by using the MUSC method every capable user gets a constant utility value, even if it contributes more to the CCDMI saving of resources by serving more number of other users T_i . Hence, the MUSC method is particularly suited when a user is concerned only with the fact that all users cooperate for the overall welfare of the users and BS.

VII. CONCLUSION

In this paper, we have addressed the problem of incentivizing users to participate in CCDMI, under the conditions of adverse selection. In CCDMI, the cellular BS selects devices with multiple radio interfaces that have good link quality, for local content delivery to nearby users and this process results in resource savings for the BS. This method incurs little overhead as the information that is utilized for user selection exists already in the network. Therefore, this method can play a significant role in meeting the requirements set for the future 5G networks. However, a mobile user that is capable of distributing content to other users within its vicinity, can be willing/unwilling to participate in the cooperation process. The BS can provide incentives to the willing users provided the BS knows exactly their degree of willingness. Since this information is unavailable at the operator BS, the adverse selection problem arises.

Although several incentive schemes have been used in previous works for inducing users to cooperate, the tool of contract theory is most suitable to deal with problems such as adverse selection that occur due to information asymmetry in the network. Therefore, we have proposed two novel self revealing, contract-based incentive methods in which the contract design ensures that the users get maximum utility by accepting those contract items which are unique to their willingness/unwillingness to participate. Moreover, as a result of implementing these contracts, the users that are capable of distributing content to other users, have higher utility when they are willing to participate as compared to their utility when they are unwilling. Our results have shown that the proposed methods of offering contracts can improve the system performance, in terms of the utility of the BS and the users.

Future work is needed to investigate the dynamic framework of contracts for designing incentive mechanisms to solve similar problems with information asymmetry. By exploring such contracts, it can be analyzed if the dynamicity in incentive mechanisms leads to an improvement in the performance of operator and the users, as compared to their performances for one-period contracts as described in this paper. Another possible extension of this work would be to design location based incentive mechanisms using contracts to solve congestion problems for situations where the BS knows the high-demand areas of a network.

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