Enabling Multi-Source Device-to-Device Content Delivery in Cellular Networks

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***Abstract*—Multi-source device-to-device (D2D) communication allows the base station (BS) to serve the content requests of the users locally through D2D links. As a result, the load on the base stations (BSs) and the consumption of radio resources reduces significantly. Clearly, the success of multi-source content delivery relies on the willingness of the content owners (COs), i.e., sources, to deliver their content to requesting user. Consequently, in this paper, we investigate the economic interaction between single BS and multiple COs for content delivery. In view of the fact that participating COs are heterogeneous with respect to the amount of content in their cache and the sensitivity towards energy consumption, there is a need to design a fair incentive mechanism which motivates COs for content delivery. To this end, we model the interaction among the BS and multiple COs as one-to-many bargaining game and design an incentive mechanism based on the Nash bargaining framework. Specifically, we obtain the optimal amount of content delivered by participating COs and their corresponding incentives under two variants of one-to-many bargaining, namely sequential bargaining and concurrent bargaining. For both variants of bargaining, the obtained optimal solutions are capable of minimizing the amount of content delivered by the BS while ensuring fair incentive transfer among the participating COs.**

***Index Terms*—D2D communication, content delivery, Nash bargaining, incentive mechanism, one-to-many bargaining**

I. Introduction

With the increasing popularity of multimedia contents among cellular users, data traffic over cellular networks is expected to increase unprecedentedly in the near future [1]. To reduce the load on the existing base stations (BSs) and the consumption of radio resources, network providers need to increase their network capacity significantly. However, traditional approaches such as infrastructure upgradation (e.g., from LTE to 5G) and network densification (e.g., through smallcells deployment) are time-consuming and costly, which may not match the requirements of perpetual data traffic demand. Thus, network operators are often unable to deliver the requested multimedia content to their requesting users (RUs) in a timely manner through cellular links [2], [3]. This leads to lower quality of experience (QoE) and dissatisfaction among the RUs. Consequently, network operators are expecting cost-effective and disruptive solutions which can enhance the QoE of RUs with a simultaneous reduction in cellular data traffic over BSs.

On the other hand, recent studies on caching and device-centric communication suggest the use of device-to-device (D2D) communication for content delivery [2]–[5]. In D2D-based content delivery schemes, the content requests of RUs are served from the cache of nearby content owner (CO), who has the requested content, in his/her vicinity through D2D communication [2], [5]. However, employing single CO's device for the transmission of large size multimedia content is difficult due to limited caching space of the COs. To overcome this challenge, recent studies exploit coordinated multi-point (CoMP) transmission, in which multiple COs are utilized to deliver the requested content to the RU, thereby giving rise to multi-source-to-single-source delivery (M2SD) [6]. In M2SD, the multimedia contents are coded with advanced coding techniques, such as Fountain coding [7] and Raptor coding [8]. Coding techniques make transmission more flexible and empower the RU to decode the requested content by receiving the encoded fractions of content from multiple COs [9], [10]. Consequently, in this work, we consider multi-source D2D content delivery in cellular networks.

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A. Motivation

Due to the potential benefits of D2D caching and CoMP transmission, the multi-source D2D content delivery approach is widely studied in the recent works [2], [3]. For example, Gabry *et al*. [11] proposed a cooperative content caching and delivery strategy to minimize the delivery time. Similarly, Kollias and Antonopoulos [12] investigated multi-source content caching and delivery for D2D-enabled cellular network. Specifically, the authors considered cache-enabled user devices and focused on content placement to reduce the content delivery delay. Further, Amer *et al*. [13] studied the D2D content delivery problem to maximize the offloading gain of BS. Aforementioned studies believe that there exists a social bonding among participating D2D users, and hence, share their contents with each other indubitably. However, because of the transmission energy cost, self-centric or rational users may not share their cached contents with other users. In consideration of this issue, there exist few incentive-based schemes in the literature, wherein D2D users are incentivized by the BS to share their cached contents with RUs [14]–[17]. However, these works concentrated on single-source-based content delivery [14], [15], [17] and overlooks the potential of multi-source-based content delivery. Further, these approaches are based on non-cooperative game-theoretic approaches. Thus, unable to capture the prospective of co-operation among the BS and COs.

In this paper, we focus on the economic interplay between single BS and multiple heterogeneous COs, wherein the BS offers certain incentives to the COs for the delivery of the requested content. To the best of our knowledge, such economic interplay has not been addressed in the existing studies on multi-source D2D content delivery. After receiving a content request, the BS initiates negotiation with the COs for the delivery of the requested content and the corresponding incentive, so as to save its radio resources required to deliver the requested content. Towards this end, we first quantify the benefit of the BS and the energy cost of COs in multi-source D2D content delivery. As the portion of requested content delivered by COs and their corresponding incentive should be approved by both the BS and the COs, we employ the Nash bargaining theory [18] to compute the desired incentives. The outcome of the Nash bargaining process is expected to maximize the social welfare while maintaining fairness, thereby, be self-regulating and acceptable by the BS and all the participating COs. We formulate the negotiation between the BS and multiple heterogeneous COs using one-to-many bargaining game [19]. The BS can bargain with multiple COs either sequentially, i.e., one by one in a sequence, or concurrently, i.e., with all the COs simultaneously. Hence, we obtain optimal solutions which comprise of both the amount of content delivery and the incentives of COs, for these two variants of one-to-many bargaining, namely sequential bargaining (SEQ-B) and concurrent bargaining (CONCR-B).

Specifically, our contributions are as follows:

- *Novel multi-source D2D content delivery approach*: We model and analyse the multi-source D2D content delivery in cellular network from economics perspective while considering the heterogeneity of the COs. Specifically, we investigate the economic interactions among the BS and participating COs using one-to-many bargaining game.
- *Bargaining solutions*: In our proposed model, we first quantify the benefit of the BS and the energy cost of heterogeneous COs in content delivery. Further, we systematically obtain the bargaining solutions, i.e., amount of content delivery and corresponding incentives, for both the SEQ-B and CONCR-B.
- *Performance Evaluations*: We verify our theoretical results through extensive numerical simulations. The simulation results show that the proposed multi-source content delivery scheme, under SEQ-B and CONCR-B is beneficial for both the BS (due to reduced amount of content delivery) and the COs (due to obtained incentives).

II. Related Work

In literature, there exist various schemes for proximity-based D2D content delivery in cellular networks. We group the existing studies broadly into two categories — *non- incentive-based content delivery* [11]–[13], [20]–[22] and *incentive-based content delivery* [14]–[17], [23].

Gabry *et al.* [11] employed maximum-distance separable encoding technique to code the content before caching. They proposed to distribute the parts of the content in cache-enabled smallcells for improving the performance delivery phase. Specifically, the authors obtained the optimal distribution of content fractions to minimize the overall energy consumption of the network. Likewise, the authors in [7] employ fountain coding to improve the content hit ratio of the networks. Further, Datsika *et al.* [22] designed an energy-efficient medium access control (MAC) protocol for cooperative D2D networks while considering the social-ties of the D2D users. The proposed protocol motivates the users to act as relays for their socially connected users, which in turn minimize the overall energy consumption of the D2D networks. Amer *et al.* [13] studied multi-source D2D content delivery problem, wherein the authors characterized the offloading gain of BS using stochastic geometry approach and obtained an optimal caching strategy of COs to maximize the offloading gain of BS. Recently, Kollias and Antonopoulos [12] investigated multi-source content caching and delivery in D2D-enabled cellular network. Specifically, the authors considered cache-enabled user devices and focused on content placement to reduce the content delivery delay. The aforementioned content delivery schemes presume that the D2D users have social bonding, and hence, are willing to share contents with each other without proper incentives. Further, works presented in [11], [20], [22] are limited for the single source-based content delivery.

On the other hand, there exist few incentive-based schemes for content delivery in D2D-enabled cellular networks. Specifically, Chen *et al.* [14] proposed a contract theory-based incentive mechanism for content delivery in D2D-enabled cellular networks to motivate the COs to share the requested content. The authors also considered the energy cost of the COs. Further, Zhao *et al.* [15] proposed a data dissemination approach wherein the BS aimed to transmit the messages to the users via D2D communication. In particular, the authors proposed a three-stage approach. In the first phase, the BS selects the initial seeds for message caching to maximize the data dissemination efficiency. Further, in the second phase, the seed users forward the cached message to other socially connected users through D2D communication. Finally, in the third phase, the users share the message with other cooperative users. The authors also proposed an incentive mechanism to motivate the D2D users to share their cached message. Huang *et al.* [16] studied the joint content placement and delivery problem wherein the network operator acts as a central entity and motivates the helper nodes to cache the contents of the content providers. Further, the helper nodes deliver their cached contents to the nearby users through D2D links. In particular, the authors employed the matching theory to find the optimal pairing among the helper nodes and the content requesters. Further, given this optimal paring, the author proposed an auction-based incentive mechanism to handle the competition among multiple content providers for the available helper nodes. Similarly, Huang *et al.* [17] also studied the multi-D2D content delivery problem in a cellular network. The authors proposed a sequential-posted-price mechanism that enables the BS to motivate the available COs by sequentially offering the incentive on take-it-or-leave-it basis. Each CO decides to accept or reject the offer based on the cost of the content delivery.

In summary, few existing works studied the incentive issues in proximity-based content delivery in cellular networks. However, these works concentrated on the single-source-based content delivery [14], [15], [17], [23] and overlooks the potential of multi-source-based content delivery. Further, these approaches are based on non-cooperative game-theoretic approaches. Thus, unable to capture the prospective of cooperation among the BS and COs. Hence, in this paper, we study the interaction of single BS and multiple heterogeneous COs using the Nash bargaining approach, wherein the BS offers certain incentives to the COs for the delivery of the requested content.

III. System Model

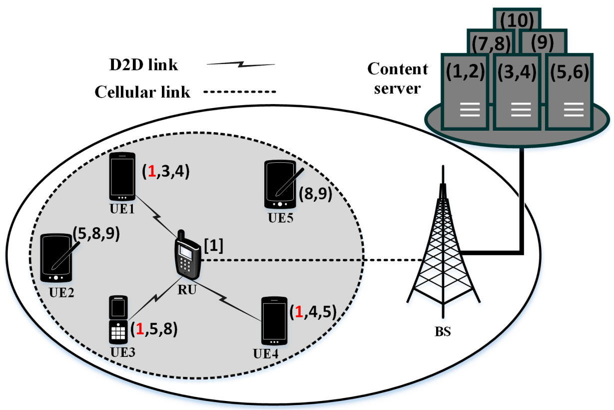


Figure 1: Multi-source content delivery

A. System Overview

We consider a wireless D2D network consisting of a RU and multiple COs in the blanket coverage of single BS as illustrated in Fig. 1. The RU requests the BS for a content of size S (in GB) which is available at a remotely located content server. The BS serves the content request of the RU either through cellular link or by utilizing the D2D links between the RU and the COs. Motivated by [24], [25], we assume that two users can communicate with each other through D2D links, if their physical distance is less than collaborative distance R_{max}. Thus, a user u in the proximity of the RU is designated to be a CO if it satisfies two conditions. First, the user u has the requested content c in his/her local cache. Second, the distance between the RU and user u is less than R_{max}. For example, in Fig. 1 the RU requests to the BS for content 1 which is in the local cache of neighboring users UE1, UE3, and UE4, and hence, these users are designated as COs. We denote the set of COs as $\mathcal{U} = \{1, 2, \ldots U\}$. Besides, we assume that the requested content is encoded using a coding scheme [8], [10] whose coding efficiency is $\gamma \in (0, 1]$. Thus, COs may have the requested content partially, in their respective cache. Let a_u denote the fraction of content available in the cache of CO u and $\mathcal{A} = (a_u)_{u \in \mathcal{U}}$ denotes the content availability profile (CaP) in the proximity of the RU. The coding makes content delivery more flexible[1] and enables RU to decode the requested content by collating $\frac{S}{\gamma}$ GB, in any order, via multiple sources. For exposition of our analysis, we assume $\gamma = 1$, which facilities RU to decode the requested content by collating exact number of bits (i.e., size of the content) [10]. Further, we assume that, during the content delivery, the BS assigns a dedicated channel for the D2D communication between the content owners (COs) and the requesting user (RU). In particular, motivated by [12], [26], we consider overlay inband D2D communication to avoid interference between the D2D users and the cellular users.

[1]at the cost of transmission of a few extra bits

B. Content Delivery Model

We focus on the delivery of a requested content, for example, in Fig. 1, the RU requests to the BS for content 1. There are mainly two approaches through which the BS can deliver the requested content. First, the BS downloads the requested content and delivers the same to the RU using cellular link. Second, the BS informs the RU to receive the available fractions of requested content from nearby COs, one by one in a predefined order, through D2D links. If the aggregated fractions of content, received from COs, is not sufficient to decode the content, the BS downloads and delivers the remaining fraction of content through cellular link. Clearly, the radio resource consumption of the BS is higher in the former approach compared to the latter one. Thus, the BS interacts with the COs for their assistance in content delivery. To this end, we model the utility of the BS and the participating COs.

C. Utility Model of BS

The BS incurs a certain cost for delivering the content to the requesting user due to the consumption of its cellular resources which may include backhaul bandwidth, spectrum, and transmitting energy, etc. This serving cost depends on the size of the requested content. Consequently, in our case, we modeled the serving cost of the BS as a increasing function of the content size. We focus on the benefit of the BS from the assistance of COs for content delivery, i.e., the reduction in serving cost due to the reduced consumption of cellular resources [19]. We introduce the cost function for the BS which signifies the cost incurred by the BS to deliver b units of the requested content, namely $\mathcal{C}(b) = \phi b$, where ϕ denotes the cost of delivering content of unit size. In particular, and assume that $\mathcal{C}(\cdot)$ is a linear function of delivered content size b. The property of the cost function models the fact that the cost of delivering content is an increasing function of the content size [27]. Now, let us consider a scenario in which the BS delivers the entire requested content of size S to the RU independently through the cellular link. Thus, the independent cost of the BS is $\mathcal{C}_{ind} = \phi S$. Next, we consider a scenario wherein the BS motivates the COs, by providing incentive, to deliver parts of the requested content. Let the BS provides z_u amount of incentive to the CO u, and correspondingly, CO u delivers $x_u \in (0, 1]$ fraction of the requested content. If the aggregated fraction received from the COs is not sufficient to decode the requested content, i.e., $\sum_{u=1}^{U} x_u < 1$, the BS delivers the remaining amount of the requested content (s_{rem}) to the RU. Mathematically,

$$s_{rem}(\boldsymbol{x}) = \min\left\{0, S - S\sum_{u=1}^{U} x_u\right\} \quad (1)$$

where $\boldsymbol{x} = (x_u)_{u \in \mathcal{U}}$ is the vector which signifies the portion of content delivered by all the COs. Thus, the modified cost of the BS which includes the serving cost and the incentive paid to the COs is as follows:

$$\mathcal{C}_{mod}(\boldsymbol{x},\boldsymbol{z}) = \mathcal{C}(s_{rem}(\cdot)) + \sum_{u=1}^{U} z_u \tag{2}$$

where $\boldsymbol{z} = (z_u)_{u\in\mathcal{U}}$ is the vector which denotes the incentives paid to the COs. Finally, we define the utility (or benefit) $\mathcal{J}(\boldsymbol{x},\boldsymbol{z})$ of BS which takes into account the reduction in serving cost, due to the assistance of COs for content delivery, and the incentives paid to the COs. Mathematically,

$$\begin{aligned}\mathcal{J}(\boldsymbol{x},\boldsymbol{z}) &= \mathcal{C}_{ind} - \mathcal{C}_{mod}(\cdot) \\ &= \underbrace{\mathcal{C}\big(\min\{S, S\sum_{u=1}^{U} x_u\}\big)}_{\text{serving cost reduction}} - \underbrace{\sum_{u=1}^{U} z_u}_{\text{incentive paid}}\end{aligned} \tag{3}$$

Two immediate conclusions can be made from Eq. (3). First, the delivery of aggregated fractions of content, beyond its size, does not improve the utility of BS. Second, the BS can improve its utility by offering properly designed incentives to COs for content delivery. Hence, BS negotiates with the COs for $\boldsymbol{x}$ and $\boldsymbol{z}$.

D. Utility Model of CO

1) Energy consumption of CO: The CO consumes a certain amount of energy to deliver the requested content to the RU through D2D link. The D2D links between the RU and the COs are characterized by different channel gains [28]. Specifically, the channel gain (g_u) between the RU and CO u is given as $g_u = K\beta_u d_u^{-\alpha}$, where K, β_u, d_u and α are system constant, exponentially distributed fast fading gain, distance between the RU and CO u, and pathloss exponent, respectively. Further, motivated by [29], we assume that the CO u delivers x_u at a given data rate r. Thus, using Shannon's channel capacity formula, the required transmitting power (p_u) of CO u to maintain the given rate r at RU is given as $p_u(r) = \frac{(2^r-1)\eta}{g_u}$, where η is additive white Gaussian noise. Note, for analytical tractability, we consider unit channel bandwidth, as given in [29]. Finally, we express the energy consumption of CO u to transmit x_u fraction of content as follows [30]:

$$e_u(x_u) = p_u(\cdot)\cdot\frac{Sx_u}{r} \tag{4}$$

The devices owned by COs have limited energy which can be utilized by them to run various applications. Hence, the energy consumption due to the content delivery causes inconvenience to the COs. We model the inconvenience caused to CO u using a cost function $\mathcal{E}_u(\theta_u, e_u)$ where, $\theta_u \in (0,1]$ is a normalized user specific parameter which indicates CO $u's$ sensitivity towards the energy consumption. We assume that, $\mathcal{E}_u(\cdot, x_u)$ is convex, differentiable, and strictly increasing function of x_u, with $\mathcal{E}_u(\cdot, x_u) = 0$ at $x_u = 0$ [31]. Besides, the fraction of requested content delivered by the COs are constrained by the availability of the same in their cache. Hence, following condition must hold:

$$0 \le x_u \le a_u \quad \forall u \in \mathcal{U} \tag{5}$$

Utility of CO: The COs receive incentive from BS to compensate their energy cost. Let user u receive z_u amount of reimbursement. Thus, the payoff $\mathcal{V}_u$ of CO u is defined as the difference between the received incentive and the energy cost. Mathematically,

$$\mathcal{V}_u(x_u, z_u) = z_u - \mathcal{E}_u(\cdot) \tag{6}$$

IV. PROBLEM FORMULATION

A. Social Welfare Maximization

The social welfare (SW), namely $\Psi(\boldsymbol{x},\boldsymbol{z})$, is defined as the aggregated payoff of the BS and all the content transmitting users. Mathematically,

$$\begin{aligned}\Psi(\cdot) &= \mathcal{J}(\cdot) + \sum_{u=1}^{U}\mathcal{V}_u(\cdot) \\ &= \mathcal{C}\big(\min\{S, S\sum_{u=1}^{U} x_u\}\big) - \sum_{u=1}^{U}\mathcal{E}_u(\cdot)\end{aligned} \tag{7}$$

It is easy to verify that, the SW is independent of incentives paid to the users and only depends on the users' delivered fraction of content. Indeed, the total incentive amount paid and received cancel each other out, and hence, the SW is the difference between the cost reduction of BS and the energy cost of participating COs. Consequently, the formulated social welfare maximization (SWM) problem is as given:

$$\begin{aligned}\textbf{SWM}: \max_{\boldsymbol{x}} \quad & \Psi(\boldsymbol{x}) \\ \text{s.t.} \quad & (5)\end{aligned} \tag{8}$$

The objective function of **SWM** is strictly concave and the constraint set defines a convex, compact, and feasible region. Thus, the above problem is a convex program and there exist an unique optimal solution $\boldsymbol{x}^*$. The BS can obtain the optimal solution $\boldsymbol{x}^*$ centrally by collecting the required information from the COs. However, by simply solving the **SWM** problem, the BS cannot determine the reimbursement of the COs for obvious reasons. Besides, we need a *fair incentive transfer* scheme which compensates COs' energy costs and encourages them to participate in content delivery. We employ a cooperative game-theoretic framework to obtain the amount of content delivered by each COs (i.e., $\boldsymbol{x}^*$) and their corresponding incentives (i.e., $\boldsymbol{z}^*$). The cooperative framework is commonly used in game theory when rational and self-centric players have conflict of interest over possible agreements and there exists a possibility to settle on a mutually profitable agreement. In our case, the BS communicates and negotiates with the COs over the amount of content delivery and their corresponding incentive while taking into account the CaP. Specifically, we model and analyze the content delivery problem using a Nash bargaining solution (NBS) approach.

V. Nash Bargaining Solution

In this section, we first discuss the preliminary of the Nash bargaining framework and the corresponding solution to the one-to-one bargaining game. Next, we analyze the more general one-to-many bargaining game under two variants — SEQ-B and CONCR-B and discuss their NBS.

A. Preliminary

Nash established a bargaining framework [18] for two persons with given disagreement payoffs. Consider a set of two players $\mathcal{N} = \{1, 2\}$ whose associated utilities are denoted by U_1 and U_2. The utilities are defined over the possible bargaining outcomes $\mathcal{O} \cup \{\mathcal{D}\}$, where set $\mathcal{O}$ denotes the set of possible agreement points and D denotes the disagreement point. Let $\mathcal{U} = \{(U_1(o), U_2(o))|o \in \mathcal{O} \cup \{\mathcal{D}\}\}$ be the set of possible payoffs. Then, according to the Nash framework, we model the bargaining problem as a game $\mathcal{G} = \langle \mathcal{N}, \mathcal{O}, \mathcal{D}, \mathcal{U} \rangle$. The solution to a bargaining problem is either an agreement point (among $\mathcal{O}$) or the disagreement point ($\mathcal{D}$). Let the possible set of payoffs ($\mathcal{U}$) be a convex and compact set and $\exists$ $o \in \mathcal{O}$ such that $U_n(o) \geq d_n$, $n \in \{1, 2\}$, where $d_1 = U_1(\mathcal{D})$ and $d_2 = U_2(\mathcal{D})$ represent the disagreement utilities of the players. Then, an agreement point $o^* \in \mathcal{O}$ is said to be the NBS if it solves the following optimization:

$$NBS: \quad \max_{o \in \mathcal{O}} (U_1(o) - d_1)(U_2(o) - d_2) \tag{9}$$
$$\text{s.t.} \quad (U_1(o), U_2(o)) \in \mathcal{U} \tag{10}$$
$$(U_1(o), U_2(o)) \geq (d_1, d_2) \tag{11}$$

It is noteworthy that, in the Nash bargaining framework the disagreement utilities (d_1, d_2) of the players have a vital role. Indeed, the players with higher disagreement utilities obtain larger utility in the Nash framework. In the subsequent subsection, we present the NBS for one-to-one bargaining between single BS and CO.

B. One-to-One Bargaining

In this subsection, we study a simplified content delivery situation consisting of single CO, i.e., $|\mathcal{U}| = 1$. Let $X_u = [0, a_u]$ and $Z_u = [0, +\infty)$ denote the feasible region for the bargaining decision variable x_u and z_u, respectively, and $\mathcal{O} = \{(x_u, z_u)\} : x_u \in X_u, z_u \in Z_u\}$ signifies the set of possible agreement points of bargaining between BS and CO u. The BS bargains with the given CO for the amount of content delivery and the corresponding incentive using one-to-one bargaining framework (one BS and one CO). To this end, we discuss the outcome of one-to-one bargaining using the Nash bargaining theory. First, we consider the case wherein the bargaining ends at the disagreement point, i.e., (x_u, z_u) = (0,0). In accordance with the utilities of the BS and CO (Eqs.(3) and (6)), at the disagreement point, the BS and the CO receive zero utility, i.e., $(\mathcal{J}^0, \mathcal{V}_u^0)$ = (0,0). The NBS (x_u^*, z_u^*) of the one-to-one bargaining between the BS and given CO is computed by solving the following optimization problem:

$$\max_{(0 \leq x_u \leq a_u, z_u \geq 0)} (\mathcal{J}(x_u, z_u) - \mathcal{J}^0)(\mathcal{V}_u(x_u, z_u) - \mathcal{V}_u^0) \tag{12}$$
$$\textit{s.t.} \quad \mathcal{J}(x_u, z_u) \geq 0; \mathcal{V}_u(x_u, z_u) \geq 0$$

Proposition 1. *The NBS of the one-to-one bargaining between the BS and CO is as given:*
$$(x_u^*, z_u^*) = \big(\hat{x}_u, \mathcal{E}_u(\hat{x}_u) + \tfrac{\Psi(\hat{x}_u)}{2}\big),$$
where $\hat{x}_u$ is the amount of content delivered by the CO which maximizes the SW.

Proof: Please refer to the supplementary file. ■

From Proposition 1 two conclusions can be drawn. First, both the BS and CO receive equal share of the SW, which is generated from the cooperative content delivery. Specifically, the incentive plays the role of transferable utility and allows the BS to share the SW in a *fair* manner. Second, the incentive paid by the BS also *compensates* the energy cost of the CO. This motivates the CO to deliver its cached content. Based on the result of one-to-one bargaining, we present the NBS for one-to-many bargaining problem under SEQ-B and CONCR-B protocol in the following sections.

C. Sequential Bargaining

Here, we consider a general scenario wherein the BS bargains with all the COs one by one in a predefined sequence. The sequence can be obtained by sorting the COs based on their channel condition, cache availability, or energy sensitivity. Specifically, the given sequence has an impact on the obtained social welfare. Further, finding a sequence that maximizes social welfare is an NP-Hard problem. Thus, we employed the energy sensitivity as a heuristic to analyse the outcome of sequential bargaining. Let the COs are sorted according to their energy sensitivity and the BS bargains with each CO in the order of $1, 2, \dots U$. The SEQ-B problem can be viewed as U coupled one-to-one bargainings between the BS and a given CO. Consequently, the solution of SEQ-B consists of U agreement or disagreement outcomes of the one-to-one bargaining problem. Specifically, the BS's payoff at a stage u, i.e., when BS bargains with CO u, depends on two factors – (a) the bargaining outcome of stage u and (b) the aggregated payoff of the past $u-1$ stages. Next, we systematically obtain the outcome of the one-to-many bargaining problem under SEQ-B protocol.

The BS initiates bargaining with CO u only if the aggregated fraction delivered by the previous $u-1$ COs is less than the total size of the requested content. Otherwise, the BS stops bargaining with the rest of the COs because accepting any further agreements will not improve the utility of the BS (see Eq. (3)). Hereafter, we assume that the aggregated fraction delivered by first $u-1$ COs is less than 1 and the BS initiates the bargaining with CO u. Hence, at the current stage, the BS already has the outcomes of past $u-1$ bargainings, i.e., $(x_n^*, z_n^*)_{n \in \{1,2,\dots,u-1\}}$. Consider the case when the BS fails to reach an agreement with CO u. We find the utility of the CO u under disagreement as $\mathcal{V}_u^0 = 0$ using Eq. (6). Similarly, we use Eq. (3) to find the BS's disagreement utility at stage u

$\mathcal{J}_u^0(\boldsymbol{x}_{u-1}^*, \boldsymbol{z}_{u-1}^*)$, which is the aggregated payoff of the past $u-1$ stages. Mathematically,

$$\mathcal{J}_u^0(\boldsymbol{x}_{u-1}^*, \boldsymbol{z}_{u-1}^*) = \mathcal{C}\big(\min\{S, S\sum_{n=1}^{u-1} x_n^*\}\big) - \sum_{n=1}^{u-1} z_n^* \quad (13)$$

Next, we consider the case when the BS reaches an agreement (x_u, z_u) with CO u at stage u. The agreement utility of the CO u is given as $\mathcal{V}_u(x_u, z_u) = z_u - \mathcal{E}_u(x_u)$ which is also the payoff gain the CO u as $\mathcal{V}_u^0 = 0$. Further, we denote the agreement utility of BS at stage u by $\mathcal{J}_u(\boldsymbol{x}_{u-1}^*, \boldsymbol{z}_{u-1}^*, x_u, z_u)$, which is stated as follows:

$$\mathcal{J}_u(\cdot) = \mathcal{C}\big(\min\{S, S(\sum_{n=1}^{u-1} x_n^* + x_u)\}\big) - \sum_{n=1}^{u-1} z_n^* - z_u \quad (14)$$

Further, we obtain the payoff gain of the BS and the CO, based on the their utilities under agreement and disagreement. The payoff gain is defined as the difference of utility values under agreement and disagreement. Consequently, the BS's payoff gain at stage u is

$$\mathcal{J}_u(\cdot) - \mathcal{J}_u^0(\cdot) = \mathcal{C}\big(\min\{S - S\sum_{n=1}^{u-1} x_n^*, x_u\}\big) - z_u \quad (15)$$

Following the analysis of one-to-one bargaining, we obtain the NBS of the bargaining problem between the BS and CO u by solving the following optimization problem –

$$\max_{(0\leq x_u \leq a_u, z_u \geq 0)} (\mathcal{J}_u(\cdot) - \mathcal{J}_u^0(\cdot))(\mathcal{V}_u(x_u, z_u) - \mathcal{V}_u^0) \quad (16)$$
$$\textit{s.t.} \quad \mathcal{J}_u(\cdot) - \mathcal{J}_u^0(\cdot) \geq 0; \mathcal{V}_u(x_u, z_u) \geq 0$$

Proposition 2. *The NBS of the bargaining between the BS and CO at stage u is as given:*
$$(x_u^*, z_u^*) = \big(x_u^0, \mathcal{E}_u(x_u^0) + \tfrac{\mathcal{M}(x_u^0)}{2}\big),$$
where x_u^0 is the amount of content delivered by the CO which maximizes the marginal SW, $\mathcal{M}(x_u)$ at stage u.

Proof: Please refer to the supplementary file. ■

Remarks: In SEQ-B protocol, the BS bargains with the COs in a given order until the delivered fractions of the content is not sufficient to meet the decoding requirement. The marginal social welfare generated due to content delivery at each bargaining step is equally shared among the BS and the CO through incentive transfer. This implies that the SEQ-B is *proportionally fair*. Besides, the amount of incentive paid by the BS to participating COs compensate their energy cost.

D. Concurrent Bargaining

Here, we present the NBS for the case wherein the BS bargains with all the COs concurrently. The CONCR-B problem can be viewed as U independent one-to-one bargaining, between BS and COs, occurring simultaneously. In what follows, we systematically obtain the fraction of content $\boldsymbol{x}$, delivered by COs and their corresponding incentives $\boldsymbol{z}$ under CONCR-B protocol. First, we consider the case wherein the BS reaches an agreement $(\boldsymbol{x}, \boldsymbol{z})$ with all the participating COs. The BS's payoff under the agreement is represented as

$$\mathcal{J}(\boldsymbol{x}, \boldsymbol{z}) = \mathcal{C}\big(\min\{S, S\sum_{u=1}^{U} x_u\}\big) - \sum_{u=1}^{U} z_u \quad (17)$$

and the payoff of CO u under agreement is as given:

$$\mathcal{V}_u(x_u, z_u) = z_u - \mathcal{E}_u(\cdot) \quad (18)$$

Eqs. (17) and (18) also signify the payoff gains of the BS and the COs, respectively. Next, we consider the case in which the outcome of the concurrent bargaining between the BS and the participating COs is disagreement. Specifically, we focus on the worst case scenario, when no CO agrees to deliver its cached content, i.e.,$(x_u = 0)_{u\in\mathcal{U}}$. Thus, the BS does not pay incentives to the COs, i.e., $(z_u = 0)_{u\in\mathcal{U}}$ and delivers the whole content using cellular link. Consequently, the utility of the BS and the COs under disagreement is zero, i.e., $\mathcal{J}^0 = 0, \mathcal{V}^0 = 0 \quad \forall u \in \mathcal{U}$.

The decision of CO u to participate in content delivery under CONCR-B protocol depends on its energy cost and the incentive received from the BS. In particular, the CO u will only participate if its energy cost $\mathcal{E}_u(x_u)$ for content delivery is no more than that of received incentive z_u, i.e., $\mathcal{V}_u(x_u, z_u) \geq 0$. Let $\mathcal{U}' \subseteq \mathcal{U}$ denotes the set of COs who participate in content delivery under CONCR-B protocol. Since the BS bargains with $|\mathcal{U}'|$ COs simultaneously and each bargaining is independent, we can model this bargaining situation as $(|\mathcal{U}'|+1)$-person Nash bargaining game. Therefore, the outcome of CONCR-B using the Nash bargaining framework is obtained by solving following optimization problem:

$$\max_{(\boldsymbol{x},\boldsymbol{z})} \quad \mathcal{J}(\boldsymbol{x}, \boldsymbol{z}) \prod_{u\in\mathcal{U}'} \mathcal{V}_u(x_u, z_u) \quad (19)$$
$$\textit{s.t.} \quad \mathcal{J}(\boldsymbol{x}, \boldsymbol{z}) \geq 0 \quad (20)$$
$$\mathcal{V}_u(x_u, z_u) \geq 0, \forall u \in \mathcal{U}' \quad (21)$$
$$0 \leq x_u \leq a_u, z_u \geq 0, \quad \forall u \in \mathcal{U}' \quad (22)$$

The goal of the Nash bargaining is to maximize the product of the payoff gains of the BS and the participating COs, as given in Eq. (19). For ease of solving, we transform the given objective function into its logarithmic form and present the equivalent logarithmic-bargaining optimization problem [32] as follows:

$$\max_{(\boldsymbol{x},\boldsymbol{z})} \quad \log\big(\mathcal{J}(\boldsymbol{x}, \boldsymbol{z})\big) + \sum_{u\in\mathcal{U}'} \log\big(\mathcal{V}_u(x_u, z_u)\big) \quad (23)$$
$$\textit{s.t.} \quad (20) - (22)$$

The objective function of given optimization is strictly convex and the set of constraints (Eqs. (20)-(22)) construct a convex and compact feasible region. Thus, the given maximization problem is convex in nature and guarantees a unique optimal solution, which can be obtained using Karush-Kuhn-Tucker (KKT) conditions [33].

Proposition 3. *Let $\Psi_{\mathcal{U}'}(\boldsymbol{x})$ signify the total SW generated* *through content delivery by all the COs in $\mathcal{U}'$. The amount of incentive paid by the BS to CO $u \in \mathcal{U}'$ for content delivery, under the Nash bargaining framework is*

$$z_u^* = \mathcal{E}_u(x_u) + \frac{1}{|\mathcal{U}'|+1}\Psi_{\mathcal{U}'}(\boldsymbol{x}) \tag{24}$$

Proof: Please refer to the supplementary file. ■

Remarks: In CONR-B protocol, the BS bargains with all the COs simultaneously to obtain a content delivery profile $\boldsymbol{x}$ which maximizes the SW. Unlike SEQ-B, in CONCR-B, the BS also has zero disagreement point. Consequently, the SW is shared among the BS and the COs equally. Hence, CONCR-B satisfies *max-min fairness*.

VI. Convergence of the Proposed Schemes

In this section, we study the convergence of the proposed sequential and concurrent bargaining-based approaches. Specifically, we show that both the approaches converge to the optimal social welfare value.

A. Convergence of sequential bargaining

In this subsection, we aim to show that the NBS of the one-to-one bargaining problems in sequential bargaining maximize the social welfare defined in Eq. (7). To this end, we present the following proposition.

Proposition 4. *When the BS bargains with all the COs, the optimal content delivery profile obtained through one-to-one bargaining among the BS and participating COs also maximizes the social welfare.*

Proof: Please refer to the supplementary file. ■

B. Convergence of concurrent bargaining

In this subsection, we aim to show that the solution of the concurrent bargaining converges to the SW value. To this end, we present the following proposition.

Proposition 5. *The optimal content delivery profile obtained through concurrent bargaining also maximizes the social welfare.*

Proof: Please refer to the supplementary file. ■

VII. Performance Evaluation

In this section, we discuss and analyze the experimental results to evaluate the performance of the proposed multi-source content delivery in cellular network. We use MATLAB to compute the numerical solutions of our proposed schemes. The simulation parameters considered for performance evaluation are presented in Table I.

A. Effectiveness of the proposed schemes

To show the effectiveness of the proposed schemes, i.e. sequential bargaining-based delivery (SEQ-D) and concurrent bargaining-based delivery (CONCR-D), we consider two different schemes as benchmarks. Further, for comparison same parameters, given in Table I, have been used for benchmark schemes.

Table I: Simulation parameters

Simulation parameter	**Value**
Number of COs, U	5
Content size, S	$[8, 12]$ GB
CaP, $\mathcal{A}$	$[0, 1]$
BS's cost function, $\mathcal{C}(b)$	$10b$
System constant, K	10^{-2} [34]
Fast fading gain, β_u	$\exp(\lambda)$, $\lambda = 1$
Distance between CO and RU, d_u	10 meter
Path loss exponent, α	4 [34]
Noise power density, η	-174dBm/Hz [34]
D2D rate, r	2 MBps [29]
CO's energy sensitivity, θ_u	[0, 1]
CO's energy cost, $\mathcal{E}_u(x_u)$	$(\theta_u e_u)^2$

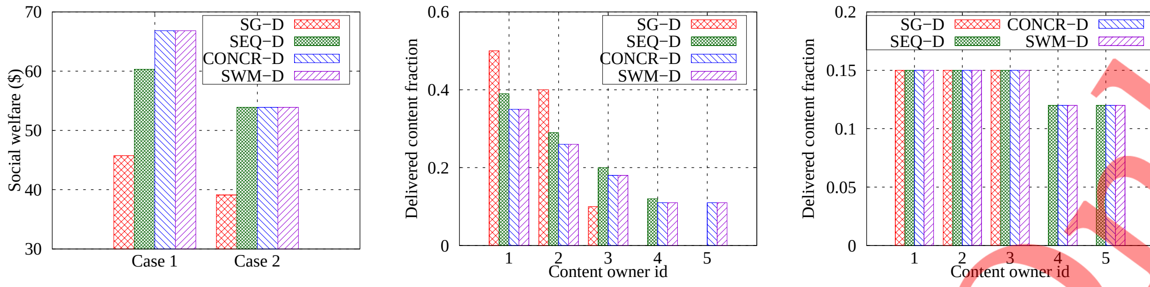
- Stackelberg game-based delivery (SG-D) [10]: In this content delivery scheme, the interaction between BS and multiple COs is modeled as a single-leader multi-follower Stackelberg game. Specifically, the BS acts as the leader and first announces the price per unit of content delivery for COs. Thereafter, the COs act as followers and based on the announced price decide the fraction of content to be delivered.
- Social welfare maximization-based delivery (SWM-D): In this scheme, a centralized entity (preferably BS) tries to maximize the aggregated payoff of both the BS and participating COs, i.e. Eq. (7).

We considered the following two different cases based on the availability of the requested content in the cache of the COs.

1) **Case 1**: the aggregated fraction of content available in the cache of COs is sufficient to decode the requested content, i.e., $\sum_{u\in\mathcal{U}} a_u \geq 1$. In this case, the BS can bargain with only a few COs for the amount of content delivered and their corresponding incentives under the sequential bargaining approach. Clearly, the *bargaining order* has an impact on the obtained social welfare. Thus, the sequential bargaining-based scheme may not result in optimal social welfare, as shown in **Fig. 2(a)**.
2) **Case 2**: The requested content can not be decoded by receiving fractions of the content from the COs, i.e., $\sum_{u\in\mathcal{U}} a_u < 1$. In this case, the BS bargains with all the COs under both the variants of one-to-many bargaining for content delivery through D2D links. Further, the BS delivers the remaining fraction through cellular links.

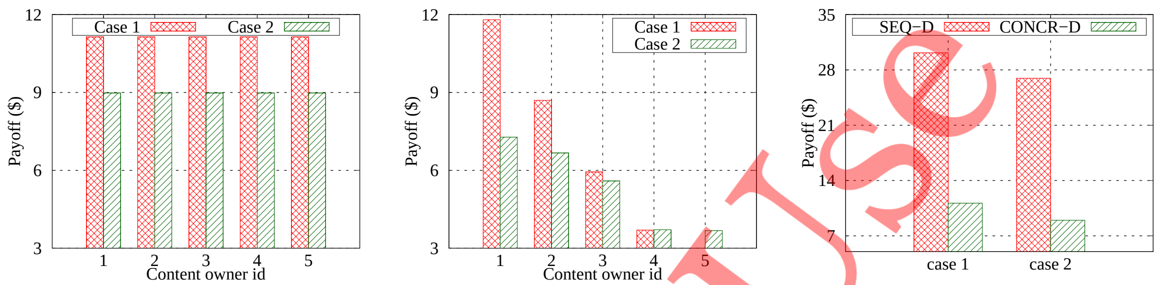
Specifically, for each user, we set $a_u = 0.5$ in Case 1 and $a_u = 0.15$ in Case 2.

Fig. 2(a) illustrates the comparison of social welfare for the aforementioned content delivery schemes. We observe that, all the schemes achieve higher social welfare value in Case 1 compared to that of Case 2. This observation is an evident one, as the social welfare is an increasing function of the delivered fraction of content and is upper bounded by a_u. Further, we observe that the proposed SEQ-D and CONCR-D



(a) Social welfare (b) Content delivery profile for Case 1 (c) Content delivery profile for Case 2

Figure 2: Comparison of the schemes



(a) COs' payoff in CONCR-D (b) COs' payoff in SEQ-D (c) BS's payoff

Figure 3: Individual rationality and fairness of CONCR-D and SEQ-D schemes

schemes always outperform the SG-D scheme. This is because, unlike the bargaining based approach, the SG-D scheme fails to capture the benefit of cooperation between BS and COs. Further, similar to SWM-D scheme, the CONCR-D scheme always attains the maximum social welfare value among the four schemes. However, the SEQ-D scheme attains maximum social welfare value only in Case 2. Since $\sum_{u \in \mathcal{U}} a_u < 1$ in Case 1, the BS does not bargain with all the participating COs. This results in decreased social welfare value for SEQ-D scheme in Case 1.

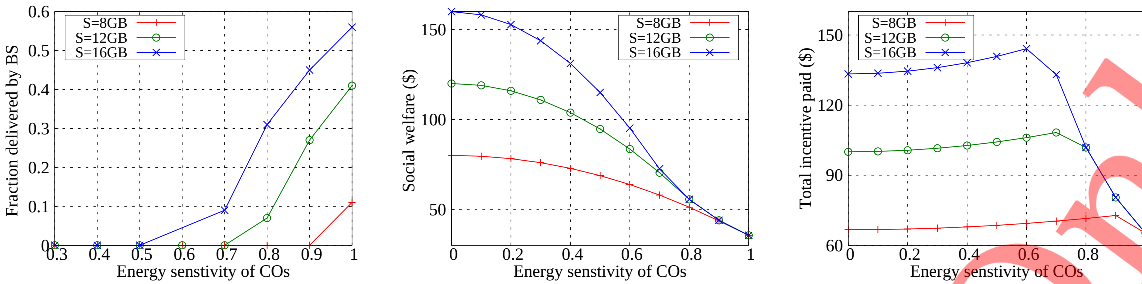
Fig. 2(b) illustrates the content fraction delivered by each CO in Case 1. Note that, the COs are arranged according to their increasing order of energy sensitivity (θ_u), i.e. [0.55, 0.64, 0.77, 0.97, 0.98]. Consequently, we observe that the amount of content delivered by the COs decreases with the increase in their energy sensitivity for all the schemes. Since CONCR-D maximizes the social welfare, the amount of content delivered by all the COs is same for both CONCR-D and SWM-D schemes. In case of SG-D, the BS selfishly tries to maximize its own payoff by motivating the lower energy sensitive COs to deliver large amount of their cached content. On the contrary, in case of SEQ-D, the content delivery profile is obtained by jointly considering the payoff of the BS and the CO. The content fraction delivered by each CO in Case 2 is shown in Fig. 2(c). We observe that, in both SEQ-D and CONCR-D, the obtained content delivery profile maximizes the social welfare.

Inference: The CONCR-D scheme always attains a content delivery profile which maximizes the social welfare. On the contrary, the SEQ-D scheme attains the maximum social welfare value only in Case 2. This is because in Case 2, BS bargains with all the participating COs and the social welfare is a function of the content delivery profile only, as shown in Equation (7).

B. Individual Rationality and Fairness

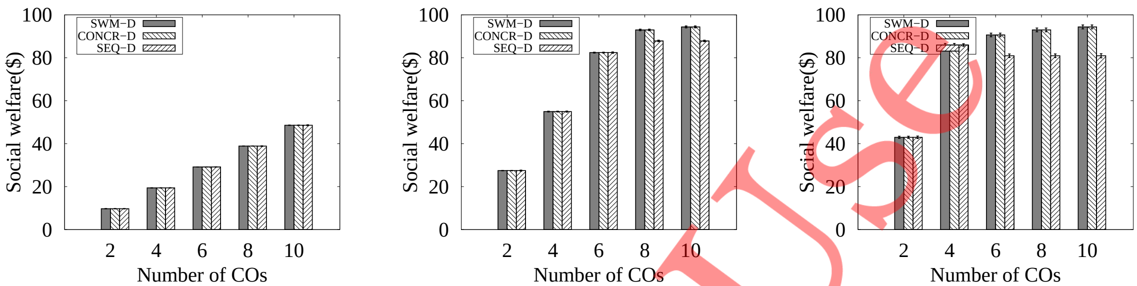
In this subsection, we investigate individual rationality and fairness of the proposed SEQ-D and CONCR-D schemes. Similar to the aforementioned setting, the COs are arranged according to their increasing order of energy sensitivity. Figs. 3(a) and 3(b) depict the individual payoff of each CO obtained in SEQ-D and CONCR-D schemes, respectively, for both Case 1 and Case 2. Further, we show the payoff of the BS in Fig. 3(c) for both the cases. From Figs. 3(a) and 3(b), we observe that, the participating COs attain non-negative payoff in both the schemes for content delivery once they agree to deliver the content. Hence, both the schemes guarantee individual rationality to all the COs. Further, from Fig. 3(c), we observe that, the BS also attains non-negative payoff under both the schemes in both the cases. Hence, the schemes also ensure individual rationality for the BS.

From Figs. 3(a) and 3(c), we observe that for both the cases, the payoff of BS is equal to the payoff of all participating COs in CONCR-B scheme. This is because, in CONCR-B, the social welfare is equally shared among the BS and the participating COs, as discussed in Section V-D. Further, by comparing Figs. 3(b) and 3(c), we observe that, the aggregated payoff of the participating COs is equal to the payoff of the BS for both cases in SEQ-B scheme. This is because, in SEQ-B, the marginal social welfare generated at each bargaining step is equally divided between the BS and the CO as discussed in Proposition 1.



(a) BS' content delivery (b) Social welfare (c) Incentive amount

Figure 4: Impact of COs' Energy Sensitivity



(a) $a_u = 0.05$ for each CO (b) $a_u = 0.15$ for each CO (c) $a_u = 0.25$ for each CO

Figure 5: Social welfare for varying number of COs and their CaP

Inference: Both the SEQ-B and CONCR-B schemes ensure individual rationality for the BS and participating COs, thereby, motivating the COs to participate in content delivery. Further, the SEQ-D scheme is proportionally fair and the CONCR-D scheme ensures max-min fairness.

C. Impact of COs' Energy Sensitivity

We investigate the impact of the COs' energy sensitivity on the performance benefits of multi-source D2D content delivery for CONCR-D scheme. More specifically, we consider fraction delivered by the BS, the social welfare, and the total incentive paid by the BS to the COs. Additionally, we consider three different content sizes, i.e. 8 GB, 12 GB, and 16 GB. In Fig. 4(a), we observe that, when the energy sensitivity of COs' increases, the fraction delivered by the BS increases. This comes as a straightforward observation, as higher value of energy sensitivity indicates higher energy cost of COs. Consequently, major fraction of the content is delivered by the BS. Also, for a fixed value of energy sensitivity of COs', increase in content size corresponds to increase in the fraction delivered by the BS.

Fig. 4(b) shows the variation of social welfare of the system against the COs' energy sensitivity. We observe that, for fixed content size, as the energy sensitivity of COs increases, the social welfare value decreases. The reason for this is twofold. First, with the increase in energy sensitivity, the energy cost of the COs increases (as shown in Eq. (7)) which, in turn, decreases the fraction of content delivered by the COs. Further, for a fixed energy sensitivity of the COs', as the content size increases, the social welfare value increases. Thus, we conclude that the benefits of content delivery are more prominent when the energy insensitive COs participate and deliver contents of larger size.

The variation of total incentive paid by the BS with respect to the energy sensitivity of the COs' is shown in Fig. 4(c). For a fixed content size, we observe that, as the COs' energy sensitivity increases, the amount of incentive paid by the BS increases initially and then decreases before convergence. This is quite evident from Eq. (24), as with the increase in the energy sensitivity of the COs, the energy cost increases in a quadratic manner and the social welfare value decreases exponentially. Also, we observe that for a fixed value of the energy sensitivity, the incentive paid by the BS increases with the increase in the content size.

D. Impact of the number of COs on the SW

In this section, we studied the effect of the number of COs and their CaP on the SW for the proposed CONCR-D and SEQ-D approaches. Fig. 5 shows the variation of social welfare with the change in the number of COs and their CaP. Specifically, we varied the number of COs between 2-10 and considered three different CaPs, i.e., a_u= 0.05, a_u= 0.15, and a_u= 0.25 for each CO $u \in \mathcal{U}$. The energy sensitivity of the COs are uniformly selected between 0 and 1. Further, the simulation was repeated for 30 times based on which the ensemble average and 95% confidence interval were computed.

From Fig. 5, we observe that irrespective of the number of COs their CaPs, the proposed CONCR-D approach always attains the maximum social welfare (SW) which is represented by SWM-D approach. This is due to the fact that, in the CONCR-D approach, the BS bargains with all the available COs. Further, in CONCR-D approach, with the increase in number of COs and their CaP, the SW increases before convergence. The value of SW converges because the amount of content to be delivered is limited by its total size, as shown in Eq. (5).

From Fig. 5, we also observe that unlike CONCR-D approach, the proposed SEQ-D approach fails to attains the maximum SW in case the aggregated CaP is greater than one. For example, in Fig. 5(b), the number of COs are eight and each CO owns 0.15 fraction of the requested content. When the aggregated CaP is greater than one, the BS can deliver the entire content to the requesting user by bargaining sequentially with fewer number of COs. Consequently, the remaining COs will be rejected by the BS from the bargaining. Hence, using proposed SEQ-D, the BS attains sub-optimal SW value.

Inference: If we increase the number of COs, provided their aggregated fraction of content is lesser than one, both the CONR-D and the SEQ-D approaches maximize the SW.

E. Impact of the content size on the SW

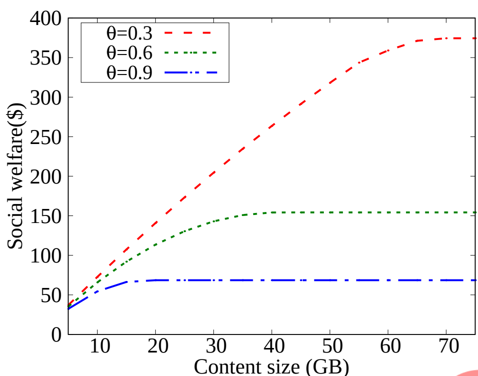


Figure 6: Effect of content size on the SW

In this section, we studied the effect of the content size (S) and the energy sensitivity of the COs on the SW of the system. Fig. 6 shows the variation of the SW with the change in the content size for different energy sensitivity values of the COs. We varied the content size between 5-75 GB and considered three different energy sensitivity values, i.e., θ= 0.3, 0.6, and 0.9. We observe that, the value of SW is higher for lower value of θ. Further, for a given value of θ, when the content size increases, the SW increases before convergence. This is due to the fact that, with the increase in the content size, the amount of content delivered by the COs also increases, resulting in lower serving cost of the BS. Furthermore, the value of SW converges because the amount of content to be delivered is limited by its total size, as shown in Eq. (1).

VIII. Conclusion

In this paper, we studied multi-source D2D content delivery in cellular networks. We analyzed the economic interactions among the BS and multiple heterogeneous COs and proposed an incentive mechanism based on the Nash bargaining framework. Specifically, we obtained the optimal amount of content delivered by the participating COs and their corresponding incentives that maximizes the social welfare while maintaining fairness, under two variants of one-to-many bargaining, namely sequential bargaining and concurrent bargaining. The analytical results demonstrated that the incentive mechanism is effective in reducing the amount of content delivered by the BS while ensuring fair incentive transfer among the participating COs.

In future, we plan take the mobility of the COs into consideration. In such scenario, the wireless channel between COs and RU changes with time and the bargaining-based incentive mechanism may not be appropriate. Another possible extension of this work is to analyze the scenario where a set of COs form a group and bargain with the BS for content delivery.

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