Joint Content Sharing and Incentive Mechanism for Cache-Enabled Device-to-Device Networks

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***Abstract*—Cache-enabled device-to-device (C-D2D) networks allow the constituent user devices to share their cached content with other user devices through D2D communication. As a result, the communication delay of participating users is minimized in C-D2D networks. Clearly, the success of C-D2D networks relies on the willingness of the participating users to share their cached content. In this paper, we analyze the interaction among participating cache-enabled D2D users and determine their caching, sharing, and reward decisions to minimize the users' total cost. In view of the fact that the participating users have heterogeneous content interest profile (CIP) and storage capacity, and are self-centric, there is a need to design a fair incentive mechanism to encourage cooperation among users. To this end, we model the interaction among the D2D users as a multi-person bargaining game and design a novel incentive mechanism using the Nash bargaining solution (NBS) approach. The proposed incentive mechanism is capable of minimizing users' total costs while ensuring fair reward transfer among participating users. Further, we proposed a distributed algorithm which allows the execution of the proposed mechanism without any involvement of base station (BS), which is much needed for autonomous D2D networks. The simulation results demonstrate that the proposed mechanism improves fairness by at least 74% and reduces the users' total cost by at least 13.83% compared to the benchmark schemes.**

***Index Terms*—Cooperative caching, autonomous D2D networks, content sharing, Nash bargaining, distributed optimization.**

I. Introduction

The unprecedented growth of mobile users and their demand for multimedia-enabled contents (e.g. videos) have been considered as a premier drivers of the data traffic over cellular backhaul [1], [2]. To reduce the cellular backhaul traffic and improve the quality of service (QoS) of the users, network provider should support advanced content delivery techniques. Recent studies on caching suggest that the popular contents can be cached in the cache-enabled user devices (e.g. smartphone and tablets) which form a content-sharing network, namely Cache-enabled device-to-device (C-D2D) network [3]–[5]. In C-D2D network, the users share the cached contents with other users (content requesters) in the vicinity using D2D communication, and hence, minimize their communication delay [6]–[8].

C-D2D networks operate in two phases – (a) placement phase, and (b) delivery phase [6]. Typically, during the placement phase, the cellular data traffic is low, and the device caches the content according to its content interest profile (CIP) and storage capacity [9]. On the other hand, in the delivery phase, the user requests the contents, which are served from its local cache, from neighbors' cache, or by directly downloading from the base station (BS). To further improve the performance of C-D2D networks, recent works suggest that the content can be encoded using coding schemes [10] before caching [11], [12]. Coding schemes make sharing more flexible by allowing users to cache a fraction of a large size content in their limited storage during the placement phase. Further, coding schemes empower users to decode the requested content by receiving the encoded fractions of content from multiple sources [6], [10], [11]. Clearly, the performance of C-D2D networks depends on the cooperative content caching and sharing during the placement and delivery phases. Consequently, in this work, we focus on cooperative coded content caching and sharing in C-D2D networks.

A. Motivation

Existing literature addressed the issue of content caching and sharing among D2D users to improve the QoS parameters of C-D2D networks, such as, content access delay [13], [14], content availability [15], [16], and energy efficiency [17]–[19]. These studies are based on the assumption that the users have social bonding, and hence, are willing to share contents with each other [20]. However, due to the transmission energy cost, a rational or self-centric user may be unwilling to share its cached contents with other users. Consequently, few studies proposed incentive-based schemes, wherein D2D users are incentivized to share the cached contents with their neighboring users [12], [21]. These incentive-based schemes need a central controller (e.g. BS) for coordination. Additionally, these schemes overlook the individual cost incurred by D2D users for content caching and sharing, and hence, are unable to motivate the heterogeneous D2D users for cooperation. Indeed, D2D users are heterogeneous with reference to their CIP, storage capacity, cellular data plans, and delay and energy sensitivity. Therefore, it is essential to design a content caching and sharing mechanism which encourages cooperation and coordination among heterogeneous D2D users in C-D2D networks.

The above discussion motivates us to conceptualize the cooperative D2D caching mechanism using an economic framework and design an incentive mechanism which encourages the heterogeneous D2D users to cooperate. Specifically, the proposed mechanism computes the caching and sharing decisions of the participating users using the Nash bargaining solution and ensures fair incentive transfer among them. Further, for autonomous D2D networks, we propose a distributed algorithm, using primal-dual decomposition [22], [23], which

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enables the participating users to distributively achieve the Nash bargaining solution (NBS). Technically, given the CIPs of users, we are concerned about the following set of questions: *i) What fraction of each content needs to be cached at the end of the D2D users during the placement phase, ii) What fraction of the cached content should be shared by the D2D users with their neighboring users during the delivery phase, iii) How much incentive should the D2D users receive for their content sharing*?

B. Contributions

To analyze the cooperative D2D caching and sharing in C-D2D networks, we construct a detailed framework wherein we first model the cost function of D2D users based on their cellular data plan, energy consumption and experienced delay. Further, to encourage cooperation among heterogeneous D2D users, an incentive scheme is designed, which enables users to pay and/or receive fair incentive for content sharing.

Specifically, our contributions are as follows:

- We conceptualize a static C-D2D network consisting of heterogeneous D2D devices which are characterized by their diverse CIP, storage capacity, cellular data plan, and energy and delay sensitivity. We also investigate the effect of these factors on the cooperation between the devices.
- We model the D2D cooperative caching and sharing decision as a bargaining situation between multiple cost-minimizing entities. Further, based on the NBS approach, we propose a new incentive mechanism which encourages the D2D users to participate in cooperative caching and sharing.
- Further, we present a distributed algorithm which enables the execution of the proposed incentive mechanism in a decentralized fashion, and hence, is also suitable for the autonomous D2D networks.

II. Related Work

In literature, there exist various schemes for enabling cooperative D2D caching and sharing in C-D2D networks. We group the existing studies broadly into two categories – *non incentive-based* [13], [15]–[17], [19], [24], [25] and *incentive-based* [12], [21], [26]–[29].

Some of the non incentive-based schemes proposed in the existing literature are discussed here. Amer *et al*. [13] studied cache placement problem in C-D2D networks to minimize the average content access delay. To this end, the authors first divided the total users into multiple clusters and proposed a greedy based algorithm to obtain a cache placement policy which minimizes the access delay within the cluster(s). Likewise, Guo *et al*. [15] proposed a caching scheme which maximizes the content hit probability within the cluster(s). The authors considered a central controller, which enables coordination among the users while accounting for the heterogeneous content interests of the users. Further, Malak *et al*. [16] proposed a D2D content caching strategy by exploiting the spatial correlation of D2D users to maximize the content hit-probability. Additionally, Lee and Molisch [17] obtained the optimal caching policy to minimize the overall energy consumption of the C-D2D networks for a given storage capacity of participating users. The authors also demonstrated the benefits of coordinated caching over independent caching. The aforementioned schemes improve the network QoS parameters and require a central controller for the coordination among D2D users.

On the other hand, there exist few incentive-based schemes for content caching. Chen *et al*. [12] employed a game theoretic approach, namely single-leader-multi-follower Stackelberg game, for content caching and sharing between D2D users. In the proposed scheme, the base station (leader) aims to minimize its service cost, whereas the D2D users (followers) minimize their average delay by caching the contents of self-interest. Fan *et al*. [26] formulated a preference-aware cooperative game in which the overall game is split into two parts, namely caching decision and space allocation sub-games. Further, the authors proposed an incentive mechanism which motivates sharing among D2D users. In the proposed scheme, the central entity computes the optimal caching decision based on the users' content preferences and demands, whereas the users independently decide the space allocation. Likewise, Doan *et al*. [27] proposed a joint caching and power allocation scheme for cache-assisted D2D networks, which minimizes the backhaul load during the delivery phase. In the proposed scheme, the central controller is agnostic of the user's D2D connection time. Likewise, Wang *et al*. [28] modeled the interactions among the mobile operator and D2D users as a Stackelberg game. In the proposed scheme, the mobile operator acts as a leader and decides the amount of incentive paid to the individual users, based on their inter-contact time, to minimize its serving cost. The author also proposed a local search algorithm to solve the formulated optimization problem. Further, Yang *et al*. [29] proposed an incentive mechanism for content dissemination in D2D networks while considering D2D link failures. Specifically, a central controller obtains the amount of rewards to be paid to content owners for content dissemination using Markov Decision Process. Similarly, Shi *et al*. [30] employed a Stackelberg game to tackle the conflicts among the mobile operator and D2D transmitters for caching. In particular, the mobile operator decides the incentive for caching and the transmitting users decide their caching policy. Further, the incentive mechanisms are explored by the researchers for task-offloading [21] and content dissemination [8] in vehicular networks, while considering the presence of a centralized entity.

Synthesis: The existing studies discussed above are mainly based on the assumption that the D2D users have social ties and hence, they cooperate with one another. However, in practice, the D2D users hesitate to share their cached content because of transmission cost. Additionally, the heterogeneous characteristics of D2D users are overlooked in existing literature, which result in inefficient and unfair caching and sharing decisions for the users. Finally, these works are limited to BS-assisted D2D caching due to the intervention of central entity. Therefore, unlike the existing works, we propose a novel distributed coordinating scheme for C-D2D network, which entitles the participating D2D users to compute their optimal caching and sharing decisions.

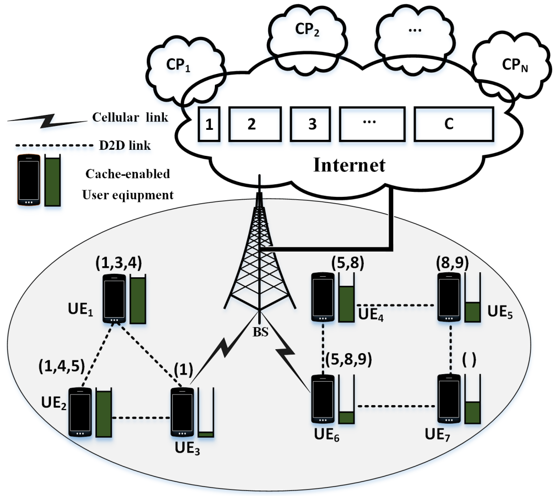


Figure 1: Cache-enabled D2D networks

III. System Model

A. System Overview

The C-D2D network in our study comprises a single BS and multiple cache-enabled D2D users. We denote the set of users by $\mathcal{U} = \{1, 2, \ldots U\}$. User $u \in \mathcal{U}$ is characterized by its storage capacity S_u and CIP $\mathcal{I}_u \subseteq \mathcal{C}$. For example, in Fig. 1, the user 1 is interested in content number 1, 3, and 4, whereas, user 2 is interested in content number 1, 4, and 5. Thus, $\mathcal{I}_1 = \{1, 3, 4\}$ and $\mathcal{I}_2 = \{1, 4, 5\}$. The users are in the coverage area of the BS and hence, cache the contents through cellular link. Additionally, the users can share the cached contents with other users in the vicinity through D2D link. The set $\mathcal{C} = \{1, 2, \ldots C\}$ signifies the *contents library*, which includes the contents of N different providers. The considered contents are of different sizes. We indicate the size of content $c \in \mathcal{C}$ by l^c. Further, we assume that the contents are encoded using systematic Raptor code [10], [12] of reception efficiency unity, and hence, a typical content request can be served by collating exact number of bytes (i.e., size of the content) from multiple sources in no specific order.

B. Cache and Service Model

The users cache the contents during the placement phase and share with other interested users during the delivery phase. Let user u cache $0 \leq x_u^c \leq 1$ fraction of content c. We define user u's caching decision as $\boldsymbol{x}_u = (x_u^c)_{c \in \mathcal{C}}$. Since user u has limited storage space, the following condition must hold:

$$\sum_{c \in \mathcal{C}} x_u^c l^c \leq S_u \qquad (1)$$

During the delivery phase, a typical user can act as a content requester and/or a content provider. Consider a case during the delivery phase where a user u requests for a content c. User u first looks for the requested content in its local cache. If the cached fraction is not enough to decode the requested content, the user receives the remaining fraction from its neighboring users through D2D communication. Motivated by [7], [31], we assume that two users are neighbor of each other and can communicate with each other through D2D links, if their physical distance is less than collaborative distance R_{max}. We denote the set of neighbors of user u by $\mathcal{N}_u = \{v : d(u, v) \leq R_{max}\}$, where $d(u, v)$ is the euclidean distance between users u and v. Let neighbor $v \in \mathcal{N}_u$ share $y_{v,u}^c$ portion of the content with user u. Since the portion of file shared is limited by the fraction of content cached by the neighboring nodes during the placement phase, the following condition must hold:

$$0 \leq y_{v,u}^c \leq x_v^c, \quad v \in \mathcal{N}_u, c \in \mathcal{C} \qquad (2)$$

In case, the total content fraction received through D2D communication along with the cached fraction is insufficient, the user downloads the residual amount directly from the BS. We denote the downloading decision of user u by $\boldsymbol{z}_u = (z_u^c)_{c \in \mathcal{C}}$, where z_u^c signifies the fraction of content c the user u downloads from BS during the delivery phase. Since the reception efficiency of coding is assumed to be unity, the following condition must hold to decode the content $c \in \mathcal{I}_u$:

$$x_u^c + \sum_{v \in \mathcal{N}_u} y_{v,u} + z_u^c = 1 \qquad (3)$$

C. Cost Model of D2D User

The goal of every D2D user $u \in \mathcal{U}$ is to minimize its total cost consisting of the experienced delay, energy consumption, and monetary factors for a given CIP $\mathcal{I}_u$. In this section, we present the formulations of these costs.

1) Delay experience cost: The D2D user u incurs a certain delay for receiving the content $c \in \mathcal{I}_c$. We denote the delay cost by $\mathcal{D}_u(\cdot)$, which depends on the delay experienced by the user u over all the contents in its CIP. The D2D and device-BS links are wireless supported and characterized by different communication rates. In fact, the D2D links are established among the devices which are in close vicinity, and hence, are considered to be faster than the device-BS link [12]. Motivated by [32], we define a parameter, namely, delay experience per byte, to signify the heterogeneous characteristics of the links. Let $d_{u,0}$, $d_{u,v}$, and $d_{u,b}$ denote the delay experience per byte of content from its local cache, from v^{th} neighbor, and from BS directly, respectively. Thus, the total delay experience by user u for content c is as follows:

$$\Delta_u^c = d_{u,0} x_u^c l^c + \sum_{v \in \mathcal{N}_u} d_{u,v} y_{v,u}^c l^c + d_{u,b} z_u^c l^c \qquad (4)$$

By definition $d_{u,0} \to 0$, i.e. the user u accesses the content from its local cache with almost no delay. Hence, for delay-sensitive users, it is necessary to cache the entire contents in CIP during the placement phase. Further, motivated by [12], [32], we assume that the delay cost function $\mathcal{D}_u(\cdot)$ is positive, increasing, and strictly convex function of the total experienced delay $\Delta_u = \sum_{c \in \mathcal{I}_u} \Delta_u^c$.

2) Energy consumption cost: We divide the u^{th} user's energy consumption, namely $\epsilon_u^c = \epsilon_u^{c,cell} + \epsilon_u^{c,D2D}$, into two categories based on the interface used to receive and transmit content c. Further, motivated by [33], [34], in this work, we consider the energy consumption per byte (Joules/byte) for each link which signifies the transmission and reception energy consumption of the users. Since the user employs the cellular interface to receive contents during the placement and delivery phases, the cellular energy consumption $\epsilon_u^{c,cell}$ is expressed as follows:

$$\epsilon_u^{c,cell} = e_{u,b}(x_u^c + z_u^c)l^c \tag{5}$$

where, $e_{u,b}^c$ is the energy consumption per byte of user u over cellular interface. Unlike cellular interface, the user employs D2D interface to receive and transmit contents to one another. Therefore, the total D2D energy consumption of user u in receiving and transmitting content c is given by

$$\epsilon_u^{c,D2D} = \sum_{v \in \mathcal{N}_u} (e_{u,v}^t y_{u,v}^c + e_{u,v}^r y_{v,u}^c) l^c \tag{6}$$

where $e_{u,v}^t$ and $e_{u,v}^r$ are the energy expenditures of user u to transmit and receive unit byte from neighbor $v \in \mathcal{N}_u$, respectively. These parameters capture the quality of the established D2D link between users u and v. Finally, we model the energy cost of user u, denoted by $\mathcal{E}_u(\cdot)$, as a linear function of the user's total energy consumption $\varepsilon_u = \sum_{c \in \mathcal{C}} \epsilon_u^c$.

3) Monetary cost: The user u pays a monetary cost to the cellular operator to cache and download contents. Typically, users are subscribed to different data plans for the placement and delivery phases [35]. Hence, the total cellular payment paid by user u depends on the amount of content cached during the placement phase and downloaded during the delivery phase. Let user u pay p_u^{off} and p_u^{on} units of charge for unit byte of content during the placement and delivery phases, respectively. Then, the total cellular payment of user u is expressed as

$$\mathcal{P}_u = \sum_{c \in \mathcal{C}} (p_u^{off} x_u^c + p_u^{on} z_u^c) l^c \tag{7}$$

Finally, we define the individual cost of user u, namely $\mathcal{J}_u(\boldsymbol{x}_u, \boldsymbol{z}_u, \boldsymbol{y}_u, \boldsymbol{y}_{-u})$, which takes into consideration the aforementioned costs as follows:

$$\mathcal{J}_u(\cdot) = \mathcal{D}_u(\boldsymbol{x}_u, \boldsymbol{y}_{-u}, \boldsymbol{z}_u) + \mathcal{E}_u(\boldsymbol{x}_u, \boldsymbol{y}_u, \boldsymbol{y}_{-u}, \boldsymbol{z}_u) + \mathcal{P}_u(\boldsymbol{x}_u, \boldsymbol{z}_u) \tag{8}$$

where $\boldsymbol{y}_u = (y_{u,v}^c)_{v \in \mathcal{N}_u, c \in \mathcal{C}}$ and $\boldsymbol{y}_{-u} = (y_{v,u}^c)_{v \in \mathcal{N}_u, c \in \mathcal{C}}$ denote the fraction of contents user u transmits to and receives from its neighbors $\mathcal{N}_u$, respectively. A typical user u aims to minimize its individual cost $\mathcal{J}_u(\cdot)$ for its given CIP $\mathcal{I}_u$. Since $\mathcal{J}_u(\cdot)$ monotonically increases with the content's size l^c, a cost-minimizing user prefers not to cache (and hence share) content of no interest, i.e., $c \notin \mathcal{I}_u$. Additionally, a user even hesitates to share its cached contents with neighbor users, since $\mathcal{J}_u(\cdot)$ is an increasing function of $\boldsymbol{y}_u$. In conclusion, rational users choose to operate independently and cache and download contents according to their CIP, since cooperative behavior of user results in *extra cost*. In particular, each user $u \in \mathcal{U}$ obtains its independent cost by solving the following optimization problem:

$$\mathbf{IP}_u : \min_{\boldsymbol{x}_u, \boldsymbol{z}_u, \boldsymbol{y}_u, \boldsymbol{y}_{-u}} \mathcal{J}_u(.) \tag{9}$$

$$\textit{s.t.} \quad (1), (2), (3)$$

$$y_{u,v}^c = 0, \quad \forall u, v \in \mathcal{U} \tag{10}$$

The objective function of the given optimization is strictly convex and the set of constraints (Eqns. (1)-(3)) construct a convex and compact feasible region. Thus, the given minimization problem $\mathbf{IP}_u$ is convex in nature and guarantees unique optimal cost, denoted by c_u^{ind}, which is the independent cost incurred by user u for the given CIP.

Indeed, the decision of the u^{th} user to cooperate depends on c_u^{ind} and so, u will only collaborate if the total cost in the case of cooperation is no more than that of c_u^{ind}. Therefore, to encourage cooperation among users, we need an incentive mechanism which affects the users' independent cost functions. Such an incentive mechanism should compensate the *extra cost* of cooperation incurred by the users.

It is noteworthy to mention that, the users' preferences are not explicitly reflected in Eq. (8). However, in the considered network, we assume that each user u is rational and minimizes its individual cost for its given content interest profile (CIP) $\mathcal{I}_u$. Since $\mathcal{J}_u(\cdot)$ monotonically increases with the content size l^c, a cost-minimizing user prefers not to cache (and hence, share) contents of no interest, i.e., $c \notin \mathcal{I}_u$, without proper incentive. Thus, in the problem formulation, the users' preferences considered implicitly.

IV. The Cooperative Content Sharing

Our goal is to design a cooperative content sharing scheme which enables D2D users to share their cached contents among one another. In this cooperative content sharing scheme, we often encounter a situation among users where *double coincidence of wants* does not occur. Specifically, a user receiving a requested content from a nearby user might not be able to compensate the user's transmitting cost directly by sharing some other content. Hence, a user collaborates only with a limited number of users who can repay its favor, which leads to the degradation in the performance of cooperative content sharing.

Motivated by opportunistic and *ad-hoc* wireless networks, we employ a virtual currency system (VCS) [36] to handle the aforementioned issue. In VCS, a user pays the virtual currency for the fraction of content it receives from neighboring users. The user utilizes the currency in order to avail services from other users. The VCS also encourages user u, who is not currently interested in any content ($\mathcal{I}_u = \phi$), to help other users in need by contributing its valuable resources and thereby, earning the corresponding reward. In particular, virtual currency plays the role of *transferable utility* and allows users to attain mutually profitable content caching and sharing decisions. In the proposed approach, the participating D2D users initiate and manage the currency system. Our virtual currency system is similar to the packet trade model (PTM) of mobile ad-hoc networks, wherein two adjacent nodes negotiate among themselves for an intended network packet [37].

Let $\tau_{u,v}^c$ denote the currency user u pays to user $v \in \mathcal{N}_u$ against the fraction of content c. Hence, the total currency reward of the u^{th} user is given as:

$$\mathcal{R}_u(\boldsymbol{\phi}_u, \boldsymbol{\phi}_{-u}) = \sum_{v \in \mathcal{N}_u} \sum_{c \in \mathcal{C}} (\phi_{v,u}^c - \phi_{u,v}^c) \tag{11}$$

where the vectors $\boldsymbol{\phi}_{-u} = (\phi_{v,u}^c)_{c \in \mathcal{C}, v \in \mathcal{N}_u}$ and $\boldsymbol{\phi}_u = (\phi_{u,v}^c)_{c \in \mathcal{C}, v \in \mathcal{N}_u}$ signify the currency reward user u receives and transfers, respectively. Clearly, negative value of $\mathcal{R}_u$ indicates the aggregated reward that user u transfers to other users in response to the received contents. The linear reward function $\mathcal{R}_u(\boldsymbol{\phi}_u, \boldsymbol{\phi}_{-u})$ indicates the risk neutral behavior of participating users [38]. The inclusion of reward function modifies the users' cost function, which, in turn, motivates them to share contents among one another. However, as users are heterogeneous, we need a fair mutual exchange of contents and rewards among them for adequate functioning of cooperative content sharing.

A. Nash Bargaining Theory: The Justification

Our aim is to minimize the total system cost which includes both the *individual cost* (defined in Eq. (8)) and *total currency reward* (defined in Eq. (11)) of the participating users. If we employ an optimization technique to minimize the total system cost, the rewards exchanged among the D2D users get canceled out in the objective function, and hence, making it infeasible to find the *fair* amount of reward transfer. Thus, we employ the Nash bargaining as the solution approach in our system model. Specifically, we model the content sharing among D2D users as a multi-player bargaining game. Thereafter, we use the NBS approach to solve the formulated game. Every element of the set $\mathcal{U}$ is modeled as a player and independent cost of the user u is adopted as its disagreement point To this end, we formally define the U-player bargaining game followed by the NBS of the game.

Consider a bargaining game $\mathcal{G} = \langle \mathcal{U}, \boldsymbol{S}, (\mathcal{T}_u^{cop}(\boldsymbol{s}))_{u\in\mathcal{U}} \rangle$, where $\mathcal{U}$ represents the set of users, $\boldsymbol{S}$ denotes the strategy space, i.e., $\boldsymbol{S} = S_1 \times S_2 \times \cdots S_U$, where S_u represents the set of strategies available to user u in the cooperative game. $\mathcal{T}_u^{cop}$ represents the total cost of user u, which depends on the action profile of all the participating users $\boldsymbol{s} = (s_1, s_2, \cdots s_U)$, $s_u \in S_u$. Thus, a strategy profile $\boldsymbol{s}^* = (s_1^*, s_2^*, \cdots s_U^*)$ is said to be the NBS if it solves the following optimization problem:

$$\max_{\boldsymbol{s}\in\boldsymbol{S}} \prod_{u\in\mathcal{U}} (\mathcal{T}_u^{ind} - \mathcal{T}_u^{cop}(\boldsymbol{s}))$$
$$\text{s.t.} \quad \mathcal{T}_u^{cop}(\boldsymbol{s}) \le \mathcal{T}_u^{ind}, \forall u \in \mathcal{U} \tag{12}$$

where, $\mathcal{T}_u^{ind}$ is the disagreement point of the u^{th} user or the maximum cost that the user expects from the cooperation, which is c_u^{ind}, in our case. Likewise, possible caching $\boldsymbol{X} = (\boldsymbol{x}_u)_{u\in\mathcal{U}}$, sharing $\boldsymbol{Y} = (\boldsymbol{y}_u)_{u\in\mathcal{U}}$, downloading $\boldsymbol{Z} = (\boldsymbol{z}_u)_{u\in\mathcal{U}}$, and currency transfer $\boldsymbol{\Phi} = (\boldsymbol{\phi}_u)_{u\in\mathcal{U}}$ decisions of users define the strategy space $\boldsymbol{S}$. The total cost $\mathcal{T}_u^{cop}(\cdot)$ of user u in the cooperative mode is given as:

$$\mathcal{T}_u^{cop}(\boldsymbol{x}_u, \boldsymbol{z}_u, \boldsymbol{y}_u, \boldsymbol{y}_{-u}, \boldsymbol{\phi}_u, \boldsymbol{\phi}_{-u}) = \mathcal{J}_u(\cdot) - \mathcal{R}_u(\cdot) \tag{13}$$

It is noteworthy that the total cost function of the user includes the reward function, which enables user u to improve his/her independent cost c_u^{ind}, either by gaining reward through content sharing or by receiving content $c \in \mathcal{I}_c$ from nearby users at relatively lower cost during the delivery phase. Further, users can freely choose to operate independently if the cooperation costs them higher. Therefore, the NBS solution unites the users for cooperative content caching and sharing, and ensures fair distribution of reward among them. To this end, we describe the problem formally and present the bargaining problem in greater details.

B. Bargaining Problem

The objective of Nash bargaining is to maximize the product of the users' gain obtained through cooperation. Hence, the objective function given in Eq. (12) is the series multiplication of users' gains. We transform the given objective into its logarithmic form for the ease of solving, and present the following equivalent logarithmic-bargaining optimization problem (**L-BP**):

$$\textbf{L-BP}: \max_{\boldsymbol{X},\boldsymbol{Y},\boldsymbol{Z},\boldsymbol{\Phi}} \sum_{u\in\mathcal{U}} \log(\gamma + c_u^{ind} - \mathcal{T}_u^{cop}(\cdot)) \tag{14}$$
$$\textit{s.t.} \quad \sum_{c\in\mathcal{C}} x_u^c l^c \le S_u, \quad \forall u \in \mathcal{U} \tag{15}$$
$$x_u^c + \sum_{v\in\mathcal{N}_u} y_{v,u}^c + z_u^c = 1, \forall u \in \mathcal{U}, c \in \mathcal{I}_u \tag{16}$$
$$y_{u,v}^c \le x_u^c, \quad \forall u \in \mathcal{U}, v \in \mathcal{N}_u, c \in \mathcal{C} \tag{17}$$
$$\mathcal{T}_u^{cop}(\cdot) \le \mathcal{T}_u^{ind}, \quad \forall u \in \mathcal{U} \tag{18}$$
$$0 \le x_u^c, y_{u,v}^c, z_u^c, \phi_{u,v}^c, y_{v,u}^c, \phi_{v,u}^c \le 1, \forall u \in \mathcal{U}, v \in \mathcal{N}_u, c \in \mathcal{C} \tag{19}$$

where $\gamma > 0$ is the additional reward that each user receives for participating. We assume that γ is very small compared to the currency received for content sharing, which does not alter the solution to the problem. Through γ, we also ensure the non-zero value of logarithmic forms. The objective function in Eq. (14) is the aggregated sum of user's cooperative gain on logarithmic scale. Eq. (15) is the storage constraint of users. Eq. (16) ensures that the received fractions of content are enough for the user to decode the interested contents. Further, constraint (17) states that the fraction of content shared by a user during the delivery phase is no more than its cached fraction. Additionally, constraint (18) guarantees that the total cost of users participating in the cooperative case is no more than that of the independent case. The user u computes its total cost in independent case c_u^{ind} by solving problem $\mathbf{IP}_u$.

The objective function of **L-BP** is a composite sum of strictly concave functions. Also, the set of constraints defines a feasible region which is convex and compact. We note that the participating users always improve their total cost even if they do not reach an agreement. In such a case, the user may prefer not to share its cached content with other users and improve their total cost due to the small participating reward γ. Therefore, the above problem is a feasible convex program and always posses a unique optimal solution $\boldsymbol{X}^*, \boldsymbol{Y}^*, \boldsymbol{Z}^*, \boldsymbol{\Phi}^*$.

In the presence of a central entity, i.e., BS-assisted D2D communication, the optimal solution of the given convex problem can be obtained by applying Karush-Kuhn-Tucker (KKT) conditions [39]. Specifically, the BS collects all the parameters from the participating users and computes the optimal solution and sends it back to the users. However, in autonomous D2D networks, there is no involvement of BS and user may be unwilling to share its private information (e.g. storage capacity, CIP, and subscribed data plan) with other users. Thus, we design a distributed collaborative mechanism which enables each user to take its decision based on its local parameters.

V. Distributed Collaborative Mechanism

The distributed collaborative mechanism gets attention in the absence of centralized entity. The distributed collaborative mechanism can provide a scalable solution to the given bargaining problem and also, ensure the privacy of users' information. However, solving the problem **L-BP** distributively is challenging because of two issues. First, the objective functions of the users are coupled, i.e., the logarithmic component corresponding to the user u depends on the sharing decision of its neighbor $v \in \mathcal{N}_u$, as shown in Eq. (13). Second, the given problem consists of coupled constraint, i.e., the decision variables of various users collectively form a constraint. In particular, the caching decision of user u depends on its neighbor's $v \in \mathcal{N}_u$ sharing decision, as shown in Eq. (16). We address the first issue (coupled objective) by introducing auxiliary variables and the corresponding equality constraints, thereby transferring the coupling of objective function in the constraints. Further, the resulting coupled-constraints problem is solved by applying the primal-dual decomposition method [22].

The total cost of user u defined in Eq. (13) depends on its local decision variables $(\boldsymbol{x}_u, \boldsymbol{y}_u, \boldsymbol{z}_u, \boldsymbol{\phi}_u)$ and its neighbor decision variables $(\mathbf{y}_{-u}, \boldsymbol{\phi}_{-u})$. We introduce auxiliary variables corresponding to each coupled argument of the total cost functions. Formally, we define

$$\alpha^c_{u,v} = y^c_{v,u}, \forall u \in \mathcal{U}, v \in \mathcal{N}_u, c \in \mathcal{I}_u \tag{20}$$

$$\beta^c_{u,v} = \phi^c_{v,u}, \forall u \in \mathcal{U}, v \in \mathcal{N}_u, c \in \mathcal{C} \tag{21}$$

where $\alpha^c_{u,v}$ and $\beta^c_{u,v}$ can be interpreted as local decision variables of user u for total cost function in place of neighbor $v \in \mathcal{N}_u$ sharing $(\boldsymbol{y}_{-u})$ and currency transfer $(\boldsymbol{\phi}_{-u})$ decision variables, respectively. Further, we relax the constraints in Eqs. (16), (20), and (21) to obtain the corresponding Lagrangian function $\mathcal{L}(\cdot)$, as shown in Eq. (22), where $\boldsymbol{\lambda} = (\lambda^c_u : u \in \mathcal{U}, c \in \mathcal{I}_c)$, $\boldsymbol{\pi} = (\pi^c_{u,v} : u \in \mathcal{U}, v \in \mathcal{N}_u, c \in \mathcal{I}_c)$, and $\boldsymbol{\psi} = (\psi^c_{u,v} : u \in \mathcal{U}, v \in \mathcal{N}_u, c \in \mathcal{C})$ are Lagrange multipliers corresponding to Eq. (16), (20), and (21), respectively.

$$\begin{aligned}\mathcal{L}(\cdot) = \sum_{u\in\mathcal{U}} \Big\{ &\log(c^{ind}_u - (\mathcal{J}_u(\boldsymbol{x}_u, \boldsymbol{z}_u, \boldsymbol{y}_u, \boldsymbol{\alpha}_u) - \mathcal{R}_u(\boldsymbol{\phi}_u, \boldsymbol{\beta}_u)))\\ + \sum_{v\in\mathcal{N}_u}\sum_{c\in\mathcal{I}_u} &\pi^c_{u,v}(\alpha^c_{u,v} - y^c_{v,u}) + \sum_{v\in\mathcal{N}_u}\sum_{c\in\mathcal{C}} \psi^c_{u,v}(\beta^c_{u,v} - z^c_{v,u})\\ &+ \sum_{c\in\mathcal{I}_u} \lambda^c_u (x^c_u + \sum_{v\in\mathcal{N}_u} y^c_{v,u} + z^c_u - 1)\Big\}\end{aligned} \tag{22}$$

We segregate the local variables of each user u in different groups and decompose $\mathcal{L}(\cdot)$ into U different user-specific Lagrangian functions $\mathcal{L}_u(\cdot)$. Mathematically,

$$\begin{aligned}\mathcal{L}_u(\cdot) = \log(c^{ind}_u - (&\mathcal{J}_u(\boldsymbol{x}_u, \boldsymbol{z}_u, \boldsymbol{y}_u, \boldsymbol{\alpha}_u) - \mathcal{R}_u(\boldsymbol{\phi}_u, \boldsymbol{\beta}_u)))\\ &+ \sum_{c\in\mathcal{I}_u}(\lambda^c_u x^c_u + \sum_{v\in\mathcal{N}_u}\lambda^c_v y^c_{u,v} + \lambda^c_u z^c_u - \lambda^c_u)\\ + \sum_{v\in\mathcal{N}_u}\Big(\sum_{c\in\mathcal{I}_u}&(\pi^c_{u,v}\alpha^c_{u,v} - \pi^c_{v,u} y^c_{u,v}) + \sum_{c\in\mathcal{C}}(\psi^c_{u,v}\beta^c_{u,v} - \psi^c_{v,u} z^c_{u,v})\Big)\end{aligned}$$

We use the primal-dual decomposition approach to define the user-specific optimization since the Lagrangian function $\mathcal{L}(\cdot)$ has a decomposable structure. The optimization problem specific to user u is as given:

$$\begin{aligned}\max_{\boldsymbol{x}_u, \boldsymbol{y}_u, \boldsymbol{z}_u, \boldsymbol{\phi}_u, \boldsymbol{\alpha}_u, \boldsymbol{\beta}_u} \quad & \mathcal{L}_u(\boldsymbol{x}_u, \boldsymbol{y}_u, \boldsymbol{z}_u, \boldsymbol{\phi}_u, \boldsymbol{\alpha}_u, \boldsymbol{\beta}_u)\\ \textit{s.t.} \quad & (15), (17)\\ & \mathcal{T}^{cop}_u(\boldsymbol{x}_u, \boldsymbol{y}_u, \boldsymbol{z}_u, \boldsymbol{\phi}_u, \boldsymbol{\alpha}_u, \boldsymbol{\beta}_u) \leq c^{ind}_u\\ & 0 \leq x^c_u, y^c_{u,v}, z^c_u, \phi^c_{u,v}, \alpha^c_{u,v}, \beta^c_{u,v} \leq 1, \quad \forall v \in \mathcal{U}, c \in \mathcal{C}\end{aligned} \tag{23}$$

Each user applies the primal-dual method to solve its specific optimization problem and updates the dual variables using the gradient-descent method. Each D2D user *signals* its content availability through dual variables $\lambda^c_u(t+1), \psi^c_{u,v}(t+1)$, and $\phi^c_{v,u}(t+1)$. Formally, user u uses the following set of equations to update its dual variables:

$$\lambda^c_u(t+1) = \lambda^c_u(t)s(t).(x^c_u + \sum_{v\in\mathcal{N}_u} y^c_{v,u} + z^c_u - 1) \tag{24}$$

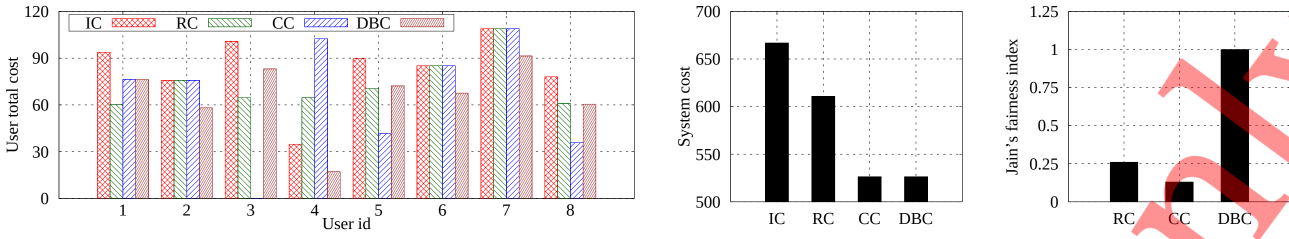
$$\pi^c_{u,v}(t+1) = \pi^c_{u,v}(t) + s(t).(\alpha^c_{u,v} - y^c_{v,u}) \tag{25}$$

$$\psi^c_{u,v}(t+1) = \psi^c_{u,v}(t) + s(t).(\beta^c_{u,v} - \phi^c_{v,u}) \tag{26}$$

where $s(t)$ is the non-negative step size selected for the t^{th} iteration.

Algorithm 1: Distributed Algorithm

Inputs : Ξ, γ
Outputs: $\boldsymbol{X}, \boldsymbol{Y}, \boldsymbol{Z}, \boldsymbol{\Phi}$
Initialize
 $\boldsymbol{X}^{(0)}, \boldsymbol{Y}^{(0)}, \boldsymbol{Z}^{(0)}, \boldsymbol{\alpha}^{(0)}, \boldsymbol{\beta}^{(0)}, \boldsymbol{\Phi}^{(0)}, \boldsymbol{\lambda}^{(0)}, \boldsymbol{\pi}^{(0)}, \boldsymbol{\psi}^{(0)}$
$converge = 0, t = 0$
while *converge = 0* **do**
  $t \leftarrow t + 1$
  for $i = 1 : \mathcal{U}$ **do**
    Compute
     $\boldsymbol{x}_u(t), \boldsymbol{y}_u(t), \boldsymbol{z}_u(t), \boldsymbol{\phi}_u(t), \boldsymbol{\alpha_i}(t), \boldsymbol{\beta_i}(t)$ by solving optimization problem in (23)
    Send $y^c_{u,v}(t), \forall v \in \mathcal{N}_u, c \in \mathcal{I}_v$
    Compute dual variables $\lambda^c_u(t+1)$, $\pi^c_{u,v}(t+1)$, and $\psi^c_{u,v}(t+1)$ using Eqs. (24)-(26)
    Send $\pi^c_{u,v}(t+1)$ $\forall c \in \mathcal{I}_v$ to $v \in \mathcal{N}_u$
    Send $\psi^c_{u,v}(t+1)$ $\forall c \in \mathcal{C}$ to $v \in \mathcal{N}_u$
  if $|\lambda^c_u(t+1) - \lambda^c_u(t)|$, $|\lambda^{t+1}_i - \lambda^t_i|$, $|\pi^c_{u,v}(t+1) - \pi^c_{u,v}(t)|$, $|\psi^c_{u,v}(t+1) - \psi^c_{u,v}(t)| \leq \Xi$ **then**
    $converge \leftarrow 1$



(a) Users' total cost (b) System cost (c) Fairness index

Figure 2: Comparison of the schemes

In each iteration, each user $u \in \mathcal{U}$ first solves its optimization problem given in Eq. (23) and computes its primal variables $(\boldsymbol{x}_u, \boldsymbol{y}_u, \boldsymbol{z}_u, \boldsymbol{\phi}_u)$ and auxiliary variables $(\boldsymbol{\alpha}_u, \boldsymbol{\beta}_u)$. Thereafter, the user updates its dual variables by using Eqs. (24)-(26) and broadcasts the updated dual variables and primal variables to the concerned neighbors. Likewise, the neighboring users also update their dual variables and broadcast the same to the concerned neighbors. This exchange of primal and dual variables among users continues till the change in dual variables in successive iterations is greater than a given threshold, namely the convergence index Ξ. The detailed procedure is given in Algorithm 1.

Proposition 1. *Algorithm 1 converges to the globally optimal solution of **L-BP** for a properly chosen $s(t)$.*

Proof: The problem **L-BP** is a convex program. Algorithm 1 converges to the globally optimal solution if the following two conditions are satisfied: (i) The step size diminishes with each iteration, and (ii) The gradients are bounded [22]. In our case, we use $s(t) = (1+q)/(t+q)$ for $q \geq 0$, which diminishes in successive iterations. The gradients given in Eqs. (24)-(26) are also bounded since the primal variables $\boldsymbol{X}$, $\boldsymbol{Y}$, $\boldsymbol{Z}$, and $\boldsymbol{\Phi}$ are bounded according to Eq. (19). Further, the auxiliary variables are also bounded by their respective users. Hence, it is guaranteed that the algorithm convergences to the global optimal solution. ■

VI. Performance Evaluation

In this section, we discuss and analyze the analytical results to evaluate the performance of the proposed scheme for C-D2D networks. We use MATLAB to compute the numerical solutions of our proposed scheme. To this end, we consider a static cache-enabled D2D network consisting of $\mathcal{U} = 8$ users in a 100×100 m^2 grid which are connected with each other in mesh topology. For numerical simulation, we set the collaborative distance of users $\mathcal{R}_{max}$ as 50 meters. Specifically, the users' coordinates are (90.67 23.66), (8.01 57.13), (98.36 31.82), (83.44 26.76), (77.95 65.28), (14.57 99.39), (10.23 20.96), (44.32 16.38). The delay and energy parameters are taken from [12] and [40], respectively. We set the data subscription plan during the placement and delivery phases as \$0.5 and \$1 per GB, respectively, and storage capacity $S_u = 10$ GB for each user. Further, we consider $|\mathcal{C}| = 20$ contents each of size 1 GB. For simplicity, we set CIP of $\mathcal{I}_u = \mathcal{C}$ for all user, i.e., each user is interested in every content. However, we discuss the effect of CIP similarity in Section VI-C. We model the delay cost of user $u \in \mathcal{U}$ using an exponential function namely, $\mathcal{D}_u = \delta_u \exp(\Delta_u)$. The parameter $\delta_u \in (0,1]$ denotes the delay sensitivity of user u. Additionally, we choose a linear function $\mathcal{E}_u(\cdot) = \xi_u \varepsilon_u + \kappa_u$ to denote the energy cost where $\xi_u \in (0,1]$ and κ_u denotes the user's energy sensitivity and device specific constant. For our simulation results, we set $\kappa_u = 0$. Further, we set the participating reward for each user as $\gamma = 0.001$.

We compare the performance of the proposed distributed bargaining-based scheme with three different benchmark schemes.

1) *Independent caching* (IC): Each user caches its content during the placement phase and downloads the remaining contents during the delivery phase.

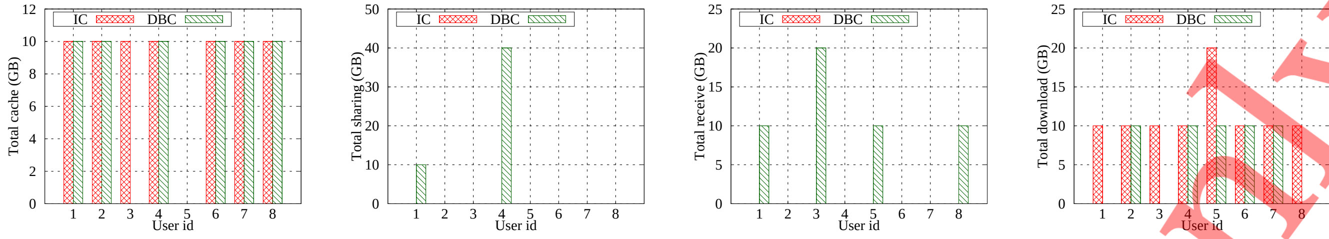
2) *Random caching* (RC): Each user randomly selects a set of contents and caches it during the placement phase. During the delivery phase, each user shares the cached content with other users through D2D communication, and downloads the rest of the contents from the BS. We show the average result of the RC scheme over 100 runs.

3) *Cost minimizing caching* (CC): A central entity computes the caching, sharing (and the corresponding currency reward received), and downloading decisions for minimizing the total users cost $(\sum_{u \in \mathcal{U}} (\mathcal{J}_u(\cdot) - \mathcal{R}_u(\cdot)))$.

A. Effectiveness of the proposed scheme

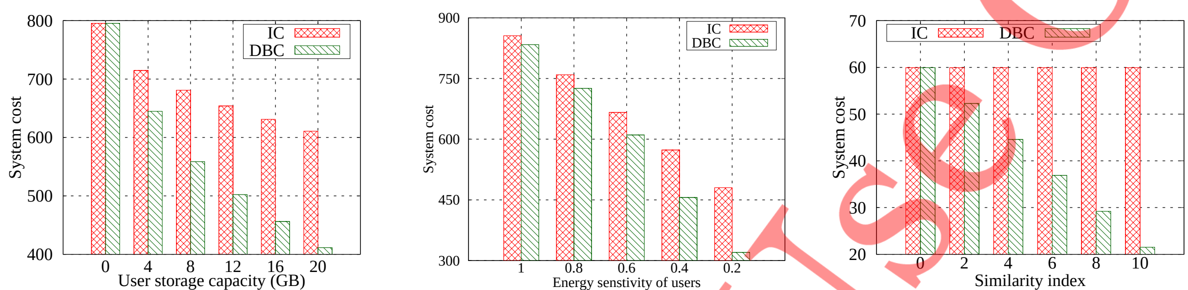
Fig. 2(a) illustrates the total cost incurred for all the participating users. The total cost of the user takes both the individual cost and the currency reward into account, as specified in Eq. (13). We observe that the total cost in case of the proposed DBC scheme is always less than the benchmarked IC scheme. This is because the DBC scheme allows each user to improve its total cost by obtaining reward $(\mathcal{R}_u)$ through content sharing. Further, unlike the other schemes (RC and CC), which also provision content sharing, in DBC scheme, users cache and share contents among one another while taking their individual costs into account (Eq. (18)). Therefore, DBC always guarantees total cost improvement for all the users compared to the IC scheme.

Fig. 2(b) illustrates the system cost, which is the cumulative total cost of the participating users, for the various schemes. We observe that the system cost is the highest for IC. This is straightforward since there is no provision of content sharing in IC, each user must download the uncached contents during



(a) Total cache (b) Total share (c) Total receive (d) Total download

Figure 3: User behavior analysis in both IC and DBC schemes



(a) Storage capacity (b) Energy sensitivity (c) Similarity index

Figure 4: Effect of system parameters on system cost

the delivery phase at higher delay ($\mathcal{D}_u$) and monetary ($\mathcal{P}_u$) cost.

In case of the RC scheme, the system cost is less than that in case of IC, but higher than the other two schemes. Indeed, the RC scheme improves the system cost by allowing content sharing among the users, but there is a high chance of duplicate caching as users randomly cache contents according to their own CIP. Further, we observe that the system cost of the CC scheme, which is the attainable minimum system cost, is 21% lesser compared to that of the IC scheme. Interestingly, the system cost in the proposed DBC scheme is the same as that of the CC scheme. This shows that the proposed DBC scheme is cost-efficient.

Fig. 2(c) depicts the fairness of the various schemes. In particular, we use Jain's fairness index [41] to characterize the fairness, i.e., $JI = \frac{(\sum_{u\in\mathcal{U}} \rho_u)^2}{U(\sum_{u\in\mathcal{U}} \rho_u^2)}$, where ρ_u is the cooperative gain of user u. We show that the proposed DBC scheme achieves highest fairness index among other schemes. This shows that the DBC scheme is fair for all the participating users.

Inferences: From Fig. 2, we conclude that the DBC scheme takes individual cost into account and minimizes the system cost while ensuring fairness among participating users. This encourages users to cooperatively cache and share their cached contents.

B. User behavior analysis

We analyze the behavior of the participating users for both the DBC and the IC schemes. Specifically, we consider the user decision during the placement phase (caching) and the delivery phase (sharing, downloading, and receiving). For this setup, we set the storage capacity of user 5 as zero, and all other parameters are set as discussed earlier. Analyzing all the figures in Fig. 3, we observe that, in the IC scheme, users either cache or download the contents of their respective CIPs. For example, user 2 caches 10 contents during the placement phase and downloads the remaining 10 contents to fulfill its need of 20 contents. However, user 5 with no caching capacity downloads its entire contents of interest during the delivery phase.

Similarly, analyzing the DBC scheme, we observe from Fig. 3(a) that the users cache the content during the placement phase. Further, the users share their cached contents with other users, as depicted in Fig. 3(b). User 4 shares its cached content (10 GB) with users 1,3,5, and 8. Likewise, user 1 shares its cached content with user 3. The fraction of contents shared by a user is limited by its cached fraction (see Eq. (17)). Fig. 3(c) shows the amount of data received by each user from their neighbors. Finally, Fig. 3(d) shows the remaining amount of content downloaded by users directly from BS. Since the DBC scheme enables users to receive contents from their neighbors, the downloading amount decreases significantly for some users. For instance, unlike in the IC scheme, the users 1,3,5, and 8 download lesser amount of contents during the delivery phase. Obviously, each user's decision of content sharing with other users depends on the respective locations, energy sensitivity, and currency transfer.

C. Effect of system parameters

We show the effect of various system parameters — user storage capacity, energy sensitivity, and CIP similarity index on the system cost (i.e., aggregated cost of the participating users) in Fig. 4. Fig. 4(a) demonstrates the variation of the system cost with respect to the user's storage capacity (S_u). We vary the storage capacity of users from 0 GB (i.e., unavailability

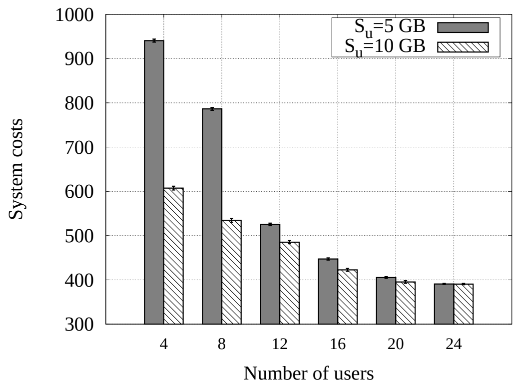


Figure 5: System costs versus number of users

of cache) to 20 GB. We compare the system cost for both the DBC and the IC schemes. In case of unavailability of user storage ($S_u = 0$), there is no provision of caching and all users need to download their contents during the delivery phase. Therefore, the system cost remains the same for both the cases. However, as the storage capacity increases, the system cost for both the IC and the DBC scheme decreases. The rate of decrement in case of DBC is higher than that of IC scheme. This is due to the fact that the increased storage capacity allows users to cache more contents (see Eqs. (15) and (17)). This, in turn, decreases the aggregated download of all users during the delivery phase.

Fig. 4(b) depicts the variation of the system cost with respect to energy sensitivity of the users. The energy sensitivity of the participants is varied in the range $[0.2, 1]$. We observe that, as the sensitivity of the users decreases, the system cost in case of both the DBC and IC schemes decreases, as from Eq. (8), the energy sensitivity is directly proportional to the individual user cost. Further, the difference of system cost between the two schemes increases with the decrease in the sensitivity of the users. This follows from the fact that, as the users become energy insensitive, they prefer to share their cached contents with others.

To analyze the effect of similarity index, we consider a system of two users (i.e., users 3 and 4). The similarity index is defined as the number of similar contents in the CIPs of the participating users, i.e., $|\bigcap_{u\in\mathcal{U}} I_u|$. Fig. 4(c) illustrates the effect of similarity index on the system cost. The similarity index is varied in the range $[0, 10]$. We observe that, in the IC scheme, the system cost is invariant of the similarity index as there is no provision of content sharing among users. However, in the DBC scheme, with the increase in the similarity index, the system cost decreases as users cooperatively cache and share the contents of mutual interest.

Inference: From Fig. 4, we conclude that the benefits of cooperative content caching and sharing are more prominent when the energy insensitive users with higher similarity index and larger storage capacity decide to collaborate.

D. Effect of number of users

In Fig. 5, we show the variation of the system cost with the change in the number of users and their caching size. We vary the number of users between 4-24 and two considered different cache sizes, i.e., S_u = 5 GB and S_u = 10 GB. We observe that, for S_u = 5 GB, when the number of users in the system increases, the overall system cost decreases non-linearly. This is due to the fact that, with the increase in the number of users, the amount of content cached also increases, resulting in higher content sharing among the D2D users. Thus, the amount of content downloaded from the BS, during the content delivery phase, decreases. The reason of non-linearity is the convex nature of the delay cost function of each user (as discussed in Section III-C1), which decreases with the increase of cooperation among the participating D2D users. Further, with the increase in cache size, i.e,, S_u = 10 GB, we observe that the system cost decreases to a value lesser than that in case of S_u = 5 GB. This is because the increase in cache size enables users to cache more content during the placement phase, thereby decreasing the overall system cost.

VII. Conclusion

In this paper, we modeled the interactions among the cache-enabled D2D users as a multi-player bargaining game to facilitate cooperative content caching and sharing. In view of the facts that the participating users have heterogeneous content interest profiles and storage capacities and that they are typically self-centric, we developed a fair incentive mechanism to encourage cooperation among the users. Further, we proposed a distributed algorithm which allows the execution of the proposed mechanism without the involvement of any central entity (e.g. BS), and hence, is not limited to BS-assisted D2D communications. The analytical results demonstrated that the proposed scheme is highly fair and effective in reducing the total cost of the users.

In future, we plan to take the mobility of the D2D users into consideration. In such a scenario, the D2D network topology keeps changing with time and the bargaining-based incentive mechanism may not be appropriate. Additionally, in this work, the users' CIP is considered to be known *a priori*. Thus, another possible extension of this work can be to consider the probabilistic CIP of the participating users.

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