Social-enabled Data Offloading via Mobile Participation – A Game-Theoretical Approach

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***Abstract*—The exploding popularity of mobile devices enables people to enjoy benefits brought by various interesting mobile apps, such as social networking, mobile video services, and location-based services, etc. However, the ever-increasing data traffic has exacerbated congestion on current cellular networks, which results in users' dissatisfaction, especially in crowded areas. Hence, how to deal with the explosive data traffic in cellular networks becomes a challenging problem. Traditional methods rely on mobile offloading techniques to deviate the data traffic targeted to cellular networks, such as small cell, Wi-Fi, and opportunistic communication. Unfortunately, mobile users will still experience severe congestion when a large number of users request for data. Facing these challenges, we introduce the concept of mobile participation to assist data offloading by leveraging the mobility of mobile users and the social features among a group of users. A mobile caching user, who precaches certain amount of contents, can roam around congested areas to participate in data dissemination in order to satisfy users' requests, which can benefit both herself and users in the crowd simultaneously. Therefore, we propose a game theoretical approach to analyze the data offloading via mobile participation with joint considerations on users' content requests, network effect brought by their social features, congestion effect, and pricing strategy. Based on detailed performance analysis, we show the feasibility and efficiency of the proposed approach.**

***Index Terms*—Data Offloading, Mobile Participation, Social-enabled, Stackelberg Game**

I. Introduction

The soaring popularity of mobile devices enables people to communicate with their social ties at anytime and from anywhere. People use their mobile apps to create and exchange a huge amount of data for their social interactions in cyberspace. Analysts from Cisco warn that monthly global mobile data traffic will surpass 24.3 exabytes and smartphones will reach three-quarters of mobile data traffic by 2019 [1]. Although cellular network operators exploit their efforts to provide better services in terms of higher data rates and lower costs, mobile users are still facing poor performance in their daily life, especially in some crowded areas, such as football stadiums, theme parks, and airports. However, the above crowded areas are the places that highly need reliable wireless communication for safety purposes, e.g., broadcasting evacuation information. As one promising solution, mobile data offloading takes advantages of small cell, Wi-Fi, and opportunistic communication to proactively reduce the data traffic targeted for cellular networks [2].

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Unfortunately, although various types of mobile offloading schemes have been proposed in both academia and industry, we are still lacking of effective methods to offload data. For example, small cell technique for data offloading is not an effective method due to the scarcity of licensed spectrum bandwidths. Even worse, deploying more small cells will incur significant costs. Regarding Wi-Fi offloading, service providers have access to much larger free spectrum to cater the Wi-Fi deployment, because it operates on unlicensed bands. However, Wi-Fi offloading cannot provide guaranteed QoS, and Wi-Fi-enabled devices may experience increased battery drainage, since it has to operate on two different radio interfaces [3]. To perform the mobile offloading, opportunistic communication has been identified as another approach, which increases communication chances by utilizing the potential social connections among users and thus is beneficial to deliver contents. In particular, some works [4–7] apply social-enabled approaches to help data dissemination among social ties or users with similar social profiles. Apparently, the opportunistic communication is not reliable for data delivery in a pure ad hoc mode, while there is lack of incentives for source users to coordinate the data dissemination. Clearly, mobile offloading has not been well developed nor widely applied.

Facing these challenges and existing solutions, we take a step further to reconsider the social-enabled approach for mobile offloading. As we can see from current social networks, many socially-related contents shared among social ties are similar or even identical (e.g., similar photo updates on Facebook), which leads us to consider how to avoid repeated requests/retrievals in order to reduce the number of accesses to the service provider. From the data perspective, a simple observation is that users with similar social interests often group together at certain location [8], which potentially results in similar data requests. For example, football fans in the stadium may request for the same information regarding the players and the game. Although their similar requests often cause wireless network's congestion when they compete for the limited bandwidth, we can take advantages of their

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social relationships for mobile offloading, i.e., **using free device-to-device (D2D) communication to enable social-based data sharing**. The intuition behind this methodology is to let a representing user download the data and further disseminate copies via D2D communication. In this work, we propose a multi-win social-enabled data offloading approach via mobile participation by introducing a mobile caching user, who bridges the gap between service providers and users when severe congestion happens. The mobile caching user first pre-caches a number of large volume contents and then physically moves to specific users when there are content requests. In addition to getting rewards from users in the crowd, the mobile caching user has social and interest-driven incentives to roam back to the crowded area for content delivery. Compared to traditional data offloading approaches, utilizing the mobile caching user is significantly cheaper than small cell build-out. Moreover, by physically moving to specific users, the mobile caching user makes data transmission more reliable than both Wi-Fi and D2D communication. At the same time, the mobile caching user has more incentives to offload data by getting rewards from requesting users, including social gains and revenue payoffs. For users in the crowd, they can get their requested contents even when there is severe congestion. To fully exploit the benefits of mobile participation, it is highly needed to thoroughly investigate users' requests, social gains, congestion effect, as well as the pricing strategy for both the mobile caching user and users in the crowd.

Our Contributions: We highlight and list out our major contributions as follows,

- The proposed data offloading scheme introduces a new concept, **mobile participation**, which takes the advantages of the mobility of mobile caching users to compensate the congestion effect for a large group of people.
- By investigating the social influence among users, the proposed social-enabled data offloading scheme greatly reduces the congestion effect for crowded areas where people are normally grouped together based on their social profiles.
- Our approach not only satisfies users' content requests, but also benefits the mobile caching user economically by jointly considering network effect and the actual request levels from the users.
- To maximize the benefits of the mobile caching user and users, we deploy a Stackberg game. The existence and uniqueness of the Stackelberg equilibrium are proved first. Following that, we calculate the best strategies under practical assumptions.

The rest of this paper is organized as follows: In Section II, we briefly review the existing data offloading approaches and economical incentives for performing data offloading. Then, we give a detailed description of the system model and formulate it as a Stackelberg game in Section III. In Section IV and V, we study the proposed game model in detail. In Section VI, the performance of our approach is evaluated, followed by the conclusion in Section VII.

II. Related Work

A. Mobile Data Offloading

Mobile data offloading [3] is a promising way to alleviate traffic congestion and reduce the energy and bandwidth consumption of the cellular network, which can be classified into two categories [9]. First, infrastructure-based mobile data offloading [10] refers to deploying small cell base stations and Wi-Fi hotspots for mobile users [11–13]. The connection between mobile users and the base station is proposed to achieve flow level load balancing under spatially heterogeneous traffic distributions in [14, 15] . However, the lack of cost-effective backhaul associations for the base station often impairs their performance in terms of offloading mobile traffic. The second category is the ad-hoc-based mobile traffic offloading, which refers to applying short range communication as the underlay to offload mobile traffic [4–7].

B. Economic Incentives for Data Offloading

The above works only focus on the technical perspective adoption of data offloading, without considering the economic incentives of mobile data offloading. This incentive issue is significant for the scenario where Wi-Fi or small cell is privately owned by third-party entities, who are expected to be reluctant to admit non-registered users' traffic without proper incentives [16]. In [17, 18], they consider the incentive framework for the so-called user-initiated data offloading, where users initiate the offloading process, and hence users offer necessary incentives in order to obtain their contents. In [16], they consider the network-initiated data offloading, where cellular networks initiate the offloading process, and hence the network operators are responsible of incentivizing Wi-Fi.

C. Network Effects and Congestion Effects

The above works do not take severe congestion into consideration, which may result in users' dissatisfaction due to not obtaining their requested contents. In [19], mobile caching user behaviors are studied by jointly considering the congestion effect in the physical wireless domain and the network effect based on users' social relationships. A social group utility maximization framework is studied in [20, 21], which captures the impact of mobile users' diverse social ties on the interactions of their mobile devices subject to diverse physical relationships. Considering the network effect brought by social ties among users, different pricing strategies of a service provider have been studied in [22]. However, it does not take congestion effect into consideration, which makes the problem more complex due to the coupling of network and congestion effects among users. Different from [22], congestion effect due to many users' requested contents simultaneously is considered in our paper. In [19], they discuss both network and congestion effects under the assumption the service provider charges the same price for all users' contents. Different from [19], an optimal situation is considered in our paper where the mobile caching user charges discriminated prices to users. A mobile caching user is introduced to assist data offloading to alleviate the network congestion. We focus

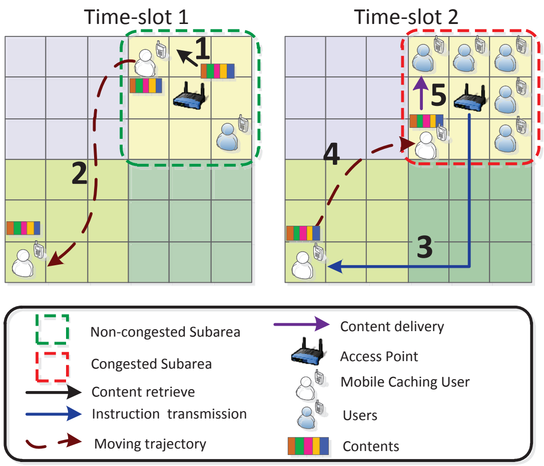


Fig. 1: System Model of Mobile Participation

on the economic incentives between the mobile caching user and users under both network and congestion effects. Perfect price discrimination is considered for users.

III. System Model and Problem Formulation

A. Overview

We give an intuitive example in our daily life as illustrated in Fig. 1 to assist our description of the proposed approach. Mobile users request for videos and live information in crowded resorts and theme parks, such as Disneyland. People normally group together based on their social profiles including interest, gender, age, *etc*., all of which are in accordance with their locations in the designated area. Assume there is no congestion in time-slot 1. Alice downloads a number of videos in the roller coaster area and continues to visit the next spot. In time-slot 2, there are increasing number of mobile users requesting for contents in that area, which results in severe congestion. Therefore, a set of visitors $\mathcal{N} = \{1, 2, \cdots, N\}$ cannot get their requested contents from the service provider. Then, the service provider asks Alice for help. Due to her interests and potential rewards, Alice moves back to the crowded roller coaster area and disseminates her videos to users who have the request. Thus, users get what they request, Alice makes profits regarding her contents, and the congestion is greatly alleviated.

B. System Model

Assume that $\mathbf{x} = \{x_1, x_2, \cdots, x_N\}^T \in [0, \infty)^N$ is denoted as content request level profile of all users. Denote u_i as the satisfaction level of user i, which is the total satisfaction that user i gains from requesting x_i level contents. It is affected by the following four parts:

Internal Effect: It displays the satisfaction level that user i derives from requesting x_i level contents irrespective of the requests of her peers. This level is quantified by the parameter a_i and b_i.

Network Effect: It captures word-of-mouth communication among users: users typically form their opinions about the quality of a content based on the information they obtain from their peers. Because the increasing content request level of a user has a positive impact on the content request level of her peers, network effect brings a great potential for the mobile caching user' revenue increase. We use $g_{ij} \geq 0$ to quantify the social influence from user j to user i. Note that $g_{ii} = 0$ for the case where user i cannot bring influence to herself.

Congestion Effect: It demonstrates the negative impacts among users due to limited wireless capacity and large content requests from users. To guarantee successful transmission, the mobile caching user has to move to each user and transmits each content to users one by one, which increases users' waiting time and makes users unsatisfied. Thus, the revenue of the mobile caching user is affected negatively. We denote d as the congestion factor.

Economical Effect: The mobile caching user charges users for the requested contents' transmission. We denote the vector $\mathbf{p} = \{p_1, p_2, \cdots, p_N\}^T$ as the unit price profile.

Denote $\mathbf{x}_{-i}$ as the content request level profile without user i. The satisfaction level of user i under network and congestion effects is,

$$\begin{aligned} u_i\left(x_i, \mathbf{x}_{-i}, p_i\right) =& a_i x_i - b_i {x_i}^2 + \sum_{j \in \mathcal{N}} g_{ij} x_i x_j \\ & - d\left(\sum_{j \in \mathcal{N}} x_j\right)^2 - p_i x_i, \forall i \end{aligned} \tag{1}$$

The revenue of the mobile caching user is,

$$R\left(\mathbf{x}, \mathbf{p}\right) = \sum_{i \in \mathcal{N}} \left(p_i - c\right) x_i \tag{2}$$

in which c denotes the unit cost that the mobile caching user spends when transmitting contents to user i, including power and move consumption, etc. It keeps unchanged among users.

C. Stackelberg Game Formulation

A two-stage Stackelberg game is utilized to model the interaction between the mobile caching user and users:

Stage I (Pricing) The mobile caching user chooses each user's price p_i to maximize her revenue. We have

$$\mathbf{p}^* = \arg \max_{\mathbf{p} \in [0,\infty)^N} \sum_{i \in \mathcal{N}} \left(p_i - c\right) x_i$$

Stage II (Request Level) Each user $i \in \mathcal{N}$ chooses her content request level x_i to maximize her satisfaction level given the price p_i and the content request levels of her peers $\mathbf{x}_{-i}$

$$x_i^* = \arg \max_{x_i \in [0,\infty)} u_i\left(x_i, \mathbf{x}_{-i}, p_i\right), \forall i$$

The game is studied from Stage II first. For users, we investigate the existence and uniqueness of a set of strategies at which no user deviates based on the price the mobile caching user charges. This is so-called Stackelberg equilibrium. For the mobile caching user in Stage I, we are interested in the pricing strategy that maximizes her revenue given the Stackelberg equilibrium of users in Stage I.

IV. USERS' BEST RESPONSE STRATEGY

In this section, a general condition is given under which there exists a unique Stackelberg equilibrium. Then, we get the users' best response strategy given the prices the mobile caching user charges.

Given the mobile caching user's pricing strategy $\mathbf{p}$ and the content request level profile $\mathbf{x}_{-i}$ without user i, user i's best content request level is computed by solving the following satisfaction level maximization problem.

$$\begin{aligned} \max_{x_i \geq 0} \quad & u_i\left(x_i, \mathbf{x}_{-i}, p_i\right) \\ s.t. \quad & \mathbf{x}_{-i} \succeq \mathbf{0} \end{aligned} \tag{3}$$

Set the derivative $\partial u_i\left(x_i, \mathbf{x}_{-\mathbf{i}}, p_i\right)/\partial x_i = 0$ as the first order condition and based on the fact that the content request level of user i is positive, user i 's best content request level strategy $\beta_i\left(\mathbf{x}_{-i}\right)$ is

$$\beta_i\left(\mathbf{x}_{-i}\right) = \max\left\{0, \frac{a_i - p_i}{2(b_i+d)} + \sum_{j\neq i} \frac{g_{ij}-2d}{2(b_i+d)} x_j\right\}, \forall i \tag{4}$$

Remark: Each user's content request level strategy is composed of two parts: internal request $\frac{a_i-p_i}{2(b_i+d)}$ which is independent of her peers, and external request $\sum_{j\neq i} \frac{g_{ij}-2d}{2(b_i+d)} x_j$ that indicates network and congestion effects her peers bring. When network effect dominates, e.g. $g_{ij} > 2d$, the increase of other users' content levels has a positive influence on the user i's content request level. Otherwise, congestion effect dominates and other users' content request levels have a negative effect on user i.

Although obtaining the best content request level strategy of each user in (4), we cannot ensure the Stackelberg equilibrium exists because each user may have great incentive to unboundedly increase her content request level provided other users' request levels are sufficiently large. To avoid above situation, a general assumption is given first under which there exists a unique Stackelberg equilibrium.

Assumption 1: $\sum\limits_{j\neq i} \frac{|g_{ij}-2d|}{2(b_i+d)} < 1, \forall i$

Due to the fact that $|\sum_{j\neq i} \frac{g_{ij}-2d}{2(b_i-2d)} x_j| \leq \sum_{j\neq i} \frac{|g_{ij}-2d|}{2(b_i+d)} x_j < \max_{j\neq i} x_j$, the Assumption 1 limits user i's external request to the maximum request level among all the other users.

THEOREM 1: Under Assumption 1, the game $\mathcal{G} = \left\{\mathcal{N}, \{u_i\}_{i\in N}, [0,\infty)^N\right\}$ always admits a Stackelberg equilibrium for users.

Proof: We mainly prove Theorem 1 by finding a equivalent game which admits a Stackelberg equilibrium. Denote $\mathbf{x}^*$ as a strategy profile and x_i^* as the largest content request level in $\mathbf{x}^*$, $x_i^* > x_j^*, \forall i \neq j$. According to (4), we have $x_i^* = \frac{a_i-p_i}{2(b_i+d)} + \sum\limits_{j\neq i} \frac{g_{ij}-2d}{2(b_i+d)} x_j^* \leq \frac{|a_i-p_i|}{2(b_i+d)} + \sum\limits_{j\neq i} \frac{|g_{ij}-2d|}{2(b_i+d)} x_i^*$. From above inequality, we get $x_i^* \leq |a_i - p_i| \Big/ \Big(2(b_i+d) - \sum_{j\neq i} |g_{ij}-2d|\Big) < \tilde{x}$. Because x_i^* is the largest content request level in $\mathbf{x}^*$, we have $x_j^* \in [0, \tilde{x}], j \in \mathcal{N}$. Thus, our game has the same strategy space with the game $\tilde{\mathcal{G}} = \left\{\mathcal{N}, \{u_i\}_{i\in\mathcal{N}}, [0,\tilde{x}]^N\right\}$, where $\tilde{x} > |a_i - p_i| \Big/ \Big(2(b_i+d) - \sum_{j\neq i} |g_{ij}-2d|\Big)$

Because the strategy space $[0,\tilde{x}]^N$ is compact and convex and the satisfaction level $u_i\left(x_i, \mathbf{x}_{-\mathbf{i}}, p_i\right)$ is continuous in x_i and $\mathbf{x}_{-i}$ and concave in x_i, the game $\tilde{\mathcal{G}}$ admits a Stackelberg equilibrium according to [23], so does the game $\mathcal{G}$. ■

THEOREM 2: Under Assumption 1, the game $\mathcal{G}$ has a unique content request level strategy.

Proof: The Jacobian matrix $\nabla\mathbf{u}(\mathbf{x})$ of the satisfaction level profile $\mathbf{u}(\mathbf{x}) \triangleq \{u_1(\mathbf{x}), u_2(\mathbf{x}), \cdots, u_N(\mathbf{x})\}$ of the game $\tilde{\mathcal{G}}$ is given by $\nabla\mathbf{u}(\mathbf{x}) = -(2\mathbf{\Lambda} - \mathbf{G})$ where $\mathbf{\Lambda} = \begin{bmatrix} b_1+d & 0 & \cdots & 0 \\ 0 & b_2+d & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b_N+d \end{bmatrix}$ and $\mathbf{G} = \begin{bmatrix} 0 & g_{12}-2d & \cdots & g_{1N}-2d \\ g_{21}-2d & 0 & \cdots & g_{2N}-2d \\ \vdots & \vdots & \ddots & \vdots \\ g_{N1}-2d & g_{N2}-2d & \cdots & 0 \end{bmatrix}$. The matrix $\mathbf{G}$ reflects interactions between different users, in which the ijth element $(g_{ij}-2d)$ represents network and congestion effects that user j brings to user i, $j \neq i$. Considering Assumption 1, we have $[2\mathbf{\Lambda}-\mathbf{G}]_{ii} \geq \sum\limits_{j\neq i} \left|[2\mathbf{\Lambda}-\mathbf{G}]_{ij}\right|, \forall i$. Therefore, $[2\mathbf{\Lambda}-\mathbf{G}]$ is strictly diagonal dominant, $-[2\mathbf{\Lambda}-\mathbf{G}] - [2\mathbf{\Lambda}-\mathbf{G}]^T$ is negative definite. Following to [23], $\nabla\mathbf{u}(\mathbf{x})$ is diagonally strictly concave and the game $\tilde{\mathcal{G}}$ has a unique Stackelberg equilibrium. According to Theorem 1, the game $\mathcal{G}$ also admits an unique Stackelberg equilibrium due to the equivalence between these two games. ■

Following Theorem 1 and 2, we compute the best content request level strategies of users given that all users would like to buy their requested contents. Then, we get general best content request level strategies in which some users may not buy the requested contents.

THEOREM 3: Assume all users would like to pay the requesting content, $x_i > 0, \forall i$. The best content request level strategies of users are $\mathbf{x}^* = (2\mathbf{\Lambda}-\mathbf{G})^{-1}(\mathbf{a}-\mathbf{p})$, in which $\mathbf{a} = \{a_1, a_2, \cdots, a_N\}^T$ denotes users' the internal demand rate profile.

Proof: Based on (4), we get $(2\mathbf{\Lambda}-\mathbf{G})\mathbf{x}^* = (\mathbf{a}-\mathbf{p})$. In addition, we can easily prove that $(2\mathbf{\Lambda}-\mathbf{G})$ is invertible according to Assumption 1. Therefore, we have Theorem 3. ■

The above discussion is based on the assumption that all users buy positive content request levels. Next, a general situation is considered where users in set $S \subseteq \mathcal{N}$ would like to buy the requested contents at the Stackelberg equilibrium.

THEOREM 4: Suppose $\overline{\mathbf{x}} = \{\overline{x}_1, \overline{x}_2, \cdots, \overline{x}_N\}$ is the best content request level profile. The unique equilibrium of the game given the price vector $\mathbf{p}_S$ takes the following form:

$$\begin{aligned}\overline{\mathbf{x}}_S &= \left(2\mathbf{\Lambda}_S - \mathbf{G}_S\right)^{-1}\left(\mathbf{a}_S - \mathbf{p}_S\right)\\ \overline{\mathbf{x}}_{\mathcal{N}-S} &= \mathbf{0}\end{aligned} \tag{5}$$

where $\overline{\mathbf{x}}_S$ is a vector of $\overline{x}_i$ such that $i \in S$ and $\overline{\mathbf{x}} = \overline{\mathbf{x}}_S \cup \overline{\mathbf{x}}_{\mathcal{N}-S}$. Vectors $\mathbf{a}_S$, $\mathbf{p}_S$ and matrices $\mathbf{\Lambda}_S$, $\mathbf{G}_S$ are the corresponding parameters defined in the set S.

The proof of Theorem 4 is similar with that of Theorem 3.

V. Mobile Caching User's Best Response Strategy

In this section, the situation where all users buy positive content levels is considered by making the following assumption. Then we discuss a general situation that some users may not buy contents where the following assumption does not hold.

Assumption 2: $a_i > c, g_{ij} > 2d, \forall i, j \neq i$

It ensures that all users would like to buy positive content levels at the Stackelberg equilibrium by limiting the relationship between the network effect and the congestion effect.

THEOREM 5: Under Assumption 2, the optimal prices are as follows:

$$\mathbf{p}^* = \mathbf{a} - \left(2\mathbf{\Lambda} - \mathbf{G}\right)\left(4\mathbf{\Lambda} - \mathbf{G} + \mathbf{G}^T\right)^{-1}\left(\mathbf{a} - \mathbf{c}\right) \tag{6}$$

Proof: To solve the best pricing strategy of the mobile caching user, we solve the following maximization problem:

$$\begin{aligned}&\max_{\mathbf{p}\in[0,\infty)^N} \sum_{i\in\mathcal{N}} \left(p_i - c\right) x_i^*\\ &\quad s.t. a_i - 2b_i x_i^* + \sum_{j\neq i} g_{ij} x_j^* - 2d \sum_{j\in\mathcal{N}} x_j^* - p_i = 0\\ &\quad\quad x_i^* \geq 0, \forall i\end{aligned} \tag{7}$$

By removing p_i, we get $\mathbf{x}^* = \left(4\mathbf{\Lambda} - \mathbf{G} + \mathbf{G}^T\right)^{-1}\left(\mathbf{a} - \mathbf{c}\right)$. Comparing it with the $\mathbf{x}^*$ in Theorem 3, Theorem 5 is proved. ■

However, network and congestion effects are independent in practice. Now we discuss how to obtain the best pricing strategy of the mobile caching user by relaxing the Assumption 2, where some users may not buy contents.

First, we find the set where users buy positive levels of contents. Then, we calculate the best pricing strategy of the mobile caching user. We relate content request level strategy $\overline{\mathbf{x}}^*$ at the equilibrium to a pricing strategy $\overline{\mathbf{p}}^*$. Because some users may not buy contents, $\overline{\mathbf{p}}^*$ does not need to be unique. The mobile caching user can set arbitrarily large price to the users who do not buy contents, and $\overline{\mathbf{x}}^*$ is unchanged. Since only the prices offered to users who buy contents play a part in the mobile caching user's revenue $\overline{R}$, $\overline{R}$ is unique. So we maximize the mobile caching user's revenue by using content request level strategy $\overline{\mathbf{x}}^*$ as variables instead of $\overline{\mathbf{p}}^*$.

$$\max_{\overline{\mathbf{x}}^* \geq \mathbf{0}} \overline{R} \tag{8}$$

where $\overline{R} = \overline{\mathbf{x}}^{*T}\left(\mathbf{a} - \mathbf{c}\right) - \overline{\mathbf{x}}^{*T}\left(2\mathbf{\Lambda} - \mathbf{G}\right)\overline{\mathbf{x}}^*$. It is acquired by substituting $\overline{\mathbf{p}}^* = \mathbf{a} - \left(2\mathbf{\Lambda} - \mathbf{G}\right)\overline{\mathbf{x}}^*$ according to Theorem 3 into (2). Note that above problem is a convex optimization problem provided that b_i, g_{ij} and d are such that $\left[2\mathbf{\Lambda} - \mathbf{G}\right] + \left[2\mathbf{\Lambda} - \mathbf{G}\right]^T$ is positive definite. After getting the best content request level strategy of users $\overline{\mathbf{x}}^*$, the mobile caching user calculates her pricing strategy according to $\overline{\mathbf{p}}^* = \mathbf{a} - \left(2\mathbf{\Lambda} - \mathbf{G}\right)\overline{\mathbf{x}}^*$. Thus, we obtain the pricing strategy of the mobile caching user even if Assumption 2 does not hold.

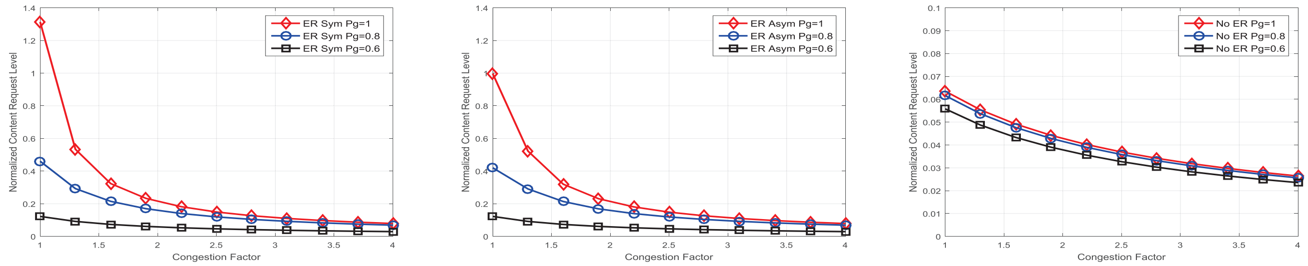
VI. Performance Evaluation

In this section, we study the performance of our data offloading scheme. The Erdős-Rényi (ER) graph [24], in which a social tie exists between users in a group with probability p_g, is deployed to investigate network and congestion effects on the performance. We assume $N \in \{20, 30, 40\}$ users take part in the game. Other parameters are set as follows: $a_i \sim \mathcal{N}(4, 2)$, $b_i \sim \mathcal{N}(10, 0.5)$, $g_{ij} \sim \mathcal{N}(4, 2)$, $d = 2$ and $c = \min(a_i) - 1$.

We investigate network and congestion effects on users' content request level strategies as illustrated in Fig.2 under different cases, with symmetric network effect, asymmetric network effect, and without network effect. In each case, the normalized content request level decreases as the congestion factor becomes large. Meanwhile, the increase of normalized content request level is in line with the increase of the probability of social ties. These two facts demonstrate the negative effect of congestion and the positive effect of social ties on users. At the same time, we can see that users in the symmetric network enjoy more benefits than users in the asymmetric network. When only congestion effect exists, users do not purchase any contents from the mobile caching user as shown in Fig.2(c). In another example, the number of users is taken into consideration. As shown in Fig.3, the mobile caching user can get more revenues if more users with strong social ties request for contents. However, the increase of the number of users cannot bring benefits to the total revenue of the mobile caching user when there is only congestion effect. This is because users cannot get extra contents' information from her peers without social ties among them. Meanwhile, users even cannot obtain their requested contents from the mobile caching user due to congestion effect. Therefore, users do not purchase any contents, which results in the low total revenue of the mobile caching user. The above results exactly match our design objective and demonstrate the importance of the social relations among users.

VII. Conclusion

In this paper, we propose a data offloading approach via mobile participation, which leverages the social relationships between users in a group to alleviate the wireless network's congestion. To investigate the maximized satisfaction levels of both the mobile caching user and users, we model the problem as a Stackelberg game. We first prove the existence and uniqueness for the Stackelberg equilibrium. Then, the best strategies for the mobile caching user and users are calculated. Based on the simulation results, we have shown the feasibility and efficiency of our approach.

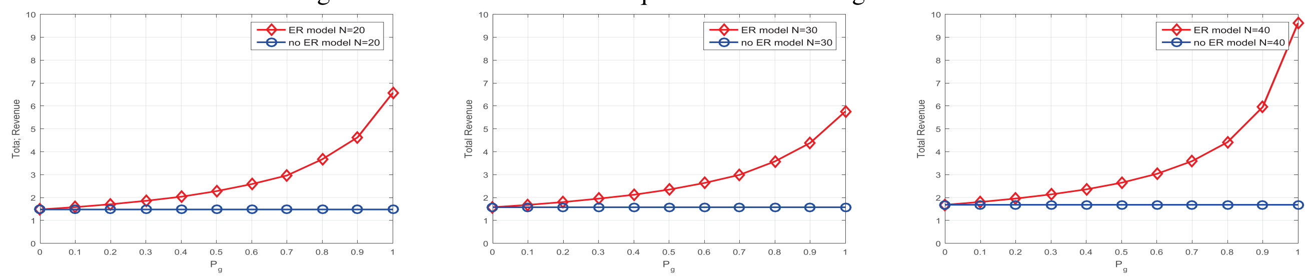


(a) Symmetric Network Effects

(b) Asymmetric Network Effects

(c) Without Network Effects

Fig. 2: Normalized Content Request Level vs. Congestion Effect



(a) N=20

(b) N=30

(c) N=40

Fig. 3: Total Revenue vs. Probability of Social Ties

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