

Green and Mobility-Aware Caching in 5G Networks

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Abstract—With the drastic increase of mobile devices, there are more and more mobile traffic and repeated requests for content. In 5G networks, small cell base stations (SBSs) caching and caching in wireless device-to-device network can effectively decrease the mobile traffic during peak hours. Currently, most of the related work is focused on how to cache content on SBSs and on mobile devices, and it is assumed that the user can download the entire requested content through the connected SBSs and mobile devices. However, few works have taken user mobility and the randomness of contact duration into consideration. How to improve the caching strategy by exploiting user mobility is still a challenging problem. Thus, in this paper, we first investigate the problem of how to conduct caching placement on SBS and on mobile devices leveraging user mobility, aiming to maximize the cache hit ratio. Specifically, the caching placement on SBSs and on mobile devices is formulated as an integer programming problem, and submodular optimization is adopted to solve the formulated problem. Then, we give the optimal transmission power of SBSs and mobile devices to deliver the caching content in order to reduce the energy cost. Simulation results prove that our caching strategy is more efficient than other existing caching strategies in terms of both cache hit ratio and energy efficiency.

Index Terms—Content caching, device-to-device communications, 5G networks, human mobility, cache hit ratio.

I. INTRODUCTION

THE demand for the capacity of wireless networks has been increasing exponentially over the past few years. According to a report by Cisco [1], the global mobile traffic will exceed 24.3 exabytes per month. As such, it is expected that the future fifth generation (5G) wireless networks have to support 1000x higher capacity and 100x lower delay. In particular, densification of wireless networks using small cells have received tremendous interests in the research communities as an effective means to meet the challenging goals.

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5G networks [2] mainly include macrocell base stations (MBSs) and small cell base stations (SBSs). By bringing the base stations closer to the device in small cell networks, the spectral efficiency can be significantly enhanced due to increased spatial reuse. However, such benefit comes at the expense of potentially intense interference and high backhaul cost. Specifically, as the density of the SBS increases, the inter-cell interference becomes more severe, which limits the spectral efficiency of the ultra-dense small cell networks. To cope with the interference issue, cooperative MIMO or, Cooperative Multi-Point (CoMP) techniques have been proposed [3]. By sharing the payload between SBSs, they can cooperatively serve multiple users and therefore eliminating cross-cell interference. However, CoMP will increase the backhaul load due to payload sharing between the SBS. Since the number of backhaul scales with the number of SBSs, the backhaul can easily become the system bottleneck in small cell networks.

On the other hand, it is reported that most of the capacity demand will originate from high quality multimedia streaming applications [4]–[8]. A few popular contents may be repeatedly requested by nearby users within a window of time. Unlike generic data applications, these content-centric applications are cacheable. If the requested contents are cached at the radio access network, i.e., at the SBS or at the devices, they may be requested by nearby users in the immediate future. In this case, the new requests can be served by the cache instead of from the core network via the backhaul. Caching at the radio access networks has the potential to significantly reduce the loading of the backhaul and can alleviate the backhaul bottleneck in ultra-dense small cell networks.

There are a number of recent works on caching in wireless networks. In [9], femto-caching has been proposed. In [10], [11], physical layer (PHY) caching has been proposed to exploit the BS cache to exploit CoMP opportunities. Specifically, when the requested contents of the users exist in the caches of multiple BSs simultaneously, the BSs can engage in CoMP without inducing extra loading to the backhaul for payload sharing. In [12], algorithms for distributed caching are proposed for the data dissemination in the downlink of heterogeneous networks. Furthermore, in [13] and [14], the optimal cache scheme was designed in terms of a small cell video caching system, and a data-driven cache strategy was proposed in [15]. In [16]–[18], caching at the devices have been proposed to enhance the capacity of D2D networks. It has been recognized that popular content should be cached on mobile devices and throughput of network may be improved by D2D communications. However, these works are based on

the assumption that user remains static, i.e., assumed fixed network topology.

Since user mobility in a caching network is a very critical problem, there are some preliminary works considering user mobility. These works can be classified into two categories, i.e., cache in SBS, and cache in mobile device. *Cache in SBS*. Due to the dense deployment, the handovers between mobile device and SBSs are quite frequent. Such mobility should be considered during the design of a caching policy. Wang *et al.* [19] discuss the femtocaching without file coding under user mobility. Poularakis *et al.* [20] tried to minimize the workload at MBS by making strategy of content caching at SBS when the user mobility is considered. Mobilecacher in [21] describes caching placement which is mobility-aware in SBSs. *Cache in mobile device*. Through transmission opportunity by D2D links, the D2D caching delivers content to contacted user by opportunistic connections. Lan *et al.* [22] proposed mobility-aware caching in D2D networks. Wang *et al.* [23], [24] further discussed the mobility-aware coded caching strategy in D2D network.

However, all of above work assume that the whole cached file [22] or encoded segments [20], [24] can be successfully delivered within the contact duration when mobile device request file from SBS or other mobile device. However, according to the study in [25], the transmission data is related to the contact duration. Thus, taking into account the contact duration randomness caused by user mobility, the above assumptions are not practical. Considering the caching system designed is consisted of two separated phases [26], i.e., content placement phase and delivery phase. Thus, the challenges of caching content on SBSs and on mobile devices under condition of the randomness of contact duration are mainly two-fold: *mobility-aware content placement* and *green content delivery*. For the former, we need to optimally determine how to cache in the mobile device and the SBSs in order to maximize the cache hit ratio. For the latter, how can we improve the energy efficiency of 5G network during the content delivery.

In order to overcome the above challenges, we present the green and mobility-aware caching model for SBSs and mobile devices, which includes mobility-aware content placement model and green content delivery model. For mobility-aware caching model, we derive a solution to maximize the cache hit ratio on the SBS and mobile devices by using submodular optimization. For green content delivery model, we analyze the optimal transmission power of SBSs and mobile devices.

In summary, the contributions of this paper include as follows.

- *How to Cache*: we considered how to conduct caching on SBSs and mobile device leveraging user mobility, aiming to maximize the cache hit ratio. This problem is formulated as a mixed integer nonlinear programming (MINLP) problem, which is NP-hard. Submodular optimization is introduced and a greedy algorithm is developed to solve this problem.
- *How to Delivery*: we analyzed the energy efficiency when SBS and mobile device deliver the cached content under condition of the randomness of contact duration.

Furthermore, we put forward the optimal transmit power of SBSs and mobile device in order to reduce the delivery energy cost.

- *Performance Analysis*: Simulation results prove that our caching strategy is more efficient than other existing caching strategies in terms of both cache hit ratio and energy efficiency. Through the experiments, we find that more popular contents are cached on SBSs and mobile devices when user mobility is low, when the mobility of users is high, it is necessary to consider the diversity of files.

The remainder of this article is organized as follows. The system model is described in Section II. We present the green and mobility-aware caching scheme in Section III and propose the solution for green and mobility-aware caching strategy optimization in Section IV. Our experimental results and discussions are provided in Section V. Finally, Section VI concludes this paper.

II. SYSTEM MODEL

In this paper, we consider a 5G network with macro cell base station (MBS), small cell base stations (SBSs), and mobile devices. A specific scenario is illustrated as Fig. 1, there are five mobile device users *Rachel*, *Eva*, *Tommy*, *Suri* and *Cindy*. The file requested by Rachel includes four encoded segments, i.e., s_1 , s_2 , s_3 , s_4 . Considering the limitation of storage capacity at user's mobile device, we assume each user only stores one coded segment. Given an example shown in Fig. 1, *Eva*, *Tommy*, *Suri* and *Cindy* store s_1 , s_2 , s_3 and s_4 , respectively. Considering user mobility to make a caching strategy, *Rachel* obtains s_1 , s_2 and s_3 from *Eva*, *Tommy*, *Suri*, while retrieving s_4 from SBS2. The example shows the reduction of the traffic load at MBS. From the above discuss, it is observed that user mobility has significant influence on the content cache of mobile device and SBS. Below we will propose a model for how to cache on mobile device and SBSs according to the user mobility. Denote by l and n the number of SBS and mobile device, respectively. Let $\mathcal{S} = \{S_1, S_2, \dots, S_l\}$ and $\mathcal{D} = \{D_1, D_2, \dots, D_n\}$ be the set of SBSs and mobile devices, respectively. The MBS can connect to the SBSs and mobile devices, and each user requests the content independently. The main notations used in this paper are given in Table I.

A. Mobility Model

The mobility model to be used in this paper is a peer-to-peer connectivity model [27] which is widely investigated in wireless network [23]–[25] and delay tolerant network [28]. Similar to [23], [25], [27], we assume pairwise contact process is independent Poisson process.

1) *The Mobility Model for Users in the Small Cell Network*: The condition for successful communication between mobile device D_i and SBS S_k is that D_i is within the communication radius of S_k . We define the contact duration $T_{i,k}$ when mobile device D_i is within communication range of SBS S_k as $T_{i,k} = \{(t - t_0) : ||\mathcal{L}_k^t - \mathcal{L}_i^t|| < R_S, t > t_0\}$, where t_0 stands for the most recent time when mobile device D_i just

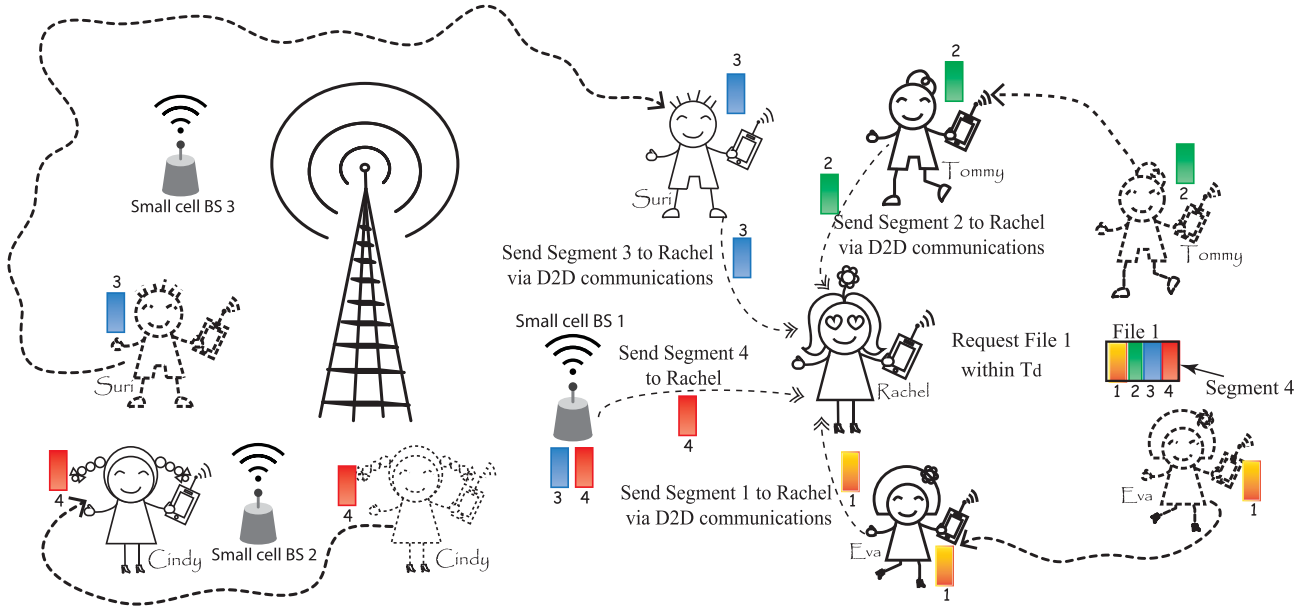


Fig. 1. An illustration of mobility-aware caching in 5G networks.

 TABLE I
 LIST OF COMMONLY USED NOTATIONS

| Notation | Explanation |
|---------------------|---|
| \mathcal{S} | The set of SBSs. |
| \mathcal{D} | The set of mobile devices. |
| \mathcal{F} | The set of files. |
| C_k^S | Cache size of SBS S_k . |
| C_i^D | Cache size of mobile device D_i . |
| p_f | Probability that a request for file F_f . |
| $\lambda_{i,k}^B$ | Exponential distribution parameter of pairwise contact duration between mobile device D_i and SBS S_k . |
| $\lambda_{i,j}^D$ | Exponential distribution parameter of pairwise contact duration between mobile device D_i and D_j . |
| $\mathcal{A}_{i,k}$ | The amount of data delivered can be sent from SBS S_k to mobile device D_i during a contact duration. |
| $\mathcal{B}_{i,j}$ | The amount of data delivered can be sent from mobile device D_i to D_j during a contact duration. |
| T_d | The deadline for user requests. |
| P_T^D | The transmission power of mobile device. |
| P_T^B | The transmission power of SBS. |
| P_C^D | The circuit power consumption of the mobile device. |
| P_C^B | The constant power of SBS. |
| W_D | The D2D channel bandwidth. |
| W_B | The downlink transmission bandwidth from SBS to mobile device. |

enter the communication range R_S of SBS S_k . \mathcal{L}_k^t and \mathcal{L}_i^t stand for the locations of SBS S_k and mobile device D_i at time t , respectively. Since the contacts process between SBS and mobile devices follows independent Poisson processes, the pairwise contact duration $T_{i,k}$ of mobile device D_i and SBS S_k follows the exponential distribution with parameter $\lambda_{i,k}^B$, where $\lambda_{i,k}^B$ is named as the contact rate of mobile device D_i and SBS S_k . In consideration of limited storage capacity of SBSs, we define cache size of SBS S_k as C_k^S .

2) *The Mobility Model for Users in the D2D Network:* Communication can only be successful when the shortest distance between any two mobile devices is within R_{D2D} . Define the contact duration $T_{i,j}$ between any two users D_i and D_j as $T_{i,j} = \{(t - t_0) : \|\mathcal{L}_i^t - \mathcal{L}_j^t\| < R_{D2D}, t > t_0\}$. Similarly, t_0 stands for the most recent moment when mobile device D_i just enter the communication range R_{D2D} of mobile

device D_j ; \mathcal{L}_i^t and \mathcal{L}_j^t stand for the locations of user D_i and D_j at moment t , respectively. Similar to the above, the contact duration between any two mobile device D_i and D_j also follows the exponential distribution with parameter $\lambda_{i,j}^D$, where $\lambda_{i,j}^D$ is termed the contact rate of mobile device D_i and D_j . In a similar way, in consideration of limited storage capacity of mobile device, we denote the cache size of mobile device as C_i^D .

3) *The Mobility Pattern:* For user's mobility, we utilize the real dataset to verify that the contact duration between user and user as well as between user and SBS follows the exponential distribution. For the contact duration between user and user, the Infocom in Cambridge/Haggle dataset provided in [29] is plotted in Fig. 2(a). The comparison therein with the exponential distribution validates the current model for peer-to-peer contact duration. For the distribution of the contact

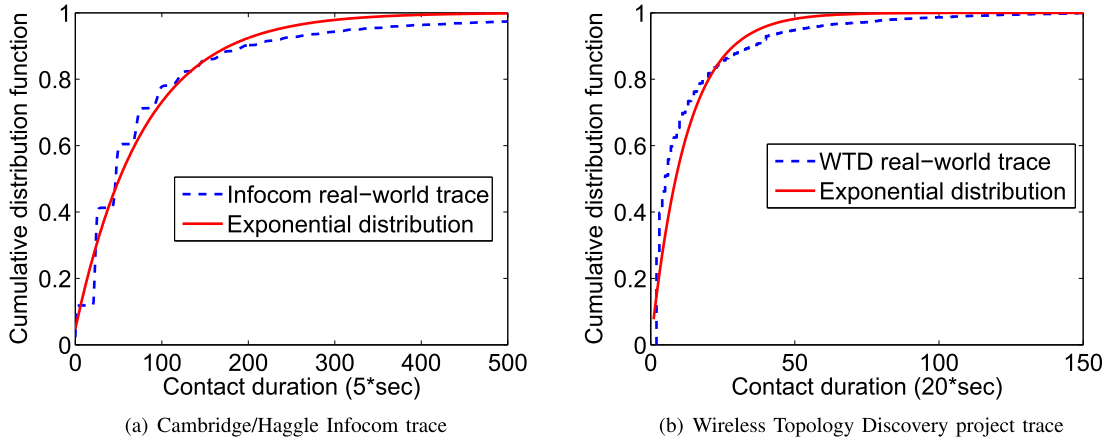


Fig. 2. Distribution of contact duration between user and user as well as between user and SBS.

duration between user and SBS, our model of contact duration between users and SBS has been developed using the dataset from the Wireless Topology Discovery (WTD) project at UCSD [30]. Similar to [20], we treat WiFi APs in the dataset as SBS and chose 2002/10/16 as the day in the experiment. This results in the curve of the contact duration of all users with SBS as shown in Fig. 2(b). It is observed from the figure that the contact duration can be also suitably modeled by the exponential distribution.

In [23], the experiments show that user contact rate is linearly proportion to the user's moving speed. A higher mobility leads to a larger contact rate. Thus, user's moving speed can be deemed as the user's contact rate. However, the contact duration is decreased accordingly with the increase of user's moving speed. When the contact duration is not enough to finish the data transmission of cached file, it will cause the failure of file transmission. Thus, it is impractical to assume 100% delivery ratio [20], [22], [24] in mobile networks. The contact duration follows exponential distribution. Thus, we assume the throughput of content delivery during the contract duration also follows exponential distribution. Let the random variable $\mathcal{A}_{i,k}^{\omega}$ denote the maximum amount of content delivered from SBS S_k to D_i during the ω th contact duration. Let the random variable $\mathcal{B}_{i,j}^{\omega}$ denote the maximum amount of content delivered from D_j to D_i during the ω th contact duration.

B. Content Request Model

Consider a content library (also called the file library) with m contents. Let $\mathcal{F} = \{F_1, F_2, \dots, F_m\}$ be the set of all files in the content library. This paper adopts coded caching strategy, i.e. file F_f can be encoded into s_f encoded segments through rateless Fountain coding [31] and each encoded segments have same size. We also assume that F_f can be restored through the s_f code segments [23], [32]. Denote size of F_f as $|F_f|$. Then, the size of each encoded segment can be calculated as $g_f = \frac{|F_f|}{s_f}$. Contents are ordered according to their popularity, i.e., ranking from the most popular file (F_1) to the least popular file (F_m). Each user requests content F_f randomly and independently from the content library with a probability

of p_f , and we assume p_f follows the Zipf distribution with parameter γ [33]. Then, We have:

$$p_f = \frac{f^{-\gamma}}{\sum_{i=1}^m i^{-\gamma}}, \quad f = 1, 2, \dots, m, \quad (1)$$

where γ indicates the uneven distribution of popularity in the contents. Let T_d denote the deadline for user requests. When a user requests content with T_d , he or she can obtain content mainly through the following three ways as shown in Fig. 3

- **Local-Caching:** The user would check his or her own mobile device. If the required content is cached on his or her device, then the user would obtain the required content from the local cache.
- **D2D-Caching or SBS-Caching:** If the required content is not cached on the mobile device, then the user may obtain the required content through one of the following two ways within T_d . (i) D2D-Caching: Assume there is another mobile device within its D2D range R_{D2D} that stores the required content. Then D2D communication will be established between them, to obtain the required content from the neighboring device. (ii) SBS-Caching: Assume there is a SBS within its communication range R_S that stores the required content. Then SBS communication will be established between them, to obtain the required content from the SBS. In this paper, we assume that the D2D communication is assisted by the SBSs [34] and the SBSs have the global information to make caching decision for all mobile devices.
- **MBS-Caching:** If within the deadline T_d for the requested content, the user cannot obtain the required content with the above-mentioned methods, then his or her request will be processed by the MBS, to obtain the required content from the MBS.

C. Energy Consumption Model

In this section, we present the energy consumption model when mobile device or SBSs send content to content requester. We present the energy cost model for D2D communications and SBS communications, respectively.

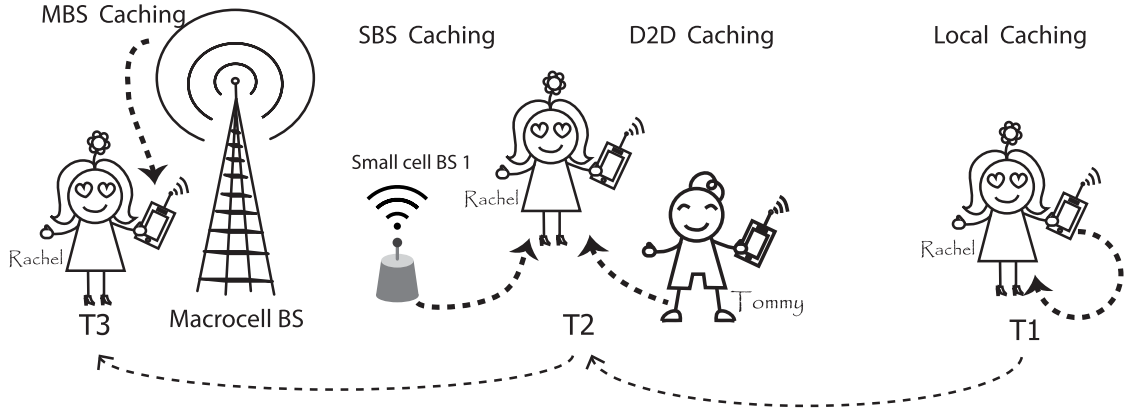


Fig. 3. Illustration of the three ways for content access: local-caching, D2D or SBS caching, and MBS caching.

1) *Energy Cost for D2D Communications*: First, we consider the energy consumption when mobile device D_j transmits cached code segment to D_i . For the sake of simplicity, the interference of D2D communications is not considered. According to [35], the average D2D data rate can be obtained:

$$R_D = \mathbb{E} \left\{ W_D \log_2 \left(1 + \frac{P_T^D h_D^2 r_D^{-\alpha}}{\sigma_D^2} \right) \right\} \approx W_D \log_2 \left(1 + \frac{P_T^D r_D^{-\alpha}}{\sigma_D^2} \right). \quad (2)$$

where P_T^D is the mobile device transmission power, W_D is the channel bandwidth from D_i to D_j , h_D represents channel gain, follow zero mean complex Gaussian distribution with unit variance, r_D is the distance between D_i and D_j , σ_D^2 denotes white Gaussian noise, α is path loss factor.

According to [36], the power consumption of D_j can be modeled as $\beta_D P_T^D + P_C^D + P_H^D$, where P_C^D represents the circuit power consumption of the mobile device D_j , and β_D is the inverse of power amplifier efficiency factor. P_H^D represents the energy consumption of caching hardware devices. In this paper, we ignore the energy consumed for delivering the cached content. Our focus is to obtain the optimal transmission power within contact duration. Thus, when D_j transmits file $\mathcal{B}_{i,j}^{\omega}$ to D_i , the corresponding energy consumption of D_j can be calculated as:

$$E_D = \frac{\mathcal{B}_{i,j}^{\omega}}{R_D} (\beta_D P_T^D + P_C^D), \quad (3)$$

2) *Energy Cost for SBS*: Here, we investigate the energy consumed SBS S_k when S_k delivers coded segment to D_i . Similar as before, we do not consider the interference between SBSs. Denoted P_T^B as the SBS transmission power. Then, the downlink speed of mobile device can be calculated as:

$$R_B = \mathbb{E} \left\{ W_B \log_2 \left(1 + \frac{P_T^B h_B^2 r_B^{-\beta}}{\sigma_B^2} \right) \right\} \approx W_B \log_2 \left(1 + \frac{P_T^B r_B^{-\beta}}{\sigma_B^2} \right), \quad (4)$$

where P_T^B is the SBS transmission power, W_B is the downlink transmission bandwidth from SBS to mobile device, h_B is the

channel power gain, follow zero mean complex Gaussian distribution with unit variance, r_B represents the distance between D_i and S_k , and σ_B^2 is the variance of additive white Gaussian noise, β means the path loss factor. Similarly, we ignore the energy consumption for file storage in SBSs. According to [36], when SBS send file $\mathcal{A}_{i,k}$ to D_i , the energy consumption at the SBS can be calculated as:

$$E_B = \frac{\mathcal{A}_{i,k}^{\omega}}{R_B} (\beta_B P_T^B + P_C^B), \quad (5)$$

where P_C^B denotes an offset of site power including the baseband processor, the cooling system and etc, and β_B is the inverse of power amplifier efficiency factor.

III. GREEN AND MOBILITY-AWARE CACHING MODEL

In this section, we present green and mobility-aware caching model. Considering the randomness of contact duration caused by user mobility, we need to decide which contents should be cached at SBSs and mobile devices, in order to maximize the cache hit ratio (the number of requests delivered by the cache server, divided by the total number of requests). Furthermore, in order to ensure the green of 5G network, we describe how to reduce the energy consumption during content delivery.

A. Motivation

We illustrate how to utilize user mobility with an example, and then design the content placement and delivery for SBSs and mobile devices, as shown in Fig. 4. In Fig. 4(a), user *Tommy* requests content includes two code segments with deadline T_d . Due to the low mobility of *Tommy*, the number of contacts with SBS and other users is relatively small, yet the contact duration is long. As shown in Fig. 4, *Tommy* obtained requested file from SBS1. For this case, the code are cached at SBS1. In Fig. 4(b), likewise, user *Tommy* requests content including two code segments with deadline T_d . However, the mobility is high for this time. Thus, *Tommy* only finishes the transmission of one code segment during the contact with SBS1. In T_d , *Tommy* meets *Rachel* and obtain code segment from *Rachel*'s cache. Thus, the caching strategy is more complicated, since both SBS1 and *Rachel* contribute requested code segments with *Tommy*'s personalized moving speed. In the delivery phase, the SBS1 and user *Rachel* deliver the content to user *Tommy* with the minimum energy consumption,

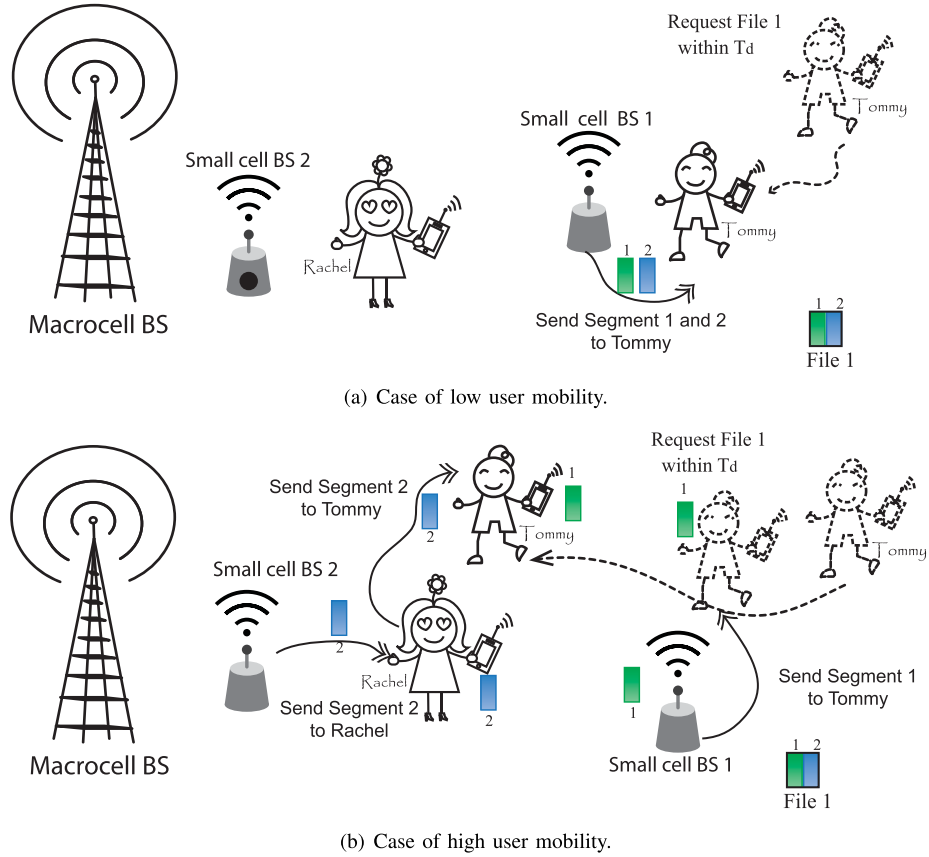


Fig. 4. Illustration for the impact of user mobility on caching.

when they are in the contact duration. So, the cache strategy are closely related to contact duration. Green and mobility-aware caching model which included mobility-aware content placement model and delivery model is shown below.

B. Mobility-Aware Content Placement Model

Let matrix $\mathbf{X}_{l \times m}$ define the caching strategy of the encoded segments in SBS, where $x_{k,f} \in \mathbf{X}$ represents the number of code segments in SBS S_k . Let matrix $\mathbf{Y}_{n \times m}$ denote the caching strategy of the encoded segments in mobile device, where $y_{j,f} \in \mathbf{Y}$ is the number of code segments cached at mobile device D_j . Define matrix $\mathbf{Z} = [\mathbf{X}; \mathbf{Y}]$ as the caching strategy matrix, which needs to be solved out. Let $\mathcal{U}_i^f(\mathbf{Z})$ denote the total amount of code segments that D_i can obtain from SBS and mobile device within T_d . Thus, the caching strategy with maximal cache hit ratio can be expressed as

$$\text{maximize}_{\mathbf{Z}} \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_f \Pr(\mathcal{U}_i^f(\mathbf{Z}) \geq s_f) \quad (6a)$$

$$\text{subject to} \quad \sum_{f=1}^m x_{k,f} g_f \leq C_k^S, \quad \forall k \in \{1, \dots, l\}, \quad (6b)$$

$$\sum_{f=1}^m y_{j,f} g_f \leq C_j^D, \quad \forall j \in \{1, \dots, n\}, \quad (6c)$$

$$x_{k,f} \in \{0, 1, \dots, s_f\}, \quad \forall k, f \quad (6d)$$

$$y_{j,f} \in \{0, 1, \dots, s_f\}, \quad \forall j, f. \quad (6e)$$

where the objective function (6a) represents how to cache in SBS and mobile device, so as to maximize the cache hit ratio.

Two constraints (6b) and (6c) mean the total size of cached files cannot exceed the cache capacities of SBS and mobile devices, respectively. Constraints (6d) and (6e) represents the number of cache is integer.

Next, we will give the solution to $\Pr(\mathcal{U}_i^f(\mathbf{Z}) \geq s_f)$. According to the mobility model discussed in Section II, the contact number between mobile device with SBS or other mobile device follows Poisson distribution. Within time T_d , let $M_{i,k}$ denote the number of contacts between D_i and S_k ; let $N_{i,j}$ denote the number of contacts between D_i and D_j . Both $M_{i,k}$ and $N_{i,j}$ are random variables following Poisson distribution. Then, the total size of file F_f , which D_i can obtained within T_d from D_j and S_k , can be calculated as:

$$V_{i,j,k}^f = \sum_{\omega=1}^{M_{i,k}} \mathcal{A}_{i,k}^{\omega} + \sum_{\omega=1}^{N_{i,j}} \mathcal{B}_{i,j}^{\omega} \quad (7)$$

where $\mathcal{A}_{i,k}^{\omega}$ follows an exponential distribution with parameter $A_{i,k}^S$, and $\mathcal{B}_{i,j}^{\omega}$ follows an exponential distribution with parameter $B_{i,j}^D$.

Since the number of contacts follows the Poisson distribution, the average contact number for D_i getting contact with S_k can be denoted as $\lambda_{ik}^B T_d$, while the average contact number for D_i getting contact with D_j is denoted by $\lambda_{ij}^D T$. Through such simplification, we can obtain

$$V_{i,j,k}^f = \sum_{\omega=1}^{\lambda_{ik}^B T_d} \mathcal{A}_{i,k}^{\omega} + \sum_{\omega=1}^{\lambda_{ij}^D T_d} \mathcal{B}_{i,j}^{\omega} \quad (8)$$

Denote $V_{i,k}^f = \sum_{\omega=1}^{\lambda_{ik}^B T_d} \mathcal{A}_{i,k}^\omega$, since $\mathcal{A}_{i,k}^\omega$ ($\omega = 1, 2, \dots, \lambda_{ik}^B T_d$) is a collection of independent and identically distributed random variables, according to [37], we obtain $V_{i,k}^f \sim \text{Gamma}(\lambda_{ik}^B T_d, A_{ik}^S)$. Denote $V_{i,j}^f = \sum_{\omega=1}^{\lambda_{ij}^D T_d} \mathcal{B}_{i,j}^\omega$, likewise, $V_{i,j}^f \sim \text{Gamma}(\lambda_{ij}^D T_d, B_{ij}^D)$. Thus, D_i can obtain the size of the file F_f as follows:

$$V_i^f = \sum_{k=1}^l V_{i,k}^f + \sum_{j=1}^n V_{i,j}^f \quad (9)$$

Now, we give the probability distribution function (PDF) of $f_{V_i^f}(v)$. Let $f_{V_{i,k}^f}(v_1)$ denote the probability distribution function of variable $V_{i,k}^f$. Let $f_{V_{i,j}^f}(v_2)$ denote the probability distribution function of $V_{i,j}^f$. According to above analysis, the probability distribution function of $f_{V_i^f}(v)$ is the discrete convolution of $f_{V_{i,1}^f}(v_1), \dots, f_{V_{i,l}^f}(v_1), f_{V_{i,1}^f}(v_2), \dots, f_{V_{i,n}^f}(v_2)$. Then,

$$f_{V_i^f}(v) = \frac{v^{\lambda_{i1}^B T_d - 1} e^{-v A_{i1}^S}}{(A_{i1}^S)^{-\lambda_{i1}^B T_d} \Gamma(\lambda_{i1}^B T_d)} \otimes \dots \otimes \frac{v^{\lambda_{il}^B T_d - 1} e^{-v B_{il}^D}}{(B_{il}^D)^{-\lambda_{il}^B T_d} \Gamma(\lambda_{il}^B T_d)} \\ \otimes \frac{v^{\lambda_{i1}^D T_d - 1} e^{-v B_{i1}^D}}{(B_{i1}^D)^{-\lambda_{i1}^D T_d} \Gamma(\lambda_{i1}^D T_d)} \otimes \dots \otimes \frac{v^{\lambda_{in}^D T_d - 1} e^{-v B_{in}^D}}{(B_{in}^D)^{-\lambda_{in}^D T_d} \Gamma(\lambda_{in}^D T_d)} \quad (10)$$

Due to the intrinsic difficulty feature to solve the convolution, Welch-Satterthwaite estimation [25] is used to obtain

$$f_{V_i^f}(v) \approx \frac{v^{\gamma-1} e^{-t\delta}}{\delta^{-\gamma} \Gamma(\gamma)} \quad (11)$$

where

$$\gamma = \frac{(\sum_{k=1}^l \lambda_{ik}^B T_d A_{ik}^S + \sum_{j=1}^n \lambda_{ij}^D T_d B_{ij}^D)^2}{\sum_{k=1}^l \lambda_{ik}^B T_d (A_{ik}^S)^2 + \sum_{j=1}^n \lambda_{ij}^D T_d (B_{ij}^D)^2}, \\ \delta = \frac{\sum_{k=1}^l \lambda_{ik}^B T_d (A_{ik}^S)^2 + \sum_{j=1}^n \lambda_{ij}^D T_d (B_{ij}^D)^2}{\sum_{k=1}^l \lambda_{ik}^B T_d A_{ik}^S + \sum_{j=1}^n \lambda_{ij}^D T_d B_{ij}^D}$$

Then, random variable V_i^f can be estimated as a gamma distribution, i.e., $V_i^f \sim \text{Gamma}(\gamma, \delta)$.

Now, we give the computation of $Pr(\mathcal{U}_i^f(\mathbf{Z}) \geq s_f)$. Since $\mathcal{U}_i^f = \min(\lfloor \frac{V_{i,f}}{g_f} \rfloor, g_f)$, and \mathcal{U}_i^f is a discrete random variable, and $V_{i,f}$ is a continuous random variable, we can conclude that:

$$Pr(\mathcal{U}_i^f(\mathbf{Z}) \geq s_f) = 1 - Pr(\mathcal{U}_i^f(\mathbf{Z}) < s_f) \\ = 1 - \sum_{a=0}^{s_f} Pr(\mathcal{U}_i^f(\mathbf{Z}) = a) \quad (12)$$

Here, we give the solution to $Pr(\mathcal{U}_i^f(\mathbf{Z}) = a)$ as follows

$$Pr(\mathcal{U}_i^f(\mathbf{Z}) = a) \\ = \begin{cases} \int_{ga}^{g(a+1)} f_{V_i^f}(v) dv, & \text{if } 0 \leq a < (x_{k,f} + y_{j,f}) \\ [1em] \int_{ga}^{\infty} f_{V_i^f}(v) dv, & \text{if } a = (x_{k,f} + y_{j,f}) \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

Finally, the distribution of $Pr(\mathcal{U}_i^f(\mathbf{Z}) \geq s_f)$ can be calculated.

C. Green Content Delivery Model

When SBS and mobile device deliver the content, energy will be consumed. This section will discuss how the SBS or mobile device deliver the content to the requested mobile device with minimal energy consumption. Given that D2D is used, we formulate the following optimization problem:

$$\begin{aligned} & \text{minimize } E_D \\ & \quad P_T^D \\ & \text{subject to: } 0 < P_T^D \leq P_{\max}^D. \end{aligned} \quad (14)$$

The objective function is to find the optimal transmit power of D_j , which send the cached content \mathcal{B}_{ij} to requesting D_i , to minimize the energy consuming by D_j . The constraint is that the transmit power P_T^D of mobile device is within $(0, P_{\max}^D]$, where P_{\max}^D is the maximized transmit power of mobile device.

Similarly, we formulate the following optimization problem for SBSs:

$$\begin{aligned} & \text{minimize } E_B \\ & \quad P_T^B \\ & \text{subject to } 0 < P_T^B \leq P_{\max}^B. \end{aligned} \quad (15)$$

The objective function is to find the optimal transmit power of S_k , which send the cached content \mathcal{A}_{ik} to requesting D_i , to minimize the energy consuming by S_k . The constraint is that the transmit power P_T^B of SBSs is within $(0, P_{\max}^B]$, where P_{\max}^B is the maximized transmit power of SBSs.

IV. GREEN AND MOBILITY-AWARE CACHING POLICY SOLUTION

In this section, we first give a solution of mobility-aware content placement model using submodular optimization. Then, we derive a solution to the content delivery model.

A. Solution of Mobility-Aware Content Placement Model

The optimization problem (6) is related with the number of cached code segments at SBS and mobile devices, which is a mixed integer programming (MIP) problem. It is proved as NP-hard problem to cache file in small cell and D2D networks [20], [22]. The problem targeted in this paper not only considers how to cache file at SBS and mobile device, we also consider the content amount per transmission. Therefore this problem is NP-hard.

In this section, we propose to utilize submodular optimization to solve the optimization problem (6). In submodular optimization problem, if object function is monotone submodular function and the constraint is matroid constraint, the greedy algorithm can be used. Furthermore, let OPT represent the optimization solution of original problem; let \mathbf{Z}^* denote the solution by greedy approach, then, $\mathbf{Z}^* \geq (1 - \frac{1}{e})OPT$, i.e., the greedy algorithm can get approximate optimal solution [38]. In the remainder of this section, original problem will be converted into a submodular optimization problem. We then present a greedy algorithm to solve the converted problem.

1) *Submodular Optimization Problem*: Define a set $Z = \{z_{i,f,v} | i = 1, \dots, l+n, f = 1, \dots, m, v = 1, \dots, s_f\} = Z^1 \cup Z^2$, where

$$Z^1 = \{z_{k,f,v} | k = 1, \dots, l, f = 1, \dots, m, v = 1, \dots, s_f\}$$

$$Z^2 = \{z_{j,f,v} | j = 1, \dots, n, f = 1, \dots, m, v = 1, \dots, s_f\}$$

That is, when $i = 1, \dots, l$ $z_{i,f,v} = z_{k,f,v}$. When $i = l+1, \dots, l+n$ $z_{i,f,v} = z_{j,f,v}$. Let set A_1 denote the caching policy at SBS, where $A_1 \subseteq Z^1$. If element $z_{k,f,v} \subseteq A_1$, it represents that small cell S_k caches v code segments of file f . Let set A_2 denote the caching strategy at mobile device, where $A_2 \subseteq Z^2$. If element $z_{k,f,v} \subseteq$, it means there are v code segments of file f stored at mobile device D_j . Let set $Z_{k,f}^1 = \{z_{k,f,v} | v = 1, \dots, s_f\}$ denote the overall configuration of code segments of file f cached at small cell S_k . Likewise, set $Z_{j,f}^2 = \{z_{j,f,v} | v = 1, \dots, s_f\}$ represent the overall configuration of code segments of file f cached at mobile device D_j . Then, the original variables $x_{k,f}$ and $y_{j,f}$ can be obtained

$$x_{k,f} = |A_1 \cap Z_{k,f}^1|, \quad y_{j,f} = |A_2 \cap Z_{j,f}^2|$$

where $|\cdot|$ represents the number of elements in the set. Define $A = A_1 \cup A_2$, then we can obtain the object function of original problem as follows:

$$f(A) = \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_f Pr \left[\min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, S_f \right) \leq S_f \right].$$

Define $Z_k^1 = \{z_{k,f,v} | f = 1, \dots, m, v = 1, \dots, s_f\}$ as all of the cached code segments at SBS S_k . Define $Z_j^2 = \{z_{j,f,v} | f = 1, \dots, m, v = 1, \dots, s_f\}$. Then, original optimization problem can be rewrite as: $I = I_1 \cup I_2$, where

$$I_1 = \{A_1 | g_f | A_1 \cap Z_k^1 \leq C_k^s, k = 1, \dots, l\}$$

$$I_2 = \{A_2 | g_f | A_2 \cap Z_j^2 \leq C_D^s, k = 1, \dots, l\}$$

Therefore, the original problem can be rewritten as:

$$\begin{aligned} & \underset{A}{\text{maximize}} \quad f(A) \\ & \text{subject to:} \quad A \subseteq I. \end{aligned} \quad (16)$$

Theorem 1: In problem (16), $f(A)$ is a monotone submodular function, and the (Z, I) is matroid constraint.

Proof: It is proved that $f(A)$ is a monotone submodular function. If $f(A)$ is a monotonic submodular function, then $\forall A \subset B \subset Z$ and $\forall z_{i,f,v} \in Z - B$, $f(A \cup z_{i,f,v}) - f(A) \geq f(B \cup z_{i,f,v}) - f(B) \geq 0$ can be proven, i.e.,

$$f(A \cup z_{k,f,v}) - f(A) \geq f(B \cup z_{k,f,v}) - f(B) \geq 0$$

$$f(A \cup z_{j,f,v}) - f(A) \geq f(B \cup z_{j,f,v}) - f(B) \geq 0$$

can be proven to be correct.

First, we prove $f(A \cup \{z_{k,f,v}\}) - f(A) \geq f(B \cup \{z_{k,f,v}\}) - f(B) \geq 0$. Since $\forall A \subset B \subset Z$, $E = B - A$, $\forall z_{i,f,v} \in Z - B$, define $V_i^f = \sum_{k=1, k \neq i}^l V_{i,k}^f + \sum_{j=1}^n V_{i,j}^f$, then where $V_{i,k}^f$ denotes the content amount obtained by D_i from SBS S_k for file f . Apply total probability formula, we can obtain, the equation as shown at the top of the next page.

$$\begin{aligned} & \text{Since } \min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |B_1 \cap Z_{k',f}^1 - E_1| + |B_2 \cap Z_{j,f}^2 - E_2| \right) \\ & \leq \min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |B_1 \cap Z_{k',f}^1| + |B_2 \cap Z_{j,f}^2| \right) \text{ and} \end{aligned}$$

$$|B_1 \cap Z_{k,f}^1 - E_1| = |B_1 \cap Z_{k,f}^1| - |E_1 \cap Z_{k,f}^1|$$

$$|B_2 \cap Z_{j,f}^2 - E_2| = |B_2 \cap Z_{j,f}^2| - |E_2 \cap Z_{j,f}^2|$$

We can further get

Similarly, we have $f(A \cup \{z_{j,f,v}\}) - f(A) \geq f(B \cup \{z_{k,f,v}\}) - f(B)$. Then, we prove that $f(A)$ is a Monotonic submodular function.

The $\{Z, I\}$ is Matroid: In other words, we prove that both (Z^1, I_1) and (Z^2, I_2) are matroid. For (Z^1, I_1) , we have:

- $\emptyset \in I_1$;
- If $B_1 \subseteq I$ and $A_1 \subseteq B_1$, then $A_1 \subseteq I$;
- If $A_1, B_1 \in I_1$ and $|A_1| < |B_1|$, there exists an element $k \in B - A$ that makes $A \cup \{k\} \in I$.

Therefore, (Z^1, I_1) is a matroid. Similarly, we can show that (Z^2, I_2) is also matroid. Hence, we conclude that (Z, I) is a matroid. ■

Though above proof, we conclude that the object function of the optimization problem (16) is monotone submodular function with constrain of a matroid. Thus, greedy algorithm can be applied for the solution. Next, we will provide the detailed algorithm.

2) *Mobility-Aware Content Placement Algorithm*: Based on Theorem 1, we can know that greedy algorithm could also resolve our optimization problem (16). The specific solution algorithm is provided below: we set an empty cache placement set A , in each iteration, we add a file which can maximize the object function until the capacity of SBS or mobile device is full.

Algorithm 1 Mobility-Aware Content Placement Algorithm

Input:

- Input All $z_{i,f,v}$ combinations, Z ;
- Reminding set of Z , Z_r ;
- Capacity for SBSs and mobile devices, C .

Output:

- Optimal cache policy, A ;
 - 1: $A \leftarrow \emptyset$, $Z_r \leftarrow Z$
 - 2: Repeat
 - 3: $z_{i^*,f^*,k^*} = \text{argmax}_{z_{i,f,k} \in Z_r} [f(Z_r + z_{i,f,k}) - f(Z_r)]$
 - 4: $A \leftarrow A + z_{i^*,f^*,v^*}$
 - 5: $Z_r \leftarrow Z_r - z_{i^*,f^*,v^*}$
 - 6: If $|A \cap Z_{i^*}| = C$, Then $Z_r \leftarrow Z_r \setminus Z_{i^*}$
 - 7: end if
 - 8: Until $|A| > (\sum_{k=1}^l C_k^S + \sum_{i=1}^n C_i^D)$
-

From step 3 we can see that caching k^* encoded segments of file F_{f^*} to SBS or mobile terminal is the optimal cache policy, so z_{i^*,f^*,k^*} is added into optimal cache strategy A in step 4. Step 6 indicates that there could not be more files to be cached in mobile device or SBS once the amount of cached files reaches their storage capacity C . So the files Z_{i^*} cached at i^* are deleted from Z_r . From step 8, we notice that the iteration proceeds until $|A| > (\sum_{k=1}^l C_k^S + \sum_{i=1}^n C_i^D)$.

$$\begin{aligned}
f(A \cup z_{k,f,v}) - f(A) &= \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_f \\
&\times \left\{ Pr \left[\min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |A_1 \cap Z_{k',f}^1| + |A_2 \cap Z_{j,f}^2| \right) + \min \left(\lfloor \frac{V_{i,k}^f}{g_f} \rfloor, |A_1 \cap Z_{k,f}^1| + 1 \right) \geq S_f \right] \right. \\
&\quad \left. - Pr \left[\min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |A_1 \cap Z_{k',f}^1| + |A_2 \cap Z_{j,f}^2| \right) + \min \left(\lfloor \frac{V_{i,k}^f}{g_f} \rfloor, |A_1 \cap Z_{k,f}^1| \right) \geq S_f \right] \right\} \\
f(A \cup z_{k,f,v}) - f(A) &= \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_f Pr \left[\lfloor \frac{V_{i,k}^f}{g_f} \rfloor \geq |A_1 \cap Z_{k,f}^1| + 1 \right] \\
&\times Pr \left[\min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |A_1 \cap Z_{k',f}^1| + |A_2 \cap Z_{j,f}^2| \right) = s_f - |A_1 \cap Z_{k,f}^1| - 1 \right] \\
&= \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_f Pr \left[\lfloor \frac{V_{i,k}^f}{g_f} \rfloor \geq |B_1 \cap Z_{k,f}^1| - E_1 + 1 \right] \\
&\times Pr \left[\min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |B_1 \cap Z_{k',f}^1| - E_1 + |B_2 \cap Z_{j,f}^2| - E_2 \right) = s_f - |B_1 \cap Z_{k,f}^1| - E_1 - 1 \right] \\
f(A \cup z_{k,f,v}) - f(A) &= \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_f Pr \left[\lfloor \frac{V_{i,k}^f}{g_f} \rfloor \geq |B_1 \cap Z_{k,f}^1| - |E_1 \cap Z_{k,f}^1| + 1 \right] \\
&\times Pr \left[\min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |B_1 \cap Z_{k',f}^1| - |E_1 \cap Z_{k',f}^1| + |B_2 \cap Z_{j,f}^2| - |E_2 \cap Z_{j,f}^2| \right) \right. \\
&\quad \left. = s_f - |B_1 \cap Z_{k,f}^1| - |E_1 \cap Z_{k,f}^1| - 1 \right] \geq \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_f Pr \left[\lfloor \frac{V_{i,k}^f}{g_f} \rfloor \geq |B_1 \cap Z_{k,f}^1| + 1 \right] \\
&\times Pr \left[\min \left(\lfloor \frac{V_i^f}{g_f} \rfloor, |B_1 \cap Z_{k',f}^1| + |B_2 \cap Z_{j,f}^2| \right) = s_f - |B_1 \cap Z_{k,f}^1| - 1 \right] = f(B \cup \{z_{k,f,v}\}) - f(B)
\end{aligned}$$

B. Solution of Green Content Delivery Model

In this section, we provide the solution of optimization problems (14) and (15), i.e., the optimal transmit powers of SBS and mobile device are given as follows:

Theorem 2: According to the optimization problems (14) and (15), we can get the optimal transmit powers of SBS and mobile device, P_T^D and P_T^B , are as shown in (20) and (21).

Proof: We first give the optimal transmit power of mobile devices. For (15), we define $x = P_T^D$, $\delta = \frac{r_D^2}{\sigma_D^2}$, $\theta = \eta_D P_C^D$. Then we can get the objective function in (15) can be transformed as follows:

$$f(x) = \frac{\mathcal{B}_{ij}(x + \theta)}{\eta_D W_D \log_2^{(1+\delta x)}} \quad (17)$$

Take the derivative of (17), Then we have

$$f'(x) = \frac{\mathcal{B}_{ij}[(1 + \delta x) \log_2^{(1+\delta x)} \ln 2 - (1 + \delta x) - (\delta\theta - 1)]}{\eta_D W_D \log_2^{2(1+\delta x)} (1 + \delta x) \ln 2} \quad (18)$$

From the (18), we can obtain that the denominator of $f'(x)$ is always positive, when the numerator of $f'(x)$ is greater than 0, $f'(x) > 0$, and vise versa. Due to $x \in (0, P_{\max}^D]$, $1 + \delta x \in (1, 1 + \delta P_{\max}^D]$, define $y = 1 + \delta x$, $\xi = \delta\theta - 1$, then

the (18) can be rewritten as:

$$f'(y) = \frac{\mathcal{B}_{ij}[y \log_2^y \ln 2 - y - \xi]}{\eta_D W_D \log_2^{2y}(y) \ln 2} \quad (19)$$

Define $g(y) = \mathcal{B}_{ij} y \log_2^y \ln 2 - y - \xi$, and taking the derivative of $g(y)$ on y , we can obtain $g'(y) = \mathcal{B}_{ij} \log_2^y \ln 2$, thus we know that when $y \in (1, 1 + \delta P_{\max}^D]$, $g(y)$ is monotonic increasing function. Further, when $y \rightarrow 1$, $g(y) < 0$. And if $g(1 + \delta P_{\max}^D) < 0$, $f'(y) < 0$, then we can know $f(x)$ is monotonic decreasing function, so it gets minimum when $x = P_{\max}^D$. Besides, if $g(1 + \delta P_{\max}^D) > 0$, there exists zero point y_0 making $g(y_0) = 0$, so we conclude that function $f(x)$ is first monotonic increasing, then monotonic decreasing, and achieves the minimum at y_0 . Finally, we obtain the optimal P_T^{D*} as follows:

$$P_T^{D*} = \begin{cases} P_{\max}^D, & \text{if } g(1 + \delta P_{\max}^D) < 0, \\ P_{y_0}, & \text{if } g(1 + \delta P_{\max}^D) \geq 0 \end{cases} \quad (20)$$

In the same way, we can get P_T^{B*} as follows:

$$P_T^{B*} = \begin{cases} P_{\max}^B, & \text{if } g(1 + \delta P_{\max}^B) < 0, \\ P_{y_0}, & \text{if } g(1 + \alpha P_{\max}^B) \geq 0 \end{cases} \quad (21)$$

■

By solving (14) and (15), we can obtain the optimal transmit power of mobile device and SBS (denoted by P_T^{D*} and P_T^{B*} , respectively). Furthermore, the minimum energy consumption of mobile device and SBS can be calculated, denoted as E_D^* and E_B^* , respectively.

Thus, the user average energy consumed when requesting file can be obtained as follows:

$$\bar{E}^* = \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_{f,i} \left(\sum_{\omega=1}^{M_{i,k}} E_B^*(\mathcal{A}_{i,k}^\omega) + \sum_{\omega=1}^{N_{i,j}} E_D^*(\mathcal{B}_{i,j}^\omega) \right) \quad (22)$$

Since the number of contacts follows the Poisson distribution, the average time count for D_i getting contact with SBS S_k can be expressed as $\lambda_{i,k}^B T_d$, while the average time count for D_i getting contact with D_j can be expressed as $\lambda_{i,j}^D T_d$. Then, we can obtain the average minimum energy consumption of network when the content is delivered as follows:

$$\bar{E}^* = \frac{1}{n} \sum_{i=1}^n \sum_{f=1}^m p_{f,i} \left(\sum_{\omega=1}^{\lambda_{i,k}^B T_d} E_B^*(\mathcal{A}_{i,k}^\omega) + \sum_{\omega=1}^{\lambda_{i,j}^D T_d} E_D^*(\mathcal{B}_{i,j}^\omega) \right) \quad (23)$$

V. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed green and mobility-aware caching system. We consider a ultra-dense cellular network including 5 SBSs and 60 mobile devices. According to [20] and [36], we set the size of each file to 10 MB and file library contains 10^4 files, each file can be encoded into 2 code segments [23]. We assume that file request probability follows a Zipf distribution with $\gamma = 0.5$ and the deadline $T_d = 600s$. For simplicity, assume the cache size for all mobile devices is the same and can cache 1 percent of file library size in maximum. Similarly, assume the cache size for all SBSs is the same and can cache 10 percent of file library size in maximum.

For user mobility parameter settings according to [23], we use Gamma distribution to represent contact rate, i.e., the contact rate $\lambda_{i,j}^D$ between mobile device D_i and D_j follows the $\Gamma(4.43, 1/1088)$, and the contact rate $\lambda_{i,k}^B$ between mobile device D_i and SBS S_k follows the $\Gamma(10, 1/100)$. Wang *et al.* [23] show that the contact rate increases with the increasing use moving speed. Thus, larger $\lambda_{i,j}^D$ and $\lambda_{i,k}^B$ are, faster a user moves. According to [20] and [23], we set the amount of data that SBS and mobile device can deliver to a requested mobile device during a contact duration follows exponential distribution with means 10 MB and 5 MB, respectively.

In our experiments, the parameters regarding energy consumption at SBS and mobile devices are referred to [35]. The simulation parameters and their values are summarized in Table II. To evaluate the system, we measure the *cache hit ratio* and *energy consumption*.

A. Comparison With Other Methods

Green and mobility-aware caching (GM-caching), proposed in this paper, is compared with three different caching strategies: *Popular caching* [39], *Random caching* [23] and

TABLE II
SIMULATION PARAMETERS OF ENERGY COST

| Parameters | Value |
|---|----------|
| Maximize transmit power of SBS, P_{\max}^B | 6.3 W |
| Constant power of SBS, P_C^B | 56 W |
| Transmission bandwidth of SBS, W_B | 20 MHz |
| Gaussian noise of SBS, σ_B^2 | -104 dBm |
| Power amplifier efficiency of SBS, $1/\beta_B$ | 0.38 |
| Transmission bandwidth of D2D, W_D | 20 MHz |
| Maximize transmit power of user mobile device, P_{\max}^D | 0.2W |
| Circuit power consume of user mobile device, P_C^D | 115.9 mW |
| Gaussian noise, σ_D^2 | -95dBm |
| Power amplifier efficiency of user mobile device, $1/\beta_D$ | 0.2 |
| Path loss factor, α, β | 4 |

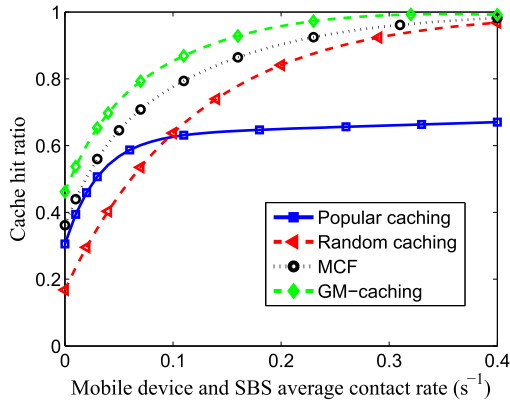
mobility-aware caching with fixed amount data can be delivered (MCF) [20], [21], [23].

- *Popular Caching*: The popular caching strategies on SBSs and on mobile devices are as follows, (i) caching strategy on SBSs: C_k^S most popular contents should be cached on each SBS S_k . (ii) caching strategy on mobile devices: C_j^D most popular contents should be cached on each mobile device D_j .
- *Random Caching*: The random caching caching strategies on SBSs and on mobile devices are as follows, (i) caching strategy on SBSs: randomly choose C_k^S contents to be cached on each SBS S_k . (ii) caching strategy on mobile device: randomly choose C_j^D contents to be cached on each mobile device D_j .
- *MCF*: Under this strategy, we assume the amount of content delivered is the average of $\mathcal{A}_{i,k}^\omega$ and $\mathcal{B}_{i,k}^\omega$.

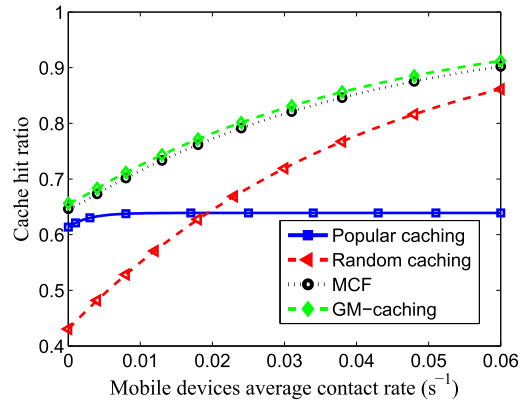
B. Evaluation Results

Impact of User Mobility: In Fig. 5, the influence of user mobility on caching strategy with three different caching strategies is demonstrated. In this experiment, for sake of convenient representation, let abscissa be $\bar{\lambda}_{i,k}^B$ and $\bar{\lambda}_{i,j}^D$, corresponding to the mean value of Gamma distribution that user mobility follows. In other words, $\bar{\lambda}_{i,k}^B$ stands for the average contact rate of mobile device D_i and SBSs S_k , and $\bar{\lambda}_{i,j}^D$ stands for the average contact rate of mobile device D_i and D_j . It can be seen from Fig. 5 that the proposed GM-caching strategy is superior to the popular caching strategy, random caching strategy and MCF caching strategy. This is because the popular caching strategy, the most popular contents are cached by SBS and mobile device, so there are less opportunities for cooperation and sharing. The random caching strategy does not consider user mobility, so it is not as good as the GM-caching. Although the MCF cache strategy takes into account the user mobility, it does not consider whether the encoded segments can be transmitted in a contact duration. Thus, the performance of the green and mobility cache strategy is the best.

From Fig. 5(a) and Fig. 5(b), we can obtain that when the user mobility is low, the cache hit ratio of GM-caching and popular caching is not significant. This is because when



(a) The impact of average contact rate of mobile devices and SBSs ($\bar{\lambda}_{i,k}^B$) on cache hit ratio.



(b) The impact of average contact rate of mobile devices ($\bar{\lambda}_{i,j}^D$) on cache hit ratio.

Fig. 5. The impact of user mobility on cache hit ratio.

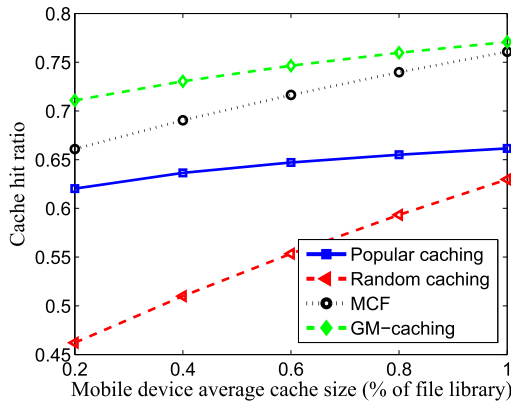


Fig. 6. The impact of cache size of mobile device on the cache hit ratio.

the user mobility is low, mobile device not only less handoff between different SBS, but also less opportunity to meet other mobile devices. However, there is great demand for popular contents. Thus, the popular contents should be cached on SBSs and on mobile devices to improve the cache hit ratio. When the mobility of user is high, we can see that the gap between the GM-caching and the random caching is small. This is because the cache network is relatively active, user have more contact opportunities with SBSs, so the probability of the user access to popular file become large. Thus, in this case, the cache hit ratio can be improved by considering the diversity of files.

Impact of Mobile Devices: As shown in Fig. 6, the relationship between cache size of mobile devices and the cache hit ratio is examined. In Fig. 6, the abscissa stands for the ratio of mobile device cache capacity to the entire file library size. For instance, abscissa 0.6 represents mobile device can store up to 0.6 percent of the entire file library size. It can be concluded from the figure that the cache hit ratio increases when the user device average cache size increases. This is because more contents can be cached when cache capacity for mobile device is larger, so as to achieve a higher cache hit ratio. Besides, it can also be seen from the figure that the influence on cache hit ratio with random

caching is greater than that with popular caching, when the cache size for mobile devices is larger. This is because the diversity of contents that can be cached with random caching is superior to that with popular caching, when storage capacity for mobile devices is larger, thus to achieve a higher cache hit ratio.

Impact of SBSs: As shown in Fig. 7(a), the influence of cache size for SBSs on cache hit ratio is presented. Similarly, when the average cache size for SBSs is larger, the cache hit ratio is higher. This is because more contents can be cached when the cache capacity for SBSs is larger, so as to achieve a higher cache hit ratio.

We explore how the number of SBSs impacts the cache hit ratio in Fig. 7(b). From the figure, we observe that when the number of SBS is less than 6, the cache hit ratio increase with the increase of the number of SBS. While when the number of SBS is more than 6, this is not significant. Furthermore, it can also be seen from the figure that, when $\gamma = 0.7$, the number of SBS to 4 when the cache hit ratio is not changed, and $\gamma = 0.9$, the number of SBS reached a little change when the number of up to 6. Thus, the deployment of SBSs should be more decentralized as popularity γ increase, i.e., the quantity of SBSs is large but the capacity for each SBS is small. This is because mobile device would be more concerned about popular content as γ increases. With decentralized deployment, the most popular content will be cached on each SBS, thus to meet the requirements of most users, so as to achieve a higher hit ratio.

Impact of Files: In Fig. 8(a), the cache strategies under different Zipf parameter γ is evaluated. It can be seen from the figure that as popularity γ increases, the cache hit ratio with GM-caching is larger. It can also be seen from the figure that with the increase of γ , the cache hit ratio of popular caching strategy increase gradually, but the cache hit ratio of random caching strategy does not change much, i.e., the influence of γ on popular caching is greater while that on random caching is less. This is because the requirements of user for popular contents are greater as γ increases, the requirements of users can be better met with popular caching. Therefore, popular caching increases as γ increases.

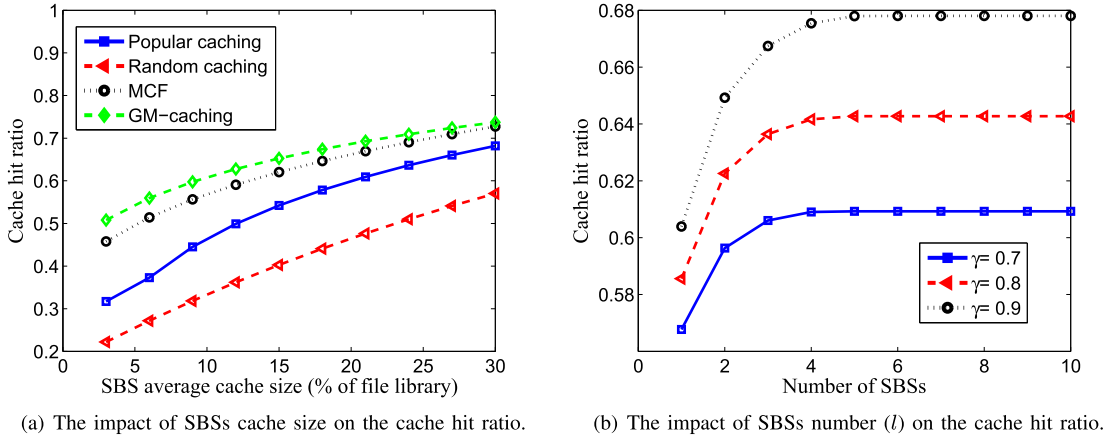


Fig. 7. The impact of SBS average cache size and density on the cache hit ratio.

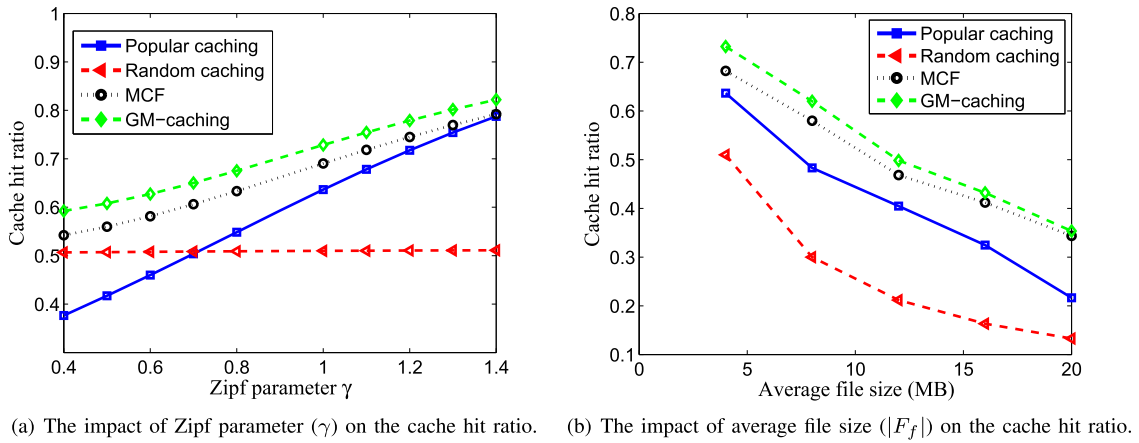


Fig. 8. The impact of Zipf parameter and file average size on cache hit ratio.

In Fig. 8(b), the influence of average file size on the cache hit ratio is presented. In this experiment, consider the entire file library size is fixed, i.e., the large size of file, the less number of file. The abscissa stands for the size of each file. From the figure, we observe that when the the size of each file is large, the cache hit ratio is smaller. This is because as the size of file is large and the cache capacity for SBSs and mobile devices is fixed, the amount of files that can be cached on SBSs and on mobile devices would be smaller, so that the cache hit ratio becomes lower.

Energy Consumption: Fig. 9(a) and Fig. 9(b) discuss the relationship between cache hit ratio and energy consumption. In this experiment, the energy consumption is normalized. From the Fig. 9(a) and Fig. 9(b), we can observe that with the increase of the cache hit ratio, energy consumption is also rising. This is because with the increase in cache hit ratio, the probability that the requested file download from SBS and mobile device increase, which increases the energy consumption of the SBS and mobile device. Furthermore, Fig. 9(a) shows that, when the mobile device D_i and SBS S_k average contact rate $\bar{\lambda}_{i,j}^B$ increase, more energy will consumes under the same cache hit ratio. Similarly, Fig. 9(b) has the same conclusion. Thus, under the same cache hit ratio, the higher

user mobility, the less energy consumed. Fig. 9(c) shows that, under the same cache hit ratio, GM-caching is more energy efficient than popular caching, random caching and MCF. This is because GM-caching not only takes into account the user mobility, but also considers the randomness of the contact duration.

C. Discussion

In this article, for user's mobility, we describe the user's mobility by utilizing the peer-to-peer connectivity model from the two perspectives: contact duration and contact frequency. The model reflects a primitive level of social interaction between users. However, the effects of more elaborate social relations and behaviours on user's mobility has not been taken into account. These effects of social networks on caching design have been studied in existing work (see e.g., [40]–[43]). It is an interesting direction for further investigation by extending the current work to include a mobility model account for more elaborate effects by social networks. Another direction warranting future research is to consider joint user-and-SBS caching powered by energy harvesting [44]. The technology can reduce transmission energy consumption but the energy randomness makes the optimal design more challenging.

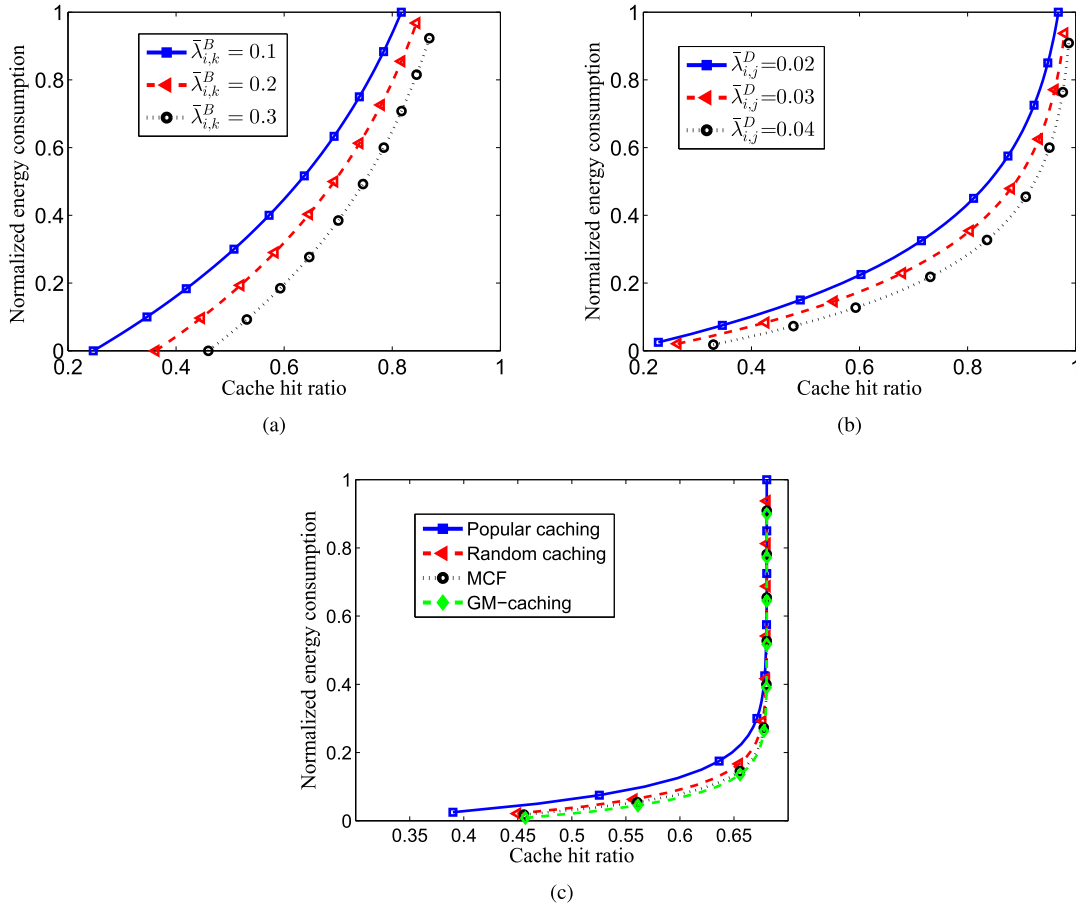


Fig. 9. Energy consumption under different caching strategies.

Furthermore, it is also a very interesting topic to consider caching and computing offloading together in edge cloud [45] to meet the delay sensitive application requirements [46].

VI. CONCLUSION

In this paper, we first studied the influence of mobility on caching on SBSs and on mobile devices, and proposed a mobility-aware content placement model, where specific caching strategies were developed for SBSs and mobile device leverages user mobility, aiming to maximize the cache hit ratio. Then, we discussed the energy consumption for delivery the caching content and given the optimal transmission power of SBS and mobile device. The simulation results showed that the proposed GM-caching strategy outperforms other caching strategies in prior work, in terms of cache hit ratio and energy efficiency of 5G networks.

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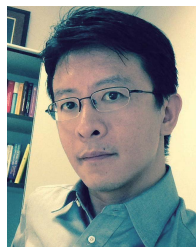
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