Mobility-Aware Caching for Content-Centric Wireless Networks: Modeling and Methodology

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**Abstract**

As mobile services are shifting from “connection-centric” communications to “content-centric” communications, content-centric wireless networking emerges as a promising paradigm to evolve the current network architecture. Caching popular content at the wireless edge, including base stations (BSs) and user terminals (UTs), provides an effective approach to alleviate the heavy burden on backhaul links, as well as lowering delays and deployment costs. In contrast to wired networks, a unique characteristic of content-centric wireless networks (CCWNs) is the mobility of mobile users. While it has rarely been considered by existing works in caching design, user mobility contains various helpful side information that can be exploited to improve caching efficiency at both BSs and UTs. In this paper, we present a general framework on mobility-aware caching in CCWNs. Key properties of user mobility patterns that are useful for content caching will be firstly identified, and then different design methodologies for mobility-aware caching will be proposed. Moreover, two design examples will be provided to illustrate the proposed framework in details, and interesting future research directions will be identified.

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This work was supported by the Hong Kong Research Grant Council under Grant No. 610113.
Mobile data traffic is undergoing an unprecedented growth, and it is being further propelled by the proliferation of smart mobile devices, e.g., smart phones and tablets. In particular, the data services subscribed by mobile users have gradually shifted from “connection-centric” communications, e.g., phone calls and text messages, to “content-centric” communications, e.g., multimedia file sharing and video streaming. One main effort to meet such a strong demand is to boost the network capacity via network densification, i.e., to deploy more access points. While this approach is expected to significantly increase the capacity in future 5G networks, it incurs a tremendous demand for backhaul links that connect the access points to the backbone network. Thus, it will cause a heavy financial burden for mobile operators who are required to upgrade the backhaul network, and such a comprehensive approach will not be cost-effective to handle content-centric mobile traffic, which may be bursty and regional. Consequently, a holistic approach is needed and cache-enabled content-centric wireless networking emerges as an ideal solution.

Nowadays, abundant caching storages are available at the wireless edge, including both base stations (BSs) and user terminals (UTs), which can be used to store popular contents that will be repeatedly requested by users. Since the prices of caching devices, e.g., solid state drives (SSDs), have been coming down year after year, it has become more and more cost-effective to deploy caches instead of laying high-capacity backhaul links [1]. Moreover, the ample storages at mobile UTs, currently as large as hundreds of gigabytes, are also potential resources to be utilized for caching. Besides reducing the demand and deployment costs of backhaul links, caching popular content is also an effective technique to lower delays and reduce network congestion [2], since mobile users may acquire the required files from the serving BSs or the proximal UTs directly without connecting to the backbone network.

The idea of content-centric networking has already been explored in wired networks, where named pieces of content are directly routed and delivered at the packet level, and content packets are automatically cached at routers along the delivery path. Accordingly, caching design at the routers, including content placement and update, is crucial to the system performance. Caching at the wireless edge can draw lessons from its wired counterpart, but it also enjoys new features. The broadcast nature of the radio propagation will fundamentally affect the content caching
and file delivery, which has recently attracted significant attention. Another important feature of content-centric wireless networks (CCWNs) is user mobility, which has been less well studied. While mobility imposes additional difficulties on caching design in CCWNs, it also brings about new opportunities. User mobility has been proved to be a useful feature for wireless network design, e.g., it has been utilized to improve the routing protocol in wireless ad hoc networks [3]. Unfortunately, most previous studies on caching design in CCWNs ignored user mobility and assumed fixed network topologies, which cannot capture the actual scenario. There have been initial efforts on caching designs by incorporating user mobility [4]. However, only some special properties of user mobility patterns were addressed and there is a lack of systematic investigation.

The main objective of this paper is to provide a systematic framework that can take advantage of user mobility to improve the caching efficiency in CCWNs. Specifically, a comprehensive discussion of spatial and temporal properties of user mobility patterns will firstly be provided, each of which will be linked to specific caching design problems. We will then propose mobility-aware caching strategies, with two typical design cases as examples. Finally, we will identify some future research directions.
II. Exploiting User Mobility in Cache-Enabled CCWNs

In this section, we will illustrate the importance of considering user mobility when designing caching strategies in CCWNs. A sample cache-enabled CCWN is shown in Fig. 1, where both BSs and UTs have cache storages and are able to cache some pieces of content from the file library. In the following, we will first introduce the main caching design problems in CCWNs, and then identify important properties of the user mobility patterns and associate them with different caching problems.

A. Key Design Problems of Caching in CCWNs

The fundamental problem in caching design for CCWNs is to determine where and what to cache. The design principles may depend on different types of side information, including long-term information obtained from observations over a long period of time, such as the statistics of users’ requests and average communication times with BSs and other UTs, and short-term information generated by instant changes, e.g., instantaneous channel state information and real-time location information. The collection of long-term information incurs a low overhead, while the usage of short-term information can provide better performance but requires frequent update. In the following, we categorize different caching design problems in CCWNs according to the timeliness of the available information.

1) Caching Content Placement: Caching content placement typically relies on long-term system information and is used to determine how to effectively pre-cache content in the available storage. To reduce overhead, the update of side information and caching content will not be very frequent. It is normally assumed that the long-term file popularity distribution is known as a priori, and the network topology can either be fixed or subject to some assumptions in order to simplify the design.

Previous works have provided some insights into caching content placement at BSs. In particular, without cooperation among BSs, the optimal caching strategy is to store the most popular files [5]. However, if users are able to access several BSs, each user will see a different but correlated aggregate cache, and in this scenario, allocating files to different BSs becomes nontrivial. Moreover, the coded caching scheme, where segments of Fountain-encoded versions of the original file are cached [5], outperforms the uncoded caching scheme where only complete files are cached. By carefully designing the caching content placement via combining multiple files
with a given logic operator, different requests can be served by a single multicast transmission [6], which results in a significant performance improvement compared to the uncoded scheme.

Meanwhile, caching content placement at UTs is also attracting noticeable attention. Caching at UTs may allow users to download requested content in a more efficient way with device-to-device (D2D) communications, where proximal users communicate with each other directly. Compared with caching at BSs, the advantages of caching at UTs come from the lower deployment costs and an automatic promotion of the storage capacity when the UT density increases, as the ensemble of UTs forms an aggregate cache; while the drawbacks include the difficulty of motivating UTs to join the aggregate cache, and the more complicated randomness in the D2D scenario. Pioneering works have shed light on caching content placement at UTs [7].

However, it is noted that previous studies rarely considered user mobility, which can be tracked without much difficulty with today’s technologies. If we could make use of long-term statistics of user mobility, such as the average steady-state probability distribution over BSs, the efficiency of content caching will be significantly improved.

2) Caching Content Update: Though long-term information incurs a low overhead to obtain, it contains less fine grained information, which may also expire after a period of time and thus cannot assure accuracy. For example, the BS-UT or UT-UT connectivity topology may change quickly due to the movement of UTs. Consequently, it may cause significant errors by using the expired long-term information to design caching strategies. If short-term information is available, such as the real-time information of the file requests and transmission links, caching content can be updated to provide a better experience for mobile users. In the following, we will introduce two caching content update problems.

  a) Adaptive caching: Since caching storage is limited, it is critical to replace the stale caching content to improve caching efficiency. Common adaptive caching schemes to increase the cache hit ratio include replacing the least recently used content and replacing the least likely requested content [8]. Another typical application of adaptive caching is to serve the users that follow regular mobility patterns and have highly predictable requirements. When the mobility regularity and request preference of mobile users are known, BSs can update the caching content according to the estimation of future requests. The main challenges come from the accurate prediction of users’ future positions and requirements, the frequency to conduct the adaptive caching strategy, as well as the replacement priorities for the caching content.
Fig. 2. The trajectories of two mobile users based on data collected on a university campus. The two users are moving within a 5000 m x 4000 m area. We assume that 20 BSs are deployed regularly in the area, with the cell indices labeled in (a). The average cell sojourn times of these two users, which denote the duration of the users being connected to each BS, are shown in (b). The transmission ranges of two mobile users are assumed to be 200 m and the timeline of users 1 and 2, including inter-contact times and contact times, is depicted in (c).

b) Proactive caching: In practice, a user can only download a portion of its requested file rather than the entire file from a BS, as the moving user may not have enough communication time with the BS. Proactive caching aims at providing seamless handover and downloading for users by pre-fetching the requested content at the BSs that will be along the users’ future paths with a high probability. Nevertheless, user requests and locations are usually unknown in realistic environments, and thus the accuracy of location prediction is critical to the performance.

B. Modeling User Mobility Patterns

As can be inferred from the above discussions, taking user mobility into consideration is critical for the caching design in CCWNs. In this subsection, we will provide detailed descriptions of different user mobility properties, which can be classified into two categories, i.e., the spatial and temporal properties. The spatial properties contain the information of user mobility patterns related to the physical locations, while the temporal properties characterize the time-related features.

1) Spatial Properties: The mobility pattern of a mobile user can be visualized by the user trajectory, i.e., the user’s moving path. Crucial information for caching design in CCWNs, e.g.,
serving BSs, and distances between BSs and mobile users, can be obtained from the trajectories of the mobile users. It is an ongoing research topic to investigate realistic models for user trajectory, e.g., the random waypoint model in [9]. As an example, the trajectories of two mobile users are shown in Fig. 2(a) which are based on data collected on a university campus [1].

The cell transition, which denotes the transition pattern of a user moving from one cell to another, implies the information of serving BSs for each mobile user, which is one of the most critical pieces of information in caching design at BSs. Compared to the user trajectory, the cell transition contains less fine grained information as the moving path inside each cell cannot be specified. It is appropriate to capture the transition property using a Markov chain model [10], where the number of states equals the number of BSs. In the Markov chain, one state denotes a specific user being served by a given BS, and the transition probabilities represent the probabilities for a specific user moving from the serving area of one BS to that of another BS.

Recently, it has been found that user mobility patterns also largely depend on the social relations among mobile users. For example, it was claimed in [11] that the mobile users having relatively strong social ties are more likely to have similar trajectories. In [12], Musolesi et al. proposed a two-level mobility model, which first establishes a social graph, where the nodes represent mobile users and the weighted edges represent the strength of the social connection between mobile users. Then, social groups are built and mobile users in each group move together. Such information will be useful for caching at UTs.

2) Temporal Properties: To capture the information of the frequency and duration that two mobile users are connected with each other, the timeline of an arbitrary pair of mobile users is represented by contact times and inter-contact times, where the contact times are defined as the time intervals during which the mobile users are within the transmission range, and the inter-contact times are defined as the time intervals between two consecutive contact times. The timeline of two users shown in Fig. 2(a) is illustrated in Fig. 2(c). Such a mobility model has been applied to routing problems in ad hoc networks. For instance, in [3], Conan et al. modeled locations of contact times in the timeline of each pair of mobile users as a Poisson Process so as to capture the average pairwise inter-contact times in an ad hoc network.

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1I. Rhee, M. Shin, S. Hong, K. Lee, S. Kim, and S. Chong, “CRAWDAD dataset ncsu/mobilitymodels (v. 2009-07-23),” Downloaded from http://crawdad.org/ncsu/mobilitymodels/20090723, Jul. 2009.
The *cell sojourn time* denotes the time duration of a specific user served by a given BS, which may affect the amount of data that this user can receive from the BS. Fig. 2(b) shows the cell sojourn times of the two users whose trajectories are shown in Fig. 2(a). Specifically, in [10], Lee et al. provided an approach to obtain the sojourn time distributions according to the associated moving history of mobile users.

The user mobility pattern always possesses a periodic property, which can be exploited to tackle the caching update problem. The *return time*, which is defined as the time for an arbitrary mobile user to return to a previous visited location, is considered as a measure to reflect the periodic property and the frequency of mobile users to revisit a given area. In [13], Gonzales et al. measured the distribution of the return time and figured out that the peaks of the return time probability are at 24 h, 48 h and 72 h.

### C. Exploiting Mobility for Caching in CCWNs

Built upon the information given in the above two subsections, potential approaches will now be proposed to take advantage of user mobility patterns to resolve different caching design problems in CCWNs, as summarized in Table [I].

1) **Caching content placement at BSs:** In CCWNs, as a user moves along a particular path, the user may download the requested file from all the BSs along this path, and different BSs may cooperatively cache this file to improve the efficiency. For this purpose, the statistic and predictive information of the BSs along the user trajectory, which can be obtained based on user trajectory or cell transition probabilities, will be needed. Compared to cell transition probabilities, the user trajectory provides additional information, i.e., different transmission distances from BSs in different cells, which can help better design the BS cooperative caching in CCWNs. For example, different transmission distances may result in different transmission rates, which will affect the amount of data that can be downloaded from different BSs. Furthermore, the cell sojourn time is also a critical factor to determine the amount of data that can be delivered, and thus will also affect the caching content placement at BSs.

2) **Caching content placement at UTs:** By enabling caching at UTs, mobile users may get the requested files via proximal D2D links. For caching design in such a setting, the information related to inter-user contacts is essential. In particular, inter-contact times and contact times will be valuable information, which will be further illustrated in the design examples in the next
section. In addition, social relations may help to decompose a large network into several small social groups, and thus reduce the complexity of caching design. Meanwhile, social groups also imply some contact information, i.e., mobile users in the same social group are more likely to have more contacts [14]. Thus, social group information can also be utilized to design caching content placement at UTs.

3) Adaptive caching: The caching content can be adjusted adaptively based on the periodical mobility pattern, for which the knowledge of return times will be very useful. Moreover, mobile users in different social groups may have different content preferences. Thus, the mobility pattern of each social group can be utilized to improve the adaptive caching design. For example, in a restaurant, there may be several customer groups with different content preferences during different time periods, e.g., elders may enjoy the morning tea, students will have lunch with friends, and office workers may have dinner together. The BSs around the restaurant may perform adaptive caching updates accordingly.

4) Proactive caching: If the user trajectory or cell transition property can be estimated based on past data, the future serving BSs for mobile users can be predicted. In this way, if a mobile user requests a certain file, the BSs that are predicted to be on its future path may proactively cache the requested file, each with a certain segment, and then the user can download the file when passing by. While it may slightly increase the backhaul traffic, such proactive caching can significantly improve the caching efficiency and reduce download latency.

The above proposals are by no means complete. Nevertheless, they clearly indicate the great potential and importance of mobility-aware caching in CCWNs. We hope this discussion will inspire more follow-up investigations.

III. MOBILITY-AWARE CACHING CONTENT PLACEMENT

In this section, we present two specific design examples for mobility-aware caching content placement, including caching at BSs and caching at UTs. Sample numerical results will be provided to validate the effectiveness of utilizing user mobility patterns in wireless caching design problems.
TABLE I
EXPLOITING MOBILITY FOR CACHING IN CCWNs

| Spatial Properties | Temporal Properties |
|--------------------|---------------------|
| User trajectory | Cell transition | Social group | User inter-contact time | Cell sojourn time | Return time |
| --- | --- | --- | --- | --- | --- |
| Caching content placement at BSs | ✓ | ✓ | — | — | ✓ | — |
| Caching content placement at UTs | — | — | ✓ | ✓ | — | — |
| Adaptive caching | — | — | ✓ | — | — | ✓ |
| Proactive caching | ✓ | ✓ | — | — | — | — |

General: ‘✓’ means that the mobility property can be utilized in the corresponding caching design problem, and ‘—’ means that the mobility property may not be utilized.

![Wireless Caching Networks](image)

(a) Caching at BSs

(b) Caching at UTs

Fig. 3. Wireless Caching Networks. BS caching is shown in (a), where a user requests a file and passes by BSs numbered {1, 2, 5, 2, 3} in sequence. The user can obtain the requested file by collecting data from these BSs. D2D caching is shown in (b), where UT 1 requests a file, and it has not stored the file in its own cache. After a period of time, UT 1 encounters UT 3 which stores the requested file, and it downloads the file from UT 3.
A. Mobility-Aware Caching at BSs

We first consider utilizing the cell sojourn time information to design caching content placement at BSs, which may be macro BSs or femto-cell BSs. A sample network is shown in Fig. 3(a). For simplicity, we assume the downlink rate for each user is the same while passing by each BS, and cell sojourn times are estimated based on available data. Mobile users will request files in the file library based on their demands, which is assumed to follow a Zipf distribution. Both uncoded and coded caching schemes are considered. In the uncoded case, we assume that each file is either fully stored or not stored at each BS. In the coded case, rateless fountain codes are applied, where each BS may store part of a coded file, and the whole file can be recovered by collecting enough coded message of that file [5]. When a mobile user requests a file, the user will try to collect the requested file while passing by each BS. The proportion of the requested file that can be downloaded from a BS is limited by the transmission rate and the sojourn time in this cell, as well as the proportion of the requested file stored at this BS. We aim to minimize the cache failure probability, which is the probability that the mobile users cannot get the requested files from cached contents at BSs. The coded caching placement problem can be formulated as a convex optimization problem, while the uncoded caching placement can be obtained by solving a mixed integer programming (MIP) problem.

We evaluate the performance of the proposed mobility-aware caching strategies based on a real-life data set of user mobility, which was obtained from the wireless network at Dartmouth College [2]. Following caching placement strategies are compared:

- Mobility-aware coded caching strategy, which is the proposed coded caching strategy obtained by solving a convex optimization problem.
- Mobility-aware uncoded caching strategy, which is the proposed uncoded caching strategy obtained by solving an MIP problem.
- MPC strategy, which is a heuristic caching strategy, for which each BS stores the most popular contents [8].

The comparison is shown in Fig. 4, where a larger value of the Zipf parameter $\gamma_p$ implies the requests from mobile users are more concentrated on the popular files. We see that the

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[2] D. Kotz, T. Henderson, I. Abyzov, and J. Yeo, “CRAWDAD dataset dartmouth/campus (v. 2009-09-09),” Downloaded from http://crawdad.org/dartmouth/campus/20090909, Sept. 2009.
mobility-aware caching strategies outperform the heuristic caching strategy, and the performance gap expands with $\gamma_p$, which demonstrates the value of the mobility information. Moreover, the coded caching strategy performs better than the uncoded caching strategy, which validates the advantage of coded caching.

There are many interesting problems for further investigation. For example, the user trajectory can be utilized to consider variant download rates, which will affect the amount of data obtained in different cells. In addition, based on the user trajectory, it is possible to jointly deal with the caching problem and interference management. Another challenge is that many BS caching problems are typically NP-hard, and thus time-efficient sub-optimal algorithms are needed.

B. Mobility-Aware Caching at UTs

In this subsection, we will focus on caching at UTs. We consider taking advantage of average inter-contact times among mobile users to improve the caching efficiency at UTs. An illustrative example is shown in Fig. 3(b) The locations of contact times in the timeline for any two mobile users are modeled as a Poisson process, as in [3], where the intensity is estimated from the history data. For simplicity, the timelines for different pairs of mobile users are assumed to be independent, and each file is assumed to be either completely stored or not stored at each UT. Mobile users will request files in the file library based on their demands, which is assumed to follow a Zipf distribution. When a mobile user generates a request, it will first try to find the
requested file in its own cache, and will then wait for encountering users storing the requested file. The delay time is defined as the time between when a user requests a file and when it encounters the first user storing the requested file. We assume that if the mobile user stores the requested file or its delay time is within a pre-determined delay threshold, it will be served via D2D links; otherwise, it will get the file from the BS. To offload the traffic from BSs and encourage proximal D2D transmissions, we set the objective as to maximize the data offloading ratio, which is the fraction of users that can get requested files via D2D links. This turns out to be a challenging problem and falls in the category of monotone submodular maximization over a matroid constraint, which can be solved by a greedy algorithm with an approximation ratio as \( \frac{1}{2} \).

The performance of mobility-aware caching at UTs is evaluated based on a real-life data set, which was collected at the INFOCOM conference\(^3\). Considering that most requests may occur in the daytime, we generate average inter-contact times according to the daytime data during the first day of the conference. The following caching placement strategies are compared:

- Mobility-aware greedy caching strategy, which is the proposed caching strategy using a greedy algorithm.
- Mobility-aware random caching strategy, which is similar to the random caching strategy proposed in [7]. In this strategy, each UT caches files according to a Zipf distribution with parameter \( \gamma_c \). The optimal value of \( \gamma_c \), which maximizes the expected fraction of users that can get requested files via D2D links, is obtained by a line search.
- MPC strategy, which is the same as the one used in Fig. 4.

Based on the data during the daytime in the second day of the conference, the performance of three caching strategies are compared in Fig. 5 by varying the file request parameter. It shows that both mobility-aware caching strategies significantly outperform the MPC strategy, and the performance gain increases as \( \gamma_c \) increases. Furthermore, the mobility-aware greedy caching strategy has a better performance than the mobility-aware random caching strategy, since the former strategy incorporates average pairwise inter-contact times more explicitly and allows more optimization variables. Through extensive simulations, we also observe that, as the number

\(^3\) J. Scott, R. Gass, J. Crowcroft, P. Hui, C. Diot, and A. Chaintreau, CRAWDAD dataset cambridge/haggle (v. 2009-05-29), downloaded from http://crawdad.org/cambridge/haggle/20090529, doi:10.15783/C70011, May 2009.
of users increases, the data offloading ratio using mobility-aware caching strategies increases, while the MPC strategy remains the same. Meanwhile, using mobility-aware strategies, the data offloading ratio increases as the user mobility increases, and the greedy caching strategy always outperforms the random one. This implies that a better utilization of user mobility patterns can further improve the caching efficiency.

While this initial study provides promising results, lots of challenges remain. For example, since the number of mobile users in a CCWN is usually very large, collecting the pairwise inter-contact times will cause a high overhead. One potential solution is to decompose the large number of mobile users into several social groups, and then design caching content placement at UTs based on the inter-contact times of mobile users within the same social group. Moreover, coded caching strategies can also be applied, which is a prominent approach to further optimize the caching efficiency.

IV. Conclusions and Future Directions

In this paper, we conducted a systematic study that investigated the exploitation of user mobility information in cache-enabled CCWNs. Useful spatial and temporal mobility properties were identified and linked to key caching design problems. Through two design examples, the advantages and effectiveness of mobility-aware caching were demonstrated. To fully exploit
mobility information in CCWNs, more works will be needed, and the followings are some potential future research directions.

- **Joint caching content placement at the wireless edge:** In practice, many caching systems consist of more than one layer of caches, which leads to a more complicated hierarchical caching architecture. In CCWNs, while most existing works, as well as our discussion in this paper, treated caching at BSs and UTs as separate problems, a joint design of caching at both BSs and UTs will be essential to further improve the system performance.

- **Dynamic user caching capacities:** Unlike BSs, the caching capacities at UTs may not be fixed, since they are related to storage usages of mobile users, which are different from user to user and are changing over time. It is thus important to investigate how to adaptively cache according to the dynamic user caching capacities, while also taking user mobility into consideration.

- **Big data analytics for mobility information extraction:** With the explosive growth of mobile devices, collecting user mobility information will generate huge amounts of data. Thus, big data analytics to extract the required mobility information is another challenge in mobility-aware caching. Meanwhile, accurate prediction is also critical. Though some existing user mobility models can predict the future mobility behavior via historical data, e.g., the Markov chain model in [10] can jointly predict the cell transition and cell sojourn time, more works will be needed, e.g., on how to predict the user trajectory. It is also important to investigate how different mobility models will affect the performance of caching strategies.

- **Privacy issues:** In order to take advantage of the user mobility pattern, some personal information, e.g., home locations and work place locations, may be divulged in the collected mobility information. This will certainly cause some concerns on the privacy issues. Thus, how to extract the useful user mobility information without touching the individual privacy is important. Location obfuscation and fake location injection mechanisms may serve as potential approaches for anonymous traces.

REFERENCES

[1] X. Peng, J. Zhang, S.H. Song, and K. B. Letaief, “Cache size allocation in backhaul limited wireless networks,” in Proc. IEEE Int. Conf. Commun. (ICC), Kuala Lumpur, Malaysia, May 2016.

[2] X. Peng, J.-C. Shen, J. Zhang, and K. B. Letaief, “Backhaul-aware caching placement for wireless networks,” in Proc. IEEE Global Commun. Conf. (GLOBECOM), San Diego, CA, Dec. 2015.
[3] V. Conan, J. Leguay, and T. Friedman, “Fixed point opportunistic routing in delay tolerant networks,” IEEE J. Sel. Areas Commun., vol. 26, no. 5, pp. 773–782, Jun. 2008.

[4] K. Poularakis and L. Tassiulas, “Exploiting user mobility for wireless content delivery,” in Proc. IEEE Int. Symp. Information Theory (ISIT), Istanbul, Turkey, Jul. 2013.

[5] K. Shanmugam, N. Golrezaei, A. Dimakis, A. Molisch, and G. Caire, “Femtocaching: Wireless content delivery through distributed caching helpers,” IEEE Trans. Inf. Theory, vol. 59, no. 12, pp. 8402–8413, Dec. 2013.

[6] M. Maddah-Ali and U. Niesen, “Fundamental limits of caching,” IEEE Trans. Inf. Theory., vol. 60, no. 5, pp. 2856–2867, May 2014.

[7] N. Golrezaei, P. Mansourifard, A. Molisch, and A. Dimakis, “Base-station assisted device-to-device communications for high-throughput wireless video networks,” IEEE Trans. Wireless Commun., vol. 13, no. 7, pp. 3665–3676, Jul. 2014.

[8] H. Ahlehagh and S. Dey, “Video-aware scheduling and caching in the radio access network,” IEEE/ACM Trans. Netw., vol. 22, no. 5, pp. 1444–1462, Oct. 2014.

[9] C. Bettstetter, H. Hartenstein, and X. Pérez-Costa, “Stochastic properties of the random waypoint mobility model,” ACM/Kluwer Wireless Netw., vol. 10, no. 5, pp. 555–567, Sept. 2004.

[10] J.-K. Lee and J. C. Hou, “Modeling steady-state and transient behaviors of user mobility: formulation, analysis, and application,” in Proc. ACM Mobile Ad Hoc Netw. and Comput. (MobiHoc), Florence, Italy, Jun. 2006.

[11] D. Wang, D. Pedreschi, C. Song, F. Giannotti, and A.-L. Barabasi, “Human mobility, social ties, and link prediction,” in Proc. ACM Knowledge Discovery and Data Mining (SIGKDD), San Diego, CA, Aug. 2011.

[12] M. Musolesi, S. Hailes, and C. Mascolo, “An ad hoc mobility model founded on social network theory,” in Proc. ACM Modeling, Anal., and Simulation of Wireless and Mobile Syst. (MSWiM), Venice, Italy, Oct. 2004.

[13] M. C. Gonzalez, C. A. Hidalgo, and A.-L. Barabasi, “Understanding individual human mobility patterns,” Nature, vol. 453, no. 7196, pp. 779–782, Jun. 2008.

[14] O. Semiari, W. Saad, S. Valentin, M. Bennis, and H. V. Poor, “Context-aware small cell networks: How social metrics improve wireless resource allocation,” IEEE Trans. Wireless Commun., vol. 14, no. 11, pp. 5927–5940, Jul. 2015.

[15] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott, “Impact of human mobility on opportunistic forwarding algorithms,” IEEE Trans. Mobile Comput., vol. 6, no. 6, pp. 606–620, Jun. 2007.