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Socially Aware Caching Strategy in Device to Device Communication Networks

Chuan Ma,, Ming Ding, *Senior Member, IEEE*,
He Chen, *Member, IEEE,* Zihuai Lin, *Senior Member, IEEE*,
Guoqiang Mao, *Fellow, IEEE*,, Ying-Chang Liang, *Fellow, IEEE*, and Branka Vucetic, *Fellow, IEEE*

***Abstract*—As a response to the challenge of data traffic explosion in wireless networks, content caching in device-to-device (D2D) communication networks has emerged as a promising solution. However, in practical deployment, D2D content caching has its own problems. In particular, not all of the user devices are willing to share the content with others due to numerous concerns such as security, battery life, and social relationship. In this paper, we consider the factor of social relationship in the deployment of D2D content caching. First, we apply stochastic geometry theory to derive an analytical expression of downloading performance for the D2D caching network. Specifically, a social relationship model with respect to the physical distance is adopted in our analysis to obtain the average download delay performance using random and deterministic caching strategies. Second, to achieve a better performance in more practical and specific scenarios, we develop a socially aware distributed caching strategy based on a decentralized learning automaton, to optimize the cache placement operation in D2D networks. Different from the existing caching schemes, the proposed algorithm not only considers the file request probability and the closeness of devices as measured by their physical distance but also takes into account the social relationship between D2D users. Our simulation results show that the proposed algorithm can converge quickly and outperforms the random and deterministic caching strategies. With these results, our work sheds insights on the design of D2D caching in the practical deployment of 5G networks.**

***Index terms*— Caching, Device-to-device, Social Networks, Stochastic Geometry**

I. Introduction

With the skyrocketing number of tablets and smart phones, wireless traffic has been increasing dramatically in the past few years. According to Cisco, an unprecedented worldwide growth of mobile data traffic is expected to continue at an annual rate of 45% over the next decade, surpassing 30 exabytes per month by 2020 [1]. Video traffic will be the major traffic source due to the growing success of on-demand video streaming services. The huge demand pushes operators to provide high-throughput wireless access services in 5th generation (5G) networks. However, the current wireless access technologies have almost approached their theoretical limits and it is imperative to develop new communication strategies to meet the ever-increasing demand from mobile subscribers [2].

One of the promising approaches to tackle this problem in 5G is content caching, as this technology can significantly offload the network traffic by optimally and intelligently storing the content files in the small base stations (SBSs) [3]-[5] and/or in mobile users' devices [6]-[21] that are closer to end-users. As a result, network congestion can be eased and users' quality-of-experience (QoE) can be significantly improved. The authors in [3] introduced the ideas of caching in heterogeneous networks, wherein one macro cell is divided into multiple small cells. Within each small cell, one low power base station, termed as the SBS, is deployed to serve the users within its coverage. The requested files by users are first transmitted from the macro BS to the SBSs through the backhaul connections between them in off-peak period and then transmitted from the SBSs to the users. To optimize the cache content placement in the SBSs, two algorithms have been proposed in the literature: a) discrete generalized pursuit algorithm (DGPA)-based scheme proposed in [4] for which the SBSs can place the content according to the local demands; b) belief propagation (BP) algorithm based on the factor graph [5], which allows the file placement to be arranged in a distributed manner between the users and SBSs. Nevertheless, it may be costly to setup and maintain the SBSs as well as the backhaul. Furthermore, the SBS caching may suffer from long latency and slow update of popular contents, which could hinder its application in practice.

With the emergence of 5G, exchanging the cached files among mobile devices through D2D communications, termed as D2D caching, has attracted considerable attention recently [6]. In [7], Ji *et al*. considered the D2D caching from the perspective of information theory and proposed deterministic and random caching schemes, both of which are shown to be able to achieve the information theoretic bound within a constant multiplicative factor. In addition, Ji *et al*. in [8] analyzed the basic principle and system performance of the D2D caching networks, and demonstrated that the gain from

C. Ma is with the School of Electrical and Information Engineering, The University of Sydney, Sydney, N.S.W. 2006, Australia and Data61, CSIRO, Australia (e-mail: chuan.ma@sydney.edu.au).

M. Ding is with Data61, CSIRO, Australia (e-mail: Ming.Ding@data61.csiro.au).

H. Chen, Z. Lin and B. Vucetic are with the School of Electrical and Information Engineering, The University of Sydney, Sydney, N.S.W. 2006, Australia (e-mail: he.chen@sydney.edu.au; zihuai.lin@sydney.edu.au; branka.vucetic@sydney.edu.au).

G. Mao is with the School of Computing and Communication, The University of Technology Sydney, Australia and Data61, CSIRO, Australia (e-mail: g.mao@ieee.org).

Y.-C. Liang is University of Electronic Science and Technology of China (UESTC), Chengdu, China (e-mail: liangyc@ieee.org). The work of Y.-C. Liang is funded by National Natural Science Foundation of China (Grant No.61571100 and Grant No.61631005).

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the unicast transmission is comparable to the gain from the coded BS multicast in [9]. However, in practice, due to limited memory and energy resources, users may be unwilling to serve data over the aforementioned D2D transmission unless they can obtain benefits (e.g., monetary incentives) from the operator [10] or other incentives (e.g., social relationship) from the users [11], [12][1], and [13]. In [14], Chen *et al.* proposed an incentive mechanism in which the BS rewards those users that share contents with others using D2D communication. But the social relationships among users are not considered. Compared with SBSs, the storage capacities at users are much smaller. In this context, different from the existing works on SBS and D2D caching (e.g., [6]-[13]), it is not optimal and practical to store same files in all users, and hence the optimization of the content placement becomes more critical and complex in the design of D2D caching strategies. Furthermore, the interactions between users should also be carefully taken into consideration [15].

To address the aforementioned issues, social relationship among mobile users can be a useful tool. The ideas of applying social characters to promote D2D communications and to design D2D caching was first proposed in [16]. In [17], [18] and [19], the social community aware D2D resource allocation framework was proposed. By using the close social ties in the same community, the resource allocation problem of D2D pairs was formulated and optimized by a two step coalitional game. Besides, the use of positive social relationship among mobile users was investigated in [11], which helps to reduce malicious or irrational users in the system. Moreover, a content dissemination scheme based on the common interest of users in a social group was proposed in [20]. A considerable delay reduction can be obtained when there is a large number of users in the same social group. In addition, in [21], a socially incentive mechanism for content distribution through D2D communications have been proposed. The contract theory investigated in this work can effectively incentivize user's participation, and increase capacity of the cellular network. However, to our best knowledge, how to design the content placement in D2D caching by incorporating the social characters between users remains to be an open question, and there is a lack of performance analysis for the socially aware D2D caching networks.

Motivated by the above observations, it is interesting and challenging to investigate the system design and performance analysis of the D2D caching networks. In this paper, we study the caching placement problem among D2D users. First, using the stochastic geometry tool, a probabilistic caching scheme is analyzed when the social relationship between users is distance-dependent. Then, a distributed caching algorithm is proposed for a deterministic network scenario.

It is important to note that our first contribution is regarding the theoretical performance bounds using the random and deterministic caching strategies. However, it still remains unclear how to implement the 5G D2D caching in practice. And more importantly, can we even do better than the derived analytical results by means of more advanced algorithms? In practice, it is desirable and might be feasible to optimize the D2D content placement on the fly, and popular content can be thus placed in particular devices to achieve high performance gains in particular areas. Therefore, our second contribution is related to devising a distributed algorithm for D2D caching with known number and locations of users in realistic scenarios. Specifically, the following contributions are made in the paper:

1) We derive an analytical expression of downloading performance for the D2D caching network using stochastic geometry. Specifically, by adopting the physical distance-dependent social model wherein the probability that two users have a social relationship is assumed to be a decreasing function of their physical distance, the average transmission probability for a D2D user is analyzed and the average downloading delay performance of the proposed scheme is derived using random and deterministic caching strategies. An interesting finding is that the successful transmission probability will become stable when the density of user is large enough.
2) Following the theoretical finding, in order to reduce the download delay, we optimize the caching strategy in a deterministic network scenario. More specifically, we develop a content caching algorithm based on a decentralized learning approach, termed DGPA. Different from most papers on D2D caching (e.g., [4]-[20]), we embrace several practical features of D2D communications, such as different cache sizes, different requesting distribution and social interaction among users, into the design of caching algorithm. To our best knowledge, the proposed caching algorithm is the first one that considers not only the file request probability and the closeness of devices as measured by their physical distance, but also takes into account the social relationship among D2D users. Furthermore, to increase the diversity of the cached contents in the network, the mutual impact between the different cached D2D users is considered. The convergence of the proposed caching algorithm is also analyzed.
3) Simulations are conducted to validate the accuracy of the analytical results. Both simulation and analytical results show that the proposed algorithm not only outperforms its counterpart using deterministic caching, but also outperforms that in the existing literature.

The rest of this paper is structured as follows. We introduce the system model and problem formulation in Section II, and analyze the average performance of the D2D caching network using stochastic geometry in Section III. In Section IV, we propose the socially aware distributed caching algorithm. Then we evaluate the performance of our scheme through extensive simulations in Section V, and conclude the paper in Section VI. To make clear the symbols used in this paper, we present the definition of main symbols and parameters in Table I.

[1]Part of this work was published in IEEE WCNC 2016 [11] and IEEE GC wkshps 2016 [12].

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TABLE I
TABLE I: PARAMETER AND SYMBOLS SUMMARY

Meaning	Symbol
Transmit power of IU m	P_m
Distance between IU m and user n	$r_{m,n}$
Request probability of file f	p^f
Social trust distance	A
The importance of IU m	$\mathcal{I}_m$
Probability of caching file i	p_i
Reward estimation of caching file i at time t	$o_i(t)$
Resolution parameter	δ
Physical influence of IU m and user n	$x_{m,n}$
Social influence of IU m and user n	$s_{m,n}$
The set of common neighbor of user m and n	$N_{m,n}$

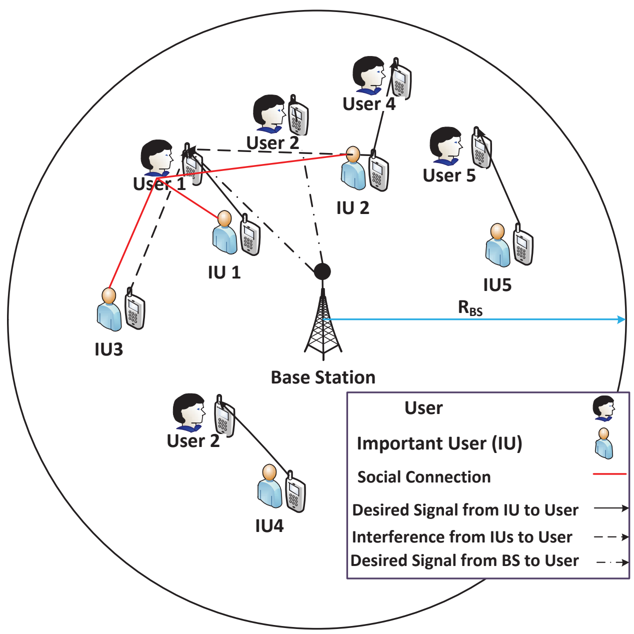

Fig. 1. Illustration of the network deployment under consideration. Within the transmission distance of the BS (R_{BS}), User 1 can acquire content either from its adjacent IU 1 with social connection or from the BS. This connection will suffer from interference from other IUs.

II. System Model and Problem Formulation

A. Transmission Model

We consider a content downloading scenario assisted by D2D overlaying communications, where dedicated radio resources are allocated to D2D users by the BS as shown in Fig. 1, and thus there is no interference between the cellular and D2D links. There are a total of N users in the network. Denote by $\mathcal{N} = \{1, 2, \cdots, N\}$ the set of mobile users and it is assumed that each user carries a mobile device with D2D communication capability. Furthermore, denote by $\mathcal{M} = \{1, 2, \cdots, M\}$ the set of important users (IUs), which is a subset of mobile users in this network. We assume that the distribution of the IUs follows a homogeneous poisson point process[2] (HPPP) of density λ UEs/m^2. The BS caches files into the memories of the IUs during the off-peak time. Once the caching process is completed, the BS and IUs are ready to act upon the downloading requests of users. The optimal selection of IUs will be explained in Sec. IV-A.

[2]We assume the UE number is a Poisson distributed random variable, and the UEs are uniformly distributed on the plane. As the IUs are the subset of UEs, we thus have the distribution of the IUs as a thinned HPPP.

We assume that a dedicated frequency band with a bandwidth of W Hz is allocated to the downlink channels for file-dissemination via D2D communications. Furthermore, we consider a "D2D-first" scheme, where each user will try to download data from its adjacent IUs first and only turn to the BS if no available D2D link exists or the requested file is not available from its adjacent IUs.

We assume that the channel between an IU and a mobile user is a Rayleigh fading channel. Furthermore, all downlink channels from the IUs to the users are assumed to be independent and identically distributed (i.i.d.). We consider the fully-loaded network scenario, where the IUs keep transmitting data to the users. This is because we intend to investigate the performance in the worst case that each user is subject to the interference imposed by all the other IUs in $\mathcal{M}$. The channel capacity between the mth IU and the nth user can be calculated based on the signal-to-interference-plus-noise ratio (SINR) as

$$C_{m,n}{=}W\log_2\left(1+\frac{P_m h_{m,n} r_{m,n}^{-\alpha}}{\sum\limits_{m'\neq m, m'\in\mathcal{M}} P_{m'} h_{m',n} r_{m',n}^{-\alpha}+\sigma^2}\right), \tag{1}$$

where $h_{m,n}$ is modeled as an exponential random variable (RV) with the mean of one due to Rayleigh fading, P_m is the transmit power of the mth IU, and σ^2 is the noise power. The path-loss between the mth IU and the nth user is modeled as $r_{m,n}^{-\alpha}$, where $r_{m,n}$ is the physical distance between the mth IU and the nth user and α is the path-loss exponent. Additionally, the channel capacity between the BS and the nth user is denoted by $C_{0,n}$.

The file library consists of F popular files, which the popularity distribution is represented by $\mathcal{P} = \{p_1, p_2, \cdots, p_F\}$. Users make independent requests of the fth file, $f \in \{1, 2, \cdots, F\}$, with a probability of p^f. We use the Zipf distribution, which is commonly used in the caching literature, to model this probability. Specifically, for the fth file, its file request probability p_f can be written as

$$p^f = \frac{\frac{1}{f^\omega}}{\sum\limits_{i=1}^{F}\frac{1}{i^\omega}}, \tag{2}$$

where F is the file library size and ω is the discounted rate in the Zipf distribution [7]. All these popular files are assumed to have the same size of L bits for simplicity. Also, we assume that the BS has a sufficiently large memory and hence can store the entire library of files, while the maximum storage of the IU is limited to $\mathcal{G}$ files, where $\mathcal{G} < F$. Denote by $\theta_{m,f} \in \{0, 1\}$ the event whether the mth IU has cached the fth file or not. Specifically, $\theta_{m,f} = 1$ if file f is cached by the mth IU, otherwise, $\theta_{m,f} = 0$. A D2D link can be established if the associated SINR of the link exceeds a predefined threshold γ and these two users have social relationship, i.e., $\varsigma_{m,n} = 1$.

B. Social Relationship Model

In this work, we investigate two social relationship models, termed as the physically distance-dependent social model and the deterministic social model, respectively.

1) The physically distance-dependent social model: It is reported in [22] that only one-third of the social friendships are independent of geography. Experimental studies have verified this property in real social networks, and theoretical models have since been proposed to capture this fact that the probability of befriending with a particular person is inversely proportional to the physical distance between them [23], [24].

Considering the practical social relations among different users, we propose to model the probability of two users having a social relationship with respect to their physical distance r [22] as

$$\mathrm{P_S}(r) = \begin{cases} 1, & \text{when } 0 < r \leq A; \\ A^2/r^2, & \text{when } r > A. \end{cases} \tag{3}$$

Equation (3) indicates that if the distance r between the receiver and the IU is smaller than a predefined distance A, the two users are surely to have stable social relationship, otherwise, this probability is dependent on their physical distance.

Remark 1. *The physically distance-dependent social model will be used to analyze the average performance of the D2D caching networks from Section III.*

2) The deterministic social model: The deterministic social model is widely adopted in open literature, e.g., [13], [25] and [19]. In this model, social characters (such as the social connections, the relationship closeness, etc.) are assumed to be known as a prior information. As such, the average successful transmission probability of the deterministic network scenario can be obtained by substituting known parameters into the analytical expression derived in Section III.

Remark 2. *The deterministic social model will be used to design a distributed caching algorithm in Section IV.*

C. Problem Formulation

Given that the storage capacity of each IU is limited, it is imperative to design an effective caching strategy to optimize the QoE (defined as the average delay required to download a file) of all users in the networks.

First, given the channel coefficients, and the specific location and the nearby information of each user, the delay of downloading a file f in $\mathcal{F}$ by the nth user can be calculated as

$$D_{n,f} = \begin{cases} \min\{\frac{L}{C_{m,n}}\}, & \exists \varsigma_{m,n} \times \theta_{m,f} \neq 0 \text{ and } \mathrm{SINR}_{m,n} \geq \gamma, \\ \frac{L}{C_{0,n}}, & \text{otherwise.} \end{cases} \tag{4}$$

Mentioned here, the delay should be zero if the request file is cached locally by the user itself, which is not considered in the delay calculation. To analyze the average downloading delay performance, we rewrite (4) as

$$D = p^{\text{trans}} \times \kappa \times \frac{L}{\overline{C}_{D2D}} + (1 - p^{\text{trans}} \times \kappa) \times \frac{L}{\overline{C_0}}, \tag{5}$$

where p^{trans} is the average transmission probability, κ is the average hitting rate used by the chosen caching strategy, $\overline{C}_{D2D}$ is the average transmission capacity of the D2D link, which is captured by the average of the $C_{m,n}$, and $\overline{C_0}$ is the average transmission capacity of the cellular link.

In order to reduce the downloading delay, it is important to analyze the baseline network performance first. Based on the average performance, the corresponding caching solutions can be evaluated. In the subsequent two sections, we first derive the successful transmission probability and the average downloading performance. Under the deterministic network scenario, we then focus on the cache placement optimization at IUs by designing a socially aware distributed caching strategy, which decreases the download delay.

III. Stochastic Geometry Based Performance Analysis

In this section, we first adopt the physical distance-dependent social model in the D2D caching network and apply the stochastic geometry theory to derive the analytical expression for the average D2D transmission probability and the average downloading delay performance under different caching strategies.

A. Average D2D Transmission Probability

Recall that we use the following user association strategy (UAS). Each D2D receiver should be associated with the IU with the highest SINR. Also, each D2D link can be established under two conditions: (1) the IU and the receiver have a social relationship; (2) the SINR of this link is above the threshold γ. Using the property of the HPPP, we study the performance of the proposed socially aware D2D networks by considering the performance of a typical receiver located at the origin o. Under these assumptions, we first investigate the average transmission probability that a typical receiver can communicate with its associated IU. The average transmission probability is defined as

$$p^{\text{trans}}(\lambda, \gamma) = \Pr[\mathrm{SINR} > \gamma], \tag{6}$$

where the SINR is computed by

$$\mathrm{SINR} = \frac{Phr^{-\alpha}}{I_d + \sigma^2}, \tag{7}$$

where the path-loss of the channel from an IU to a receiver is simplified to $r^{-\alpha}$, and each IU is assumed to have same transmission power P. Furthermore, I_d is the cumulative interference given by

$$I_d = \sum_{i: b_i \in \Phi \backslash b_0} P h_i r_i^{-\alpha}, \tag{8}$$

where b_0 denotes the IU serving the typical receiver and located at distance r from the typical receiver. Besides, for notation simplicity, we rewrite the rest parameters in (1): b_i, and r_i denote the ith interfering IU and the distance between b_i and the receiver, respectively.

Given the definition of the average transmission probability presented in (6), in the following we will analyze the performance measures for the considered UAS. Base on the proposed social relationship model in (3), we present our main result of $p^{\text{trans}}(\lambda,\gamma)$ in Theorem 1.

Theorem 1. *Considering the proposed social relationship model in (3), $p^{\text{trans}}(\lambda,\gamma)$ can be derived as*

$$p^{\text{trans}}(\lambda,\gamma)=\int_0^A \Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2}>\gamma\right] f_{R1}(r)dr + \int_A^\infty \Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2}>\gamma\right] f_{R2}(r)dr, \tag{9}$$

where $f_{R1}(r)$ and $f_{R2}(r)$ are the piece-wise PDFs of the random variable (RV) R_1 and R_2, and R_1 and R_2 are the distance that the typical receiver has a nearest IU with social relationship, and they represent different distance intervals. Moreover, $f_{R1}(r)$ and $f_{R2}(r)$ are represented by

$$f_{R1}(r)=\exp(-\pi\lambda r^2)2\pi\lambda r,\quad (0<r\le A), \tag{10}$$

and

$$f_{R2}(r)=\exp[-(\pi\lambda A^2+2\pi\lambda A^2(\ln r-\ln A)] \times 2\pi\lambda A^2\frac{1}{r},\quad (r>A). \tag{11}$$

Furthermore, $\Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2}>\gamma\right]$ *is computed by*

$$\Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2}>\gamma\right]=\exp\left(-\frac{\gamma r^\alpha\sigma^2}{P}\right)\mathcal{L}_{I_d}\left(\frac{\gamma r^\alpha}{P}\right), \tag{12}$$

where $\mathcal{L}_{I_d}(s)$ is the Laplace transform of RV I_d evaluated at s.

Proof. See Appendix A. □

Because the physically distance-dependent social model in (3) takes the form of a piece-wise functions, we need to evaluate the interference $\mathcal{L}_{I_d}(s)$ for two regions of r, i.e., $0<r\le A$ and $r>A$.

To compute $\mathcal{L}_{I_{d1}}(s)$ in (9) for the range of $0<r\le A$, we attain Lemma 1.

Lemma 1. *$\mathcal{L}_{I_{d1}}(s)$ in the range of $0<r\le A$ can be calculated by*

$$\mathcal{L}_{I_{d1}}(s)=\exp\left(\frac{-2\pi\lambda r^2\gamma}{\alpha-2}\times\nabla_1(\alpha,\gamma)\right),\ (0<r\le A), \tag{13}$$

where $\nabla_1(\alpha,\gamma)={}_2F_1\left[1,1-\frac{2}{\alpha};2-\frac{2}{\alpha};-\gamma\right]$, ${}_2F_1[\cdot,\cdot;\cdot;\cdot]$ is the hyper-geometric function [26] *and $\alpha>2$.*

Proof. See Appendix B. □

Same as before, we have the following Lemma 2 to compute $\mathcal{L}_{I_{d2}}(s)$ in (9) for the range of $r>A$.

Lemma 2. *$\mathcal{L}_{I_{d2}}(s)$ in the range of $r>A$ can be calculated by*

$$\mathcal{L}_{I_{d2}}(s)=\exp\left(-2\pi\lambda\gamma^2\frac{1}{\alpha}\left(\ln\left(1+\frac{1}{\gamma}\right)-\ln\left(\frac{1}{\gamma}\right)\right)\right) \times\exp\left(\frac{-2\pi\lambda A^{2-\alpha}r^\alpha\gamma}{\alpha-2}\times\nabla_2(\alpha,A,r,\gamma)\right) \times\exp\left(\frac{2\pi\lambda A^2}{\alpha}\left[\ln(1+\frac{A^\alpha r^{-\alpha}}{\gamma})-\ln(\frac{A^\alpha r^{-\alpha}}{\gamma})\right]\right),\quad (r>A) \tag{14}$$

where $\nabla_2(\alpha,A,r,\gamma)={}_2F_1\left[1,1-\frac{2}{\alpha};2-\frac{2}{\alpha};-A^{-\alpha}r^\alpha\gamma\right]$, ${}_2F_1[\cdot,\cdot;\cdot;\cdot]$ is the hyper-geometric function [26] *and $\alpha>2$.*

Proof. See Appendix C. □

Substituting equations (10)-(14) into (9), $p^{\text{trans}}(\lambda,\gamma)$ for the proposed model can be obtained.

Remark 3. *The results showed in Theorem 1 reveal an interesting finding. Specifically, the successful transmission probability becomes stable when the density of users is large enough. More discussion are relegated to Sec. V-A. In order to reduce the download delay from (5), the following approach is to optimize the caching content in IU, which will increase the hitting rate.*

B. Average Downloading Delay Performance

We first introduce two popular caching strategies to estimate the average downloading performance.

1) Random Caching (RC): The random caching is realized by randomly picking files from the file library to cache into IUs, and we denote this hitting rate by κ_{ran}, and $\kappa_{ran}=\mathcal{G}/F$.

2) Deterministic Caching (DC): The deterministic caching is realized by caching the most popular files according to the file request probability. Then we denote the hitting rate used in the deterministic caching strategy by κ_{det}, and $\kappa_{det}=\sum_1^{\mathcal{G}}p^f$, where p^f is the file request probability and defined in (2).

Substituting different hitting rates into (5), we can get the average downloading delay performances. Note that such an average delay performance can be achieved by simple caching schemes such as the RC and DC schemes, where every IU caches same files and it provides a theoretical understanding of the D2D caching network. With various numbers and locations of users, the trends regarding to the user density or file request probability are obtained. In practice, more sophisticated content caching algorithms can be devised and implemented when more information are available, such as social relationship, physical distance, etc. In this case, each IU may cache files according to its local feedback that in turn increase the hitting rate.

In the following section, we will explore new implementation algorithms based on the decentralized learning technique to optimize the caching content in IUs.

IV. Socially Aware Distributed Caching Algorithm

In the previous section, we adopt the physically distance-dependent social model in the D2D caching network and study the performance under different caching strategies. Such analysis provides us a theoretical understanding of the network performance for the considered D2D caching network with various numbers and locations of users. As to be shown in the section on simulations and discussions, our analysis is useful to qualitatively predict the performance trend of D2D caching in 5G. However, it still remains unclear how to implement the 5G D2D caching in practice. And more importantly, can we even do better than the derived analytical results by means of more advanced algorithms? If yes, by how much better? Note that in our theoretical analysis conducted in the previous section, only simple D2D caching strategies such as RC and DC, have been analyzed, where each IU caches the same files. In practice, it is desirable and might be feasible to optimize the D2D content placement on the fly, and popular content can be specifically placed in particular devices to achieve high performance gains in particular areas. Therefore, in this section, we consider a deterministic D2D caching scenario with fixed number and locations of users, and devise a distributed algorithm to enable each IU to optimize its content placement.

To this end, we develop a distributed learning automation that enables each IU to optimize the cache placement according to its local demands. The proposed algorithm is inspired by the DGPA [27]. In the following, by adopting the deterministic social network model, in which the successful transmission probability among IUs and users is invariant, we first introduce a scheme to select the IUs in the considered network, then provide some preliminaries of DGPA before formally presenting the proposed algorithm. Furthermore, we also design a scheme to characterize the mutual impacts of content placement in different IUs, which enables the proposed algorithm to be implemented in large-scale networks.

A. Selection of The Important Users

The important users (IUs) in the proposed network will precache files from the BS during the off peak hours and transmit these files to other users. We first determine the number of the IUs in the network.

Throughout the paper, a user is called a neighbor of another user if there is a social relationship between them. According to [28], in social networks, the distribution of the node degree, i.e., the number of neighbors of a node, decays according to a power law distribution given by

$$p(k) = c_k \times k^{-\varphi}, \tag{15}$$

where $\sum\limits_{k=0}^{\infty} c_k k^{-\varphi} = 1$, and $p(k)$ is the probability that a randomly chosen node has k neighbors, and φ is the decaying coefficient. Let M_k be the number of nodes that have at least k neighbors in a network with total N nodes. Using the aforementioned power law degree distribution, M_k can be calculated as

$$M_k = \lfloor N \times \sum_{i=k}^{N-1} p(i) \rfloor, \tag{16}$$

where $\lfloor x \rfloor$ is the floor function, retrieving the largest integer that is equal or smaller than x. In the following, we ignore the subscript of M_k, and rewrite as M for notational convenience. We assume that these M users can download contents directly from BSs and they are regarded as the important users (IUs).

Next, we present a scheme to sort these M IUs. In our process of sorting the IUs, the betweenness centrality $\mathcal{B}$ and the available storage capacity $\mathcal{G}$ are used to characterize the importance, which is denoted by $\mathcal{I}$. For the mth IU, the importance is defined as

$$\mathcal{I}_m = \mu \times \mathcal{B}_m + \nu \times \mathcal{G}_m, \tag{17}$$

where μ and ν are tunable parameters satisfying $\mu + \nu = 1$ [29]. Betweenness centrality $\mathcal{B}$ measures the social importance of one user. According to [30], the betweenness centrality of the mth user can be calculated as

$$\mathcal{B}_m = \sum_{j=1}^{N} \sum_{j<k} \frac{g_{jk}(m)}{G_{jk}}, \tag{18}$$

where G_{jk} is the number of shortest links between user j and user k, and $g_{jk}(m)$ is the number of those shortest links between user j and user k that include or pass user m.

After collecting each user equipment's available storage capacity $\mathcal{G}_i$, the BS can get a list of the importance, which is denoted by $\mathfrak{I} = \{\mathcal{I}_1, \mathcal{I}_2, ..., \mathcal{I}_m\}$. Then these M IUs are sorted by the list $\mathfrak{I}$ in the descending order.

B. Discrete Generalized Pursuit Algorithm

The goal of the DGPA is to determine an optimal action out of a set of allowable actions $\mathcal{F} = [1, 2, ..., F]$. The DGPA has a probability vector $\mathbf{P}(t) = [p_1(t), p_2(t), ..., p_F(t)]$, where $p_i(t)$ is the probability that the automaton will select the action i at iteration t with $\sum\limits_{i=1}^{F} p_i(t) = 1$. The updating of the probability vector is performed based on the reward estimation $\mathbf{o}(t) = [o_1(t), o_2(t), ..., o_F(t)]$ and each reward estimation is determined by the environment feedback [27]. In the considered D2D caching system, at each learning process, an action of each IU is to choose one file from the file library to cache. This action is performed according to the file request probability. A certain action will get a positive reward from the aggregate environment feedback if it is beneficial to the system.

The DGPA generalizes the concepts of the pursuit algorithm by "pursuing" all the actions that have higher reward estimates than the current chosen action. In the algorithm, the action probability vector $\mathbf{P}(t)$ is recursively updated by the following equation:

$$\mathbf{P}(t+1) = \mathbf{P}(t) + \frac{\Delta}{K(t)} \times \mathbf{e}(t) - \frac{\Delta}{F - K(t)} \times [\mathbf{u} - \mathbf{e}(t)], \tag{19}$$

where $\mathbf{u}$ is a vector in which $u_i = 1, i = 1, 2, ..., F$, and $\mathbf{e}$ is a direction vector given by:

$$\begin{aligned} e_i(t) &= \begin{cases} 1, & \text{if } o_i(t) = \max\{o_j(t)\}\ j \in 1, ...F; \\ 0, & \text{otherwise.} \end{cases} \\ e_j(t) &= \begin{cases} 0, & \text{if } o_j(t) \le o_i(t); \\ 1, & \text{if } o_j(t) > o_i(t). \end{cases} \end{aligned} \tag{20}$$

According to (19), the probabilities of the chosen action i and other action j are updated as following:

$$\begin{cases} p_j(t+1) = \min\{p_j(t) + \frac{\Delta}{K(t)}, 1\}, \text{if } o_j(t) > o_i(t); \\ p_j(t+1) = \max\{p_j(t) - \frac{\Delta}{F-K(t)}, 0\}, \text{if } o_j(t) < o_i(t); \\ p_i(t+1) = 1 - \sum\limits_{j \ne i} p_j(t+1). \end{cases} \tag{21}$$

At each iteration of the DGPA, the number of actions which has a higher reward estimation $o(t)$ than the current chosen

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one is counted, denoted by $K(t)$. At the end of an iteration, the probability of all actions with a higher reward estimation $o(t)$ will increase by an amount of $\Delta/K(t)$, and the probability of all the other actions except the chosen one will decrease by an amount of $\Delta/(F-K(t))$, where F is the action library size. Besides, $\Delta = 1/F\delta$ and it is a resolution step and δ is the resolution parameter.

In order to update the probability of each action, the reward estimation $o(t)$ should be estimated at first. The updating equations of reward estimation $o(t)$ for the chosen action i are as follows:

$$\begin{cases} Z_i(t+1) = Z_i(t) + 1; \\ W_i(t+1) = W_i(t) + \beta(t); \\ o_i(t+1) = \frac{W_i(t+1)}{Z_i(t+1)}, \end{cases} \tag{22}$$

where $Z_i(t)$ represents the number of times that action i has been chosen, and $W_i(t)$ represents the number of times that action i has been rewarded. $\beta(t) \in \{0, 1\}$ is a binary factor reflecting the positive or negative feedback. If the feedback is positive (i.e., $\beta = 1$), then this action i is rewarded.

In the next subsection, based on the above preliminaries of DGPA, we will design the functions of the aggregate environment feedback in the proposed socially aware D2D networks.

C. Environment Feedback

In our model, the BS can acquire the position of every user, thus BSs will provide each IU with its relevant downloaders' information (e.g., the file request probability) and each IU can broadcast the cached files to its relevant downloaders. In this sense, different cached files (actions) at a certain IU would lead to different influences on its neighbors and other IUs. In the process of learning, when the mth IU caches the file f according to its downloading neighbor n's request, we define the aggregate environment reward $R^f_{m,n}$ as a weighted sum of the request probability (p^f_n) of file f, the physical influence ($x_{m,n}$) between IU m and its neighbor n, and the social influence ($s_{m,n}$) between them, which can be expressed by:

$$R^f_{m,n} = \tau_1 \times p^f_n + \tau_2 \times x_{m,n} + \tau_3 \times s_{m,n}, \tag{23}$$

where τ_1, τ_2 and τ_3 are tunable parameters and they satisfy $\tau_1 + \tau_2 + \tau_3 = 1$. We provide detailed explanation of each term in (23) as follows.

1) The request probability p^f_n: The BS will record the request files of each user, and provide this probability to the IUs. According to (2), for the fth file, its file request probability p_f by user n can be written as

$$p^f_n = \frac{\frac{1}{f^\omega}}{\sum\limits_{i=1}^{F_n} \frac{1}{i^\omega}}, \tag{24}$$

where F_n is the file library size of user n.

2) The physical influence $x_{m,n}$: Intuitively speaking, there will be significant influence if the distance between the mth IU and user n is small [31]. In order to provide the shortest download time, the request file by the nearest user n, for example, should be cached by the IU m. In this sense, the physical influence is modeled as

$$x_{m,n} = \frac{1}{1 + r_{m,n}}, \tag{25}$$

where $r_{m,n}$[3] represents the distance between the mth IU and the user n.

3) The social influence $s_{m,n}$: The degree of similarity among users has an important effect in information dissemination [32]. Particularly, when the degree of similarity between two users is lower, more time would need for transmitting the same length of information since they may not have the required content. As a result, we use the degree of similarity to characterize the social influence $s_{m,n}$.

The degree of similarity can be measured by the ratio of common neighbors between individuals. According to [32], we assume that the mth IU is connected to user n. Let $V(m)$, $V(n)$ denote the set of neighbors of users m and n, respectively. Let z be one of the common neighbors of them and let $V(z)$ denote the number of user $z's$ neighbor. We can then define the similarity between IU m and its neighbor n as:

$$q_{m,n} = \sum_{z \in V(m) \cap V(n)} \frac{1}{V(z)}. \tag{26}$$

If m and n have no common neighbors, then $q_{m,n} = 0$. In order to make the three factors of the environment feedback comparable, we normalize the similarity $s_{m,n}$ as follows:

$$s_{m,n} = \frac{q_{m,n}}{\sum\limits_{m \in M} q_{m,n}}. \tag{27}$$

Now, we are ready to calculate the environment feedback using the reward functions. Denote by N_m the neighbor set of the mth IU, at each learning iteration, IU m will choose a file f to cache, and its neighboring users will also ask a file to download according to their own file request probabilities. If the mth IU and one of its neighbors n choose the same file, such as the file f, we define this action as a positive one, which brings a positive reward (Ψ_P). If not, this action will be determined as a negative action (Ψ_N). Mathematically, the reward functions are defined as:

$$\begin{cases} \Psi_P = R^f_{m,n}, & \text{if } m \text{ and } n \text{ choose the same file;} \\ \Psi_N = -R^f_{m,n}, & \text{if } m \text{ and } n \text{ choose different files.} \end{cases} \tag{28}$$

Thus, for the mth IU, the aggregate environment feedback function of choosing the file f can be expressed as :

$$F^f_m = \sum_{n=1}^{N_m} (\Psi_P + \Psi_N). \tag{29}$$

[3] $C_{m,n}$ can be the considered parameter instead of $r_{m,n}$ if the channel condition and other interference signals are known, and it will provide more sense than the distance between users.

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If $F_m^f > 0$, then $\beta = 1$ and this action that the mth IU caches the file f will get a positive feedback from the environment. The estimation vector $o(t)$ is updated by (22).

According to the aggregate environment feedback, the mth IU will keep learning and acquiring the request files from BSs until its available storage is full.

Remark 4. *From (23) we can see that the design of environment feedback is important and different feedback functions will lead to different learning results. More discussion are relegated to Sec. V-D.*

D. The Mutual Impact of Nearby IUs

The decision of content placement for the mth IU will affect its nearby IUs, which have common neighbors with the mth IU. If there are two IUs in the nearby area, the content placement of these two IUs should be made different as much as possible to serve different requests of their common neighbors. In this case, the BS should update the file request probability of the common neighbors according to the former IUs who have already cached contents.

IUs start learning in the order determined by the list $\mathfrak{I}$. To update the file request probability of the common neighbors, all the IUs should report the cached files to the BS after learning. This update should consider both the cached files and the physical distance. For example, if two previous IUs m and m' have already cached files f and f', respectively, then for the next IU n, it should first estimate which IU has a larger physical influence (a shorter distance) to IU n. If IU m has a larger physical influence than IU m', i.e., $r_{n,m} < r_{n,m'}$, then file f cached by IU m should be considered when updating the file request probability of their common neighbors. Let $N_{m,n}$ denote the set of the common neighbor of the mth IU and the nth IU, then the request probability ($Y_f^{N_{m,n}}$) of file f for the common neighbor ($N_{m,n}$) can be updated as

$$Y_f^{N_{m,n}} = Y_f^{N_{m,n}} \times \frac{1}{1 + r_{n,m}}, \tag{30}$$

where $r_{n,m}$ represents the physical distance between the nth IU and the mth IU and α is the path loss exponent.

After updating the probability of every cached file by the mth IU, the file probabilities $Y^{N_{m,n}}$ of the common neighbors between the mth IU and the nth IU will be normalized, and the nth IU can start its learning process.

To sum up, the proposed algorithm has been formally presented in Algorithm **1** by using the variable definitions presented in the previous subsections.

E. Convergence

We now analyze the convergence of the proposed algorithm. If the algorithm converges, then the result would give the optimal cached file decided by the environment feedback. According to [27], if the algorithm possesses the moderation and monotonicity properties, the algorithm is ε-optimal in all random environments and it will converge. Therefore, we show the proof of convergence in the following lemma.

Algorithm 1 Distributed and Socially Aware D2D Caching Algorithm for the mth IU

Start

Initialization for the mth IU.

1: Choose one IU m' in $\mathfrak{I}$, which has the biggest physical influence to m, and update the file request probability of m in (30).

2: Normalize the file request probability of m and set it as $P(0)$.

3: Randomly choose files according to $P(0)$, and record the aggregate environment feedback β, until each file is selected at least $Z(0)$ times.

4: Record the rewarded times of each file ($W_i(0)$).

5: Initializes $o_f(0)$, where $o_f(0) = \frac{W_f(0)}{Z_f(0)}$.

Learning Process for the mth IU. Do:

1: At time t choose file f according to $P(t)$. Let $\alpha(t) = \alpha_f$.

2: updates $P(t)$ according to equation (21).

3: updates $o(t)$ according to equation (22).

Until: max$P_f(t) > \delta$, where δ is a convergence threshold.

Repeat Initialization and Learning until the storage of the mth IU is full.

Until: every IU finishes learning.

End

Lemma 3. *The proposed algorithm possesses the moderation and monotone property.*

Proof. Please refer to Appendix A. □

Since the proposed algorithm possesses the moderation and monotony properties, the convergence is guaranteed [27]. Thus, after learning, each IU will cache the content according to the learning results. To calculate the hitting rate of the proposed algorithm, the learning result will be compared with the target in the algorithm, and subsequently, the downloading performance in the considered social model can be obtained from the hitting rate.

V. PERFORMANCE EVALUATION

In this section, we first focus on the proposed network with IUs distributed following a HPPP, where we investigate the average transmission probability and the average performance of the two caching strategies, i.e., DC[4] and RC. Then we consider the network with a fixed number of IUs. Using the average transmission probability, we investigate the delay performance of the proposed caching algorithm and compare it to the benchmarks, including DC and a simple reward function which also uses the DGPA learning algorithm proposed in [11]. Note that the physical layer parameters in our simulations, such as the path-loss exponent, noise power and transmit power of the IUs and the BS, are chosen to be practical and in line with

[4]Before caching, the macro BS will broadcast the most request files of the past 24 hours to the IUs first. Then the IUs can cache the most popular files according to this information.

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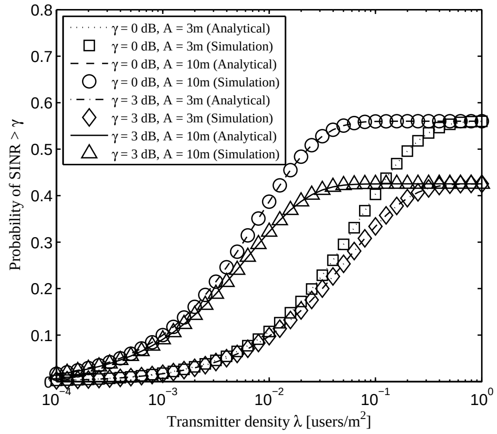

Fig. 2. The transmission probability $p^{\text{trans}}(\lambda, \gamma)$ vs. density of the IU λ with various SINR thresholds γ and different social trust distance A

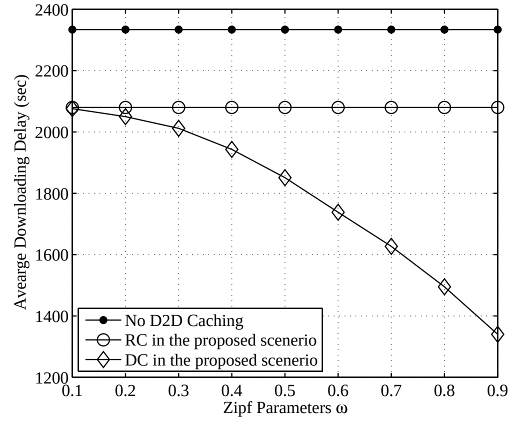

Fig. 3. Average downloading delay D vs. the Zipf parameter ω under different scenarios

the values set by 3GPP standards. For instance, the coverage of the BS is 25 km^2, and the transmission power of IUs is 25 dBm. Unless specified otherwise, we set the path loss exponent $\alpha = 3$, and the noise to $\sigma^2 = -95$ dBm. All the simulations are executed using MATLAB.

A. Average Transmission Probability of D2D Link

We first compare our simulation and analytical results in the proposed network with different transmitter densities, different social trust distances and various SINR thresholds. As can be observed from Fig.2, our analytical results perfectly match the simulation results. Due to the significant accuracy of $p^{\text{trans}}(\lambda, \gamma)$, we will only use analytical results of $p^{\text{trans}}(\lambda, \gamma)$ in our discussion later.

From Fig.2 we can observe that the transmission probability first increases with the transmitters density because more transmitters provide better coverage in noise-limited networks. Then, when λ is large enough ($\lambda > 10^{-1}$ users/m^2), the transmission probability becomes independent of λ since the network is pushed into the interference-limited region. From this finding, in order to reduce the download delay, we should optimize the caching content in each IU. Another two observations are that when the smallest social trust distance A is same, the transmission probabilities of different SINR thresholds show similar trends as they converge at same λ, and when the SINR threshold γ is same, the transmission probabilities of different small social trust distances saturate to the same level at different λ.

B. Average Delay of Downloading Performance for the Physical Distance-dependent Social Model

We evaluate the average delay of downloading performance for the RC and the DC strategy in Fig. 3. We also simulate the no D2D caching scenario for comparison. For the simulation results of this subsection, we assume a SINR threshold of $\gamma = 0$ dB, a file size of $L = 10^9$ bits, an IU density of $\lambda = 10^{-2}$ users/m^2 and a smallest social trust distance of $A = 10$ m.

Fig. 3 illustrates the average downloading delay associated with different ω values. We can see that DC always outperforms RC, and the performance gap between these two strategies becomes larger with increasing ω, while the no D2D caching scheme behaves the worst.

C. Convergence of the Socially Aware Distributed Caching Algorithm

After presenting the system performance of the physical distance-dependent social model, let us now focus on the socially aware distributed caching algorithm which applies the deterministic social model in the following subsections. We first test and verify the convergence of the proposed algorithm. A small-scale mobile network is considered, which consists of 3 IUs and each of them has 6 neighboring downloaders. The algorithm is considered to converge when the probability of taking one action (caching one file) is greater than 0.999 and we record the number of the executed iterations and each point in the figures is obtained by averaging the results over 50 independent run of the proposed algorithm.

Fig. 4(a) shows the executed iterations of different δ, in which more complex algorithm will cost more iterations to converge, and more time to finish the learning process. As the file library size grows, the average number of iterations increases. Moreover, different resolution parameters δ show different increasing trends, and require different numbers of iterations to converge. For example, when $\delta = 0.5$, the average number of iterations is nearly half (49.2%) of that when $\delta = 1$. We also compare the proposed algorithm with the work [11]. As can be observed from Fig. 4(a), the algorithm presented in the work [11] requires fewer iterations on average compared with the proposed algorithm in this paper. This is because the algorithm in [11] was based on a simple environment feedback functions, in which the physical distance influences were not considered.

As can be observed from Table II, we present the reward times of different δ when the file library size is 10. Using the reward times, the average reward probability can be calculated for different file library size. Fig. 4(b) depicts the average

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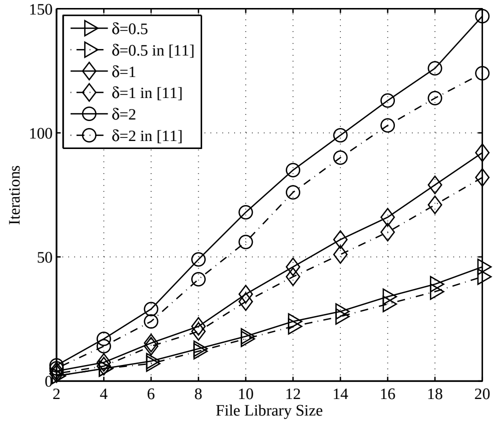
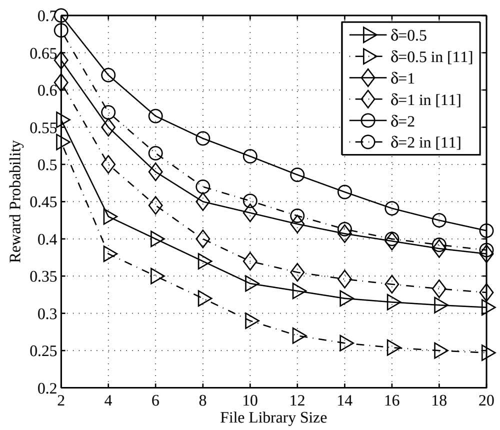


(a) The average number of iterations to converge of different resolution parameters δ



(b) The average reward probability of different resolution parameters δ

Fig. 4. The performances of the proposed algorithm for different resolution parameters

TABLE II
REWARD TIMES AFTER REPEATING 50 TIMES LEARNING WHEN THE FILE LIBRARY SIZE IS 10

	IU1	IU2	IU3	Reward probability
$\delta = 0.5$	20	17	16	0.353
$\delta = 0.5$ in [11]	15	16	15	0.307
$\delta = 1$	25	22	20	0.446
$\delta = 1$ in [11]	20	19	20	0.393
$\delta = 2$	29	26	25	0.514
$\delta = 2$ in [11]	23	23	22	0.453

reward probability of different resolution parameters δ. It is shown that with the increasing size of the file library, the average reward probability decreases. Also the proposed algorithm can get a higher reward probability than the algorithm in [11]. Considering both Fig. 4(a) and Fig. 4(b), although a larger resolution parameter δ implies more time to converge, it can achieve a higher reward probability. Moreover, for the proposed algorithm, although it takes more time to converge compared with [11] with the same δ, the reward probability is much better. Finally, it can be observed that the proposed algorithm strikes a fine balance between performance

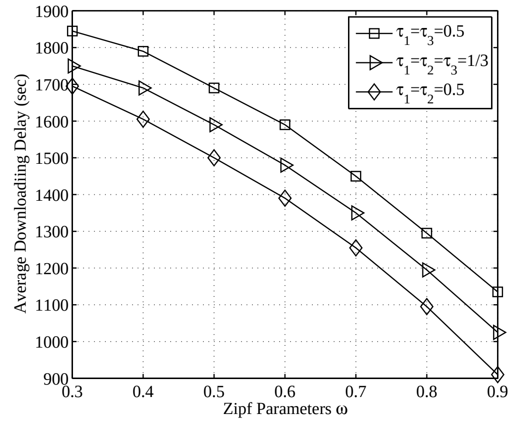


Fig. 5. Average downloading delay D vs. the Zipf parameter ω under different environment feedbacks

and complexity compared with the algorithm presented in [11]. This is because the proposed algorithm requires less iterations than the algorithm in [11] to achieve a similar reward probability performance. For example, the proposed algorithm only needs about 92 iterations to converge while the algorithm in [11] needs about 124 iterations to get a similar reward probability when there are totally 20 files.

D. Delay Performance of the Socially Aware Distributed Caching Algorithm

In this subsection, we first investigate the parameters in the environment feedback. As discussed in the Section IV-C, different combinations of the proportions of the request probability (p^f), the physical influence (x) and the social influence of (s) will lead to diverse optimized caching content.

As shown in the Fig. 5, different environment feedbacks are considered when the density of IU is 10^{-2} users/m^2. In this network scenario, the average transmission probability is around 0.56. We consider 3 cases in this figure: Case 1 gives the equal weights to all three components, while the physical influence is not considered in Case 2 and the social influence is not considered in Case 3.

We can see from Fig. 5, the proposed algorithm can reduce the download delay when it allocates more weights on the physical influence, as shown by the comparison between Case 2 and Case 3. Moreover, with the increasing value of ω, the gap between these two cases is enlarged. This is because the physical influence shows a more important effect when we have a larger value of ω. In more details, users tend to download the same files when we have a lager value of ω, then the delay among IUs and users are mainly depend on the physical distance. So if we allocate more weights on the physical influence, the learning results will show a better downloading performance.

In the following, we study the delay performance of the socially aware distributed caching algorithm. The proposed algorithm is compared with the work in [11]. The DC scheme in the physically distance-dependent social model is used as the benchmark. Same with the previous subsection, we assume

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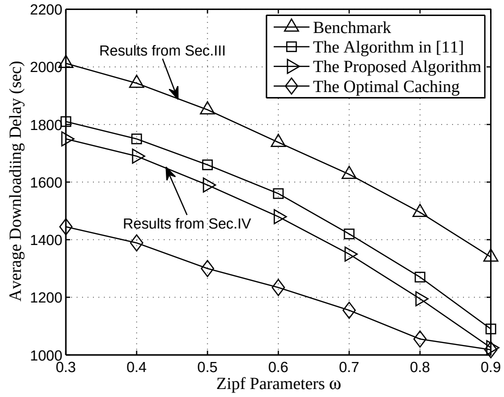

Fig. 6. Average downloading delay D vs. the Zipf parameter ω under various caching schemes

a file size of $L = 10^9$ bits, a IU at least has 5 neighbors ($k = 5$), equal environment feedback composition. In the process of sorting IUs, we collect each IU's social importance and available storage capacity, and treat them as a descending order according the importance list. As a result, the density of IU is around 10^{-2} users/m^2 and each IU can store 3 files at last.

Fig. 6 shows the simulation results of the delay performance. From this figure, we can see that the average delay decreases as the value of ω increases, and the benchmark (i.e., DC scheme applied in the physically distance-dependent social model) shows the worst performance. This figure also demonstrates that the analytical results can qualitatively predict and assess the performance. However, using more advanced algorithms can achieve better performance in the practical 5G settings. In addition, our proposed algorithm always performs better than the algorithm in [11]. For example, in comparison with the counterparts, the average delay of the proposed algorithm is reduced by 7.8%. Furthermore, the performance improvement between the proposed algorithm and the algorithm in [11] is obvious. This is because in [11] no mutual impact is considered, thus, nearby IUs may cache similar contents, and cannot provide downloading service for other popular contents. In contrast, our proposed algorithm encourages the IUs to cache different contents in order to achieve caching diversity.

Moreover, we provide an average downloading delay performance using the optimal caching (OC) scheme in this figure. The OC scheme is obtained by the non-causal algorithm [33], in which we remove the limit on the storage of each IU and IUs have the knowledge of the entire network. From the figure we can find that the gap between the proposed algorithm and the OC scheme is relatively large when ω is small, but it becomes small as ω increases. This is because the proposed algorithm considers a more practical situation than OC. In the OC scheme, it only sets the downloading delay as an optimization target regardless of other practical factors, such as the social relationship among users. In the proposed algorithm, a complex environment feedback consisting of multiple factors are incorporated, which not only considers the average delay performance, but also considers the feasibility in a practical

TABLE III
THE AVERAGE NUMBER OF FILES CACHED IN EACH IU

ω	0.3	0.4	0.5	0.6	0.7	0.8	0.9	average
OC	6.7	6.2	5.6	4.8	4.5	4.2	4.1	5.08

situation. For example, when ω is small, the popular files are sparse and the proposed algorithm cannot satisfy all the demands. With the decreasing number of popular files, such as a large ω, the outcome of the proposed algorithm will gradually satisfy the demands. To make a fair comparison with these two schemes, we also record the average number of files cached in each IU for OC in Table III, whereas the IUs can only cache 3 files in our proposed algorithm. In this sense, the proposed algorithm can achieve a performance close to that of OC, while economizing the storage space. For example, compared with the optimal caching scheme, the proposed algorithm has a similar delay (1025s v.s. 1018s), but only requires less caching storage (3 v.s. 4.1) when $\omega = 0.9$.

VI. CONCLUSION

In this paper, we conducted performance analysis using stochastic geometry to have a basic understanding of the average network performance under varying numbers and locations of the users. Specifically, we adopted a social relationship model considering the physical distance between users, and developed an analytical result of downloading delay. To achieve a better performance under practical 5G settings, we developed a distributed and socially aware framework based on a learning automaton to solve the optimum cache placement problem in D2D overlaying networks. Specifically, in order to promote content dissemination in D2D communications, we updated our algorithm with the aggregate environment feedback including the social relationship between users. Also the mutual user impacts were considered in this scheme to enable its application in the large-scale networks. The average performance obtained by stochastic geometry analysis agreed well with the simulations results. Furthermore, the proposed algorithm has fast convergence speed and can achieve significant system throughput gain when compared with the existing caching strategies.

APPENDIX A
PROOF OF THEOREM 1

For clarity, we first summarize our ideas to prove Theorem 1. In order to evaluate $p^{\text{trans}}(\lambda, \gamma)$, the first key step it to calculate the distance probability density function (PDF) for the event that the typical receiver is associated with a nearest transmitter which also have social relationship with it, so that the integral of Pr[SINR $> \gamma$] can be performed over the distance r. The second key step is to calculate Pr[SINR $> \gamma$] for the typical case conditioned on the distance r.

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From (3) and (6), we can derive $p^{\text{trans}}(\lambda,\gamma)$ in a straightforward way as

$$\begin{aligned} p^{\text{trans}}(\lambda,\gamma) &= \int_{r>0} \Pr\left[\text{SINR} > \gamma | r\right] f_R(r)dr \\ &= \int_{r>0} \Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2} > \gamma\right] f_R(r)dr \\ &= \int_0^A \Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2} > \gamma\right] f_{R1}(r)dr \\ &+ \int_A^\infty \Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2} > \gamma\right] f_{R2}(r)dr, \end{aligned} \tag{31}$$

where $f_{R1}(r)$ and $f_{R2}(r)$ are the different PDFs of the RV $R1$ and $R2$, and $R1$ and $R2$ are in the different intervals with respect of r.

According to our offline social relation model, when $0 < R_1 \le A$, the PDF of R_1 can be represented as following. According to [34] and [35], the complementary cumulative distribution function (CCDF) of R_1 can be written as

$$F_{\text{R1}}^{\text{S}}(r) = \exp\left(-\int_0^r \text{P}_{\text{S}}(\mu)2\pi\mu\lambda d\mu\right) = \exp\left(-\pi\lambda r^2\right). \tag{32}$$

Taking the derivative of $(1-F_{\text{R1}}^{\text{S}}(r))$ with regard to r, we can get the PDF of R_1 as

$$f_{R1}(r) = \exp(-\pi\lambda r^2) \times 2\pi\lambda r. \tag{33}$$

When $R_2 > A$, the PDF of R_2 can be expressed as following. Same as (32), the CCDF of R_2 can be written as

$$\begin{aligned} F_{\text{R2}}^{\text{S}}(r) &= \exp\left(-\int_0^r \text{P}_{\text{S}}(\mu) \times 2\pi\mu\lambda d\mu\right) \\ &= \exp\left(-\left(\pi\lambda A^2 + 2\pi\lambda A^2(\ln r - \ln A)\right)\right). \end{aligned} \tag{34}$$

So taking the derivative of $(1 - F_{R2}^{S}(r))$ with regard to r, we can get the PDF as

$$f_{\text{R2}}(r)=\exp[-(\pi\lambda A^2+2\pi\lambda A^2(\ln r-\ln A)]\times 2\pi\lambda A^2\times\frac{1}{r} \tag{35}$$

Having obtained $f_{R1}(r)$ and $f_{R2}(r)$, we move on to evaluate $\Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2} > \gamma\right]$ in (31) as

$$\begin{aligned} &\Pr\left[\frac{Phr^{-\alpha}}{I_d+N_0} > \gamma\right] = \mathbb{E}_{I_d}\left\{\Pr\left[h > \frac{\gamma r^\alpha (I_d+\sigma^2)}{P}\right]\right\} \\ &= \mathbb{E}_{I_d}\left\{\exp\left(-\frac{\gamma r^\alpha (I_d+\sigma^2)}{P}\right)\right\} \\ &= \exp\left(-\frac{\gamma r^\alpha \times \sigma^2}{P}\right)\mathcal{L}_{I_d}\left(\frac{\gamma r^\alpha}{P}\right), \end{aligned} \tag{36}$$

where $\mathcal{L}_{I_d}$ is the Laplace transform of RV I_d evaluated at s.

Our proof of Theorem 1 is completed by plugging (33), (35) and (36) into (9).

Appendix B
Proof of Lemma 1

Based on the considered UAS, it is straightforward to derive $\mathcal{L}_{I_{d1}}$ as

$$\begin{aligned} &\mathcal{L}_{I_{d1}}(s) = \mathbb{E}_{[\Phi,\{h_i\}]}\left\{exp\left(-s\sum_{i\in\Phi/b_0} Ph_i d^{-\alpha}\right)\right\} \\ &\overset{(a)}{=} \exp\left(-2\pi\lambda\int_r^\infty (1-\mathbb{E}_{[h]}\{\exp(-sPhu^{-\alpha})\})udu\right) \\ &\overset{(b)}{=} \exp\left(-2\pi\lambda\int_r^\infty (1-\mathbb{E}_{[h]}\{\exp(-r^\alpha\gamma hu^{-\alpha})\})udu\right) \end{aligned} \tag{37}$$

where the step (a) is obtained from [35] and the step (b) is plugging $s = r^\alpha\gamma P^{-1}$ into (37).

The part in (37) $\left(\mathbb{E}_{[h]}\left\{exp(-r^{-\alpha}\gamma hu^{-\alpha})\right\}\right)$ consider interferences from both social and non-social paths, thus, $\mathcal{L}_{I_d}(s)$ should be further derived as

$$\begin{aligned} &\mathcal{L}_{I_{d1}}(s) = \\ &\exp\Bigg(-2\pi\lambda\int_r^\infty \text{P}_{\text{S}}(u)\Bigg\{1-\mathbb{E}_{[h]}\left\{\exp(\frac{-\gamma h}{r^\alpha u^\alpha})\right\}\Bigg\}udu\Bigg)\times \\ &\exp\Bigg(-2\pi\lambda\int_r^\infty \text{P}_{\text{NS}}(u)\Bigg\{1-\mathbb{E}_{[h]}\left\{\exp(\frac{-\gamma h}{r^\alpha u^\alpha})\right\}\Bigg\}udu\Bigg) \end{aligned} \tag{38}$$

where $\text{P}_{\text{NS}}(u) = 1 - \text{P}_{\text{S}}(u)$. Plugging (3) into (38), we can get

$$\begin{aligned} &\mathcal{L}_{I_{d1}}(s) = \\ &\exp\left(-2\pi\lambda\int_r^\infty \left\{1-\mathbb{E}_{[h]}\left\{\exp(\frac{-\gamma h}{r^\alpha u^\alpha})\right\}\right\}udu\right) \\ &= \exp\left(-2\pi\lambda\times\int_r^\infty\left\{1-\frac{1}{1+r^\alpha\gamma u^{-\alpha}}\right\}udu\right) \\ &= \exp\left(\frac{-2\pi\lambda r^2\gamma}{\alpha-2}\,{}_2F_1\left[1,1-\frac{2}{\alpha};2-\frac{2}{\alpha};-\gamma\right]\right), \end{aligned} \tag{39}$$

where ${}_2F_1[\cdot,\cdot;\cdot;\cdot]$ is the hyper-geometric function [26] and $\alpha > 2$.

Appendix C
Proof of Lemma 2

From Appendix B, the second part of (31) can be expressed as

$$\begin{aligned} &\int_A^\infty \Pr\left[\frac{Phr^{-\alpha}}{I_d+\sigma^2} > \gamma\right] f_{R2}(r)dr \\ &= \int_A^\infty \exp\left(-\frac{\gamma\times r^\alpha\times\sigma^2}{P}\right)\mathcal{L}_{I_{d2}}\left(\frac{\gamma\times r^\alpha}{P}\right), \end{aligned} \tag{40}$$

where $\mathcal{L}_{I_{d2}}(s)$ also need to consider the interferences from both social and non-social paths.

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Thus $\mathcal{L}_{I_{d2}}(s)$ can be expressed as

$$\begin{aligned}
&\mathcal{L}_{I_{d2}}(s) = \\
&\exp\left(-2\pi\lambda \int_r^\infty (1-\mathbb{E}_{[h]}\{\exp(-r^\alpha \gamma h u^{-\alpha})\}) u du\right) \\
&=\exp\left(-2\pi\lambda \int_r^\infty \frac{A^2}{u^2}\left\{1-\mathbb{E}_{[h]}\{\exp(\frac{-\gamma h}{r^\alpha u^\alpha})\right\} u du\right)\times \\
&\exp\left(-2\pi\lambda \int_A^\infty \frac{u^2-A^2}{u^2}\left\{1-\mathbb{E}_{[h]}\{\exp(\frac{-\gamma h}{r^\alpha u^\alpha})\right\} u du\right) \\
&= \exp\left(-2\pi\lambda\gamma^2 \frac{1}{\alpha}\left(\ln\left(1+\frac{1}{\gamma}\right)-\ln\left(\frac{1}{\gamma}\right)\right)\right) \\
&\times \exp\left(\frac{-2\pi\lambda A^{2-\alpha} r^\alpha \gamma}{\alpha-2}\times \nabla_2(\alpha, A, r, \gamma)\right)\times \\
&\exp\left(2\pi\lambda A^2 \frac{1}{\alpha}\left(\ln(1+\frac{A^\alpha r^{-\alpha}}{\gamma})-\ln(\frac{A^\alpha r^{-\alpha}}{\gamma})\right)\right), \\
&\qquad\qquad\qquad\qquad\qquad\qquad (r > A),
\end{aligned} \tag{41}$$

where $\nabla_2(\alpha, A, r, \gamma) = {}_2F_1\left[1, 1-\frac{2}{\alpha}; 2-\frac{2}{\alpha}; -A^{-\alpha} r^\alpha \gamma\right]$, ${}_2F_1[\cdot,\cdot;\cdot;\cdot]$ is the hyper-geometric function [26] and $\alpha > 2$.

Appendix D
Proof of Lemma 3

In this appendix, we first prove that the proposed algorithm possesses the moderation property. That is, the magnitude of decrement of any action probability is bounded by a certain value.

From equation (21), the amount that a probability decrease is computed by

$$p_j(t) - p_j(t+1) = \frac{\Delta}{F-K(t)} = \frac{1}{F\delta}\times\frac{1}{F-K(t)} < \frac{1}{F\delta}, \tag{42}$$

So the magnitude of decrement is bounded by the value $1/F\delta$ and the proposed algorithm possesses the moderation property.

Then we prove that the proposed algorithm possesses the monotone property. That is, if there exists an index i and a time instant $t' < \infty$, such that

$$d_i(t) > d_j(t),\ for\ j \neq i\ and\ t > t', \tag{43}$$

then there exists an integer F_0 such that for all $F > F_0$, $p_i(t) \to 1$ with probability one as $t \to \infty$. Consider

$$\Delta p_i(t) = E[p_i(t+1) - p_i(t)|\mathbf{o}(t)], \tag{44}$$

where $\mathbf{o}(t)$ is the estimator vector.

From equation (21), $p_i(t+1)$ can be expressed as:

$$\begin{aligned}
&p_i(t+1) = p_i(t) + \frac{\Delta}{K(t)}, \\
&\qquad\qquad if\ \alpha_j\ is\ chosen\ and\ d_i > d_j. \\
&p_i(t+1) = 1 - \sum_{j\neq i}(p_j(t) - \frac{\Delta}{F}) \\
&\qquad\quad = p_i(t) + \frac{\Delta(F-1)}{F}, \\
&\qquad\qquad if\ \alpha_i\ is\ chosen\ and\ d_i\ is\ max.
\end{aligned} \tag{45}$$

Hence, for all $t > t'$ and $F > K(t) \geq 1$, $\Delta p_i(t)$ can be expressed by:

$$\begin{aligned}
&\Delta p_i(t) \\
&= \sum_{j\neq i}\frac{\Delta}{K(t)}\times p_j(t) + \Delta\times\frac{(F-1)}{F}\times p_i(t) \\
&= \frac{\Delta}{K(t)}(1-p_i(t)) + \Delta\times\frac{(F-1)}{F}\times p_i(t) \\
&> \frac{\Delta}{K(t)} + \Delta\times p_i(t)\times(\frac{K(t)^2-K(t)-K(t)}{FK(t)}) \\
&\geq \Delta - \Delta\frac{P_i(t)}{F} = \Delta\times(1-\frac{P_i(t)}{F}) > 0.
\end{aligned} \tag{46}$$

Therefore, $p_i(t)$ is a submartingale and according to the submartingale convergence theorem [27], $p_i(t)$ will converge to one with probability one. Therefore, the monotone of the algorithm is proved.

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Chuan Ma received the B.S. degree from the Beijing University of Posts and Telecommunications, Beijing, China, in 2013. Now, he is currently pursuing his Ph.D in Telecommunication from the University of Sydney. His research interests with Dr. Ding and Dr. Lin i include stochastic geometry, device-to-device communication, wireless caching networks and machine learning.

Ming Ding (M'12-SM'17) received the B.S. and M.S. degrees (with first class Hons.) in electronics engineering from Shanghai Jiao Tong University (SJTU), Shanghai, China, and the Doctor of Philosophy (Ph.D.) degree in signal and information processing from SJTU, in 2004, 2007, and 2011, respectively. From April 2007 to September 2014, he worked at Sharp Laboratories of China in Shanghai, China as a Researcher/Senior Researcher/Principal Researcher. He also served as the Algorithm Design Director and Programming Director for a system-level simulator of future telecommunication networks in Sharp Laboratories of China for more than 7 years. Currently, he is a senior research scientist at Data61, CSIRO, in Sydney, NSW, Australia. He has authored more than 50 papers in IEEE journals and conferences, all in recognized venues, and about 20 3GPP standardization contributions, as well as a Springer book "Multi-point Cooperative Communication Systems: Theory and Applications". Also, as the first inventor, he holds 15 CN, 7 JP, 3 US, 2 KR patents and co-authored another 100+ patent applications on 4G/5G technologies. He is or has been Guest Editor/Co-Chair/Co-Tutor/TPC member of several IEEE top-tier journals/conferences, e.g., the IEEE Journal on Selected Areas in Communications, the IEEE Communications Magazine, and the IEEE Globecom Workshops, etc. For his inventions and publications, he was the recipient of the President's Award of Sharp Laboratories of China in 2012, and served as one of the key members in the 4G/5G standardization team when it was awarded in 2014 as Sharp Company Best Team: LTE 2014 Standardization Patent Portfolio.

He (Henry) Chen (S'10-M'16) received the Ph.D. degree in Electrical Engineering (Telecommunications) from the University of Sydney, Sydney, Australia, in 2015. He is currently a Postdoctoral Research Fellow at the School of Electrical and Information Engineering, University of Sydney. His current research interests are in the field of wireless communications, with a particular focus on ultra-reliable low latency communications, non-orthogonal multiple access, millimeter wave wireless communications, and wireless energy harvesting and transfer.

He received the Outstanding Bachelor Thesis of Shandong University, the Outstanding Master Thesis of Shandong Province, and the Chinese Government Award for Outstanding Self-Financed Students Abroad. He served as a Guest Editor of the 2016 special issue of millimeter wave wireless communications and networks in MDPI Sensors, and an organizer and Co-Chair of GLOBECOM 2016 workshop on wireless energy harvesting communication networks. He has been serving as a Regular Reviewer for more than 10 prestigious IEEE journals as well as the TPC members of several IEEE flagship conferences, such as GLOBECOM and ICC.

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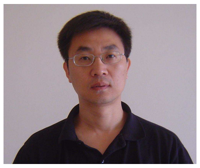

Zihuai Lin (S'98-M'06-SM'10) received the Ph.D. degree in Electrical Engineering from Chalmers University of Technology, Sweden, in 2006. Prior to this he has held positions at Ericsson Research, Stockholm, Sweden. Following Ph.D. graduation, he worked as a Research Associate Professor at Aalborg University, Denmark and currently at the School of Electrical and Information Engineering, the University of Sydney, Australia. His research interests include source/channel/network coding, coded modulation, MIMO, OFDMA, SC-FDMA, radio resource management, cooperative communications, small-cell networks, 5G cellular systems, IoT, etc.

Guoqiang Mao (S'98-M'02-SM'08-F'18) joined the University of Technology Sydney in February 2014 as Professor of Wireless Networking and Director of Center for Real-time Information Networks. Before that, he was with the School of Electrical and Information Engineering, the University of Sydney. He has published about 200 papers in international conferences and journals, which have been cited more than 5000 times. He is an editor of the IEEE Transactions on Wireless Communications (since 2014), IEEE Transactions on Vehicular Technology (since 2010) and received "Top Editor" award for outstanding contributions to the IEEE Transactions on Vehicular Technology in 2011, 2014 and 2015. He is a co-chair of IEEE Intelligent Transport Systems Society Technical Committee on Communication Networks. He has served as a chair, co-chair and TPC member in a large number of international conferences. He is a Fellow of IEEE and IET. His research interest includes intelligent transport systems, applied graph theory and its applications in telecommunications, Internet of Things, wireless sensor networks, wireless localization techniques and network performance analysis.

Ying-Chang Liang (F'11) is a "Thousand Programme" Professor at University of Electronic Science and Technology of China (UESTC), China. He was a Principal Scientist and Technical Advisor in the Institute for Infocomm Research (I2R), Singapore from 2004 - 2014, and a visiting scholar in Department of Electrical Engineering, Stanford University, USA from 2002 - 2003. Dr Liang was elected a Fellow of the IEEE in December 2010, and was recognized by Thomson Reuters as a Highly Cited Researcher in 2014, 2015 and 2016. He received the Institute of Engineers Singapore (IES)'s Prestigious Engineering Achievement Award in 2007, and the IEEE Standards Association's Outstanding Contribution Appreciation Award in 2011. He has also received numerous paper awards, with the recent ones including IEEE ICC Best Paper Award in 2017, IEEE ComSoc's TAOS Best Paper Award in 2016, and IEEE Jack Neubauer Memorial Award in 2014. Dr Liang is Founding Editor-in-Chief of IEEE Journal on Selected Areas in Communications - Cognitive Radio Series, and key founder of the new journal IEEE Transactions on Cognitive Communications and Networking. He was the Chair of IEEE Communications Society Technical Committee on Cognitive Networks, and served as Guest/Associate Editor of IEEE Transactions on Wireless Communications, IEEE Journal of Selected Areas in Communications, IEEE Signal Processing Magazine, IEEE Transactions on Vehicular Technology, and IEEE Transactions on Signal and Information Processing over Network. He is now an Associate Editor-in-Chief of the World Scientific Journal on Random Matrices: Theory and Applications. Dr Liang was a Distinguished Lecturer of the IEEE Communications Society and the IEEE Vehicular Technology Society. He served as TPC Chair and Executive Co-Chair of IEEE Globecom'17.

Branka Vucetic (SM'00-F'03) is an ARC Laureate Fellow and Professor of Telecommunications, Director of the Centre of Excellence in Telecommunications at the University of Sydney. During her career she has held research and academic positions in Yugoslavia, Australia, UK and China. Her research interests include coding, communication theory and signal processing and their applications in wireless networks and industrial internet of things.

Prof Vucetic co-authored four books and more than four hundred papers in telecommunications journals and conference proceedings. She is a Fellow of the Australian Academy of Technological Sciences and Engineering and a Fellow of the IEEE.