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# Information Caching Strategy for Cyber Social Computing Based Wireless Networks

# XING ZHANG, (Senior Member, IEEE), YONGJING LI, YAN ZHANG, (Senior Member, IEEE), JIAXIN ZHANG, HAILING LI, SHUO WANG, AND DANYANG WANG

X. Zhang is with the Beijing Advanced Innovation Center for Future Internet Technology, Beijing University of Technology, and the Key Laboratory of Universal Wireless Communications (Ministry of Education), Beijing University of Posts and Telecommunications (BUPT), China Y. Li, J. Zhang, S. Wang, and Danyang Wang are with the School of Information and Communication Engineering,

Beijing University of Posts and Telecommunications (BUPT), Beijing, 100876, China Y. Zhang is with University of Oslo and Simula Research Laboratory, Norway

H. Li is with CNCERT/CC & Institute of Information Engineering, CAS, Beijing, 100029, China

CORRESPONDING AUTHOR: X. ZHANG (zhangx@ieee.org)

ABSTRACT Cyber social computing has brought great changes and potential intelligent technologies for wireless networks. Among these technologies, information caching strategies are promising approaches to achieving lower delay, higher throughput and energy efficiency (EE) of user equipment (UE) in 5G wireless networks, by deploying intelligent caching and computing at the mobile edge. However, the static information caching strategies ignore the relevance of traffic fluctuation among different base stations (BSs) and the variance of users' interests. Thus in this paper, an information caching strategy for cyber social computing based wireless network is proposed, taking advantages of two layer social cyberspaces in both traffic correlation between BSs and the social relationship between UEs. In the first layer, a base station social network (BSSN) is constructed based on the social relationship between BSs, which is defined as social-tie factor (STF). In the second layer, the Indian Buffet Model (IBM) is used to describe the social influence of one UE to another. To reduce base station's traffic load, users with similar social interest can share the contents they cached with each other. Therefore, device-to-device (D2D) communication is taken as the underlay to cellular networks in our proposed information caching strategy. By utilizing the social characteristic of BSSN, the very important BSs (VIBSs) with higher averages STF are selected. Then the normal small cells (NSCs) within the VIBS's coverage are linked to the VIBSs only and the other unique small cells (USCs) will be routed back into the core network (CN) directly. Limited cache and backhaul capacity in the whole network are only shared by VIBSs and USCs. UEs will communicate with each other via D2D links only if they have i) similar interests, ii) enough encounter duration between users and iii) are adjacent with each other. Otherwise, the UE shall obtain the required contents via cellular networks. With the tool of stochastic geometry process, key performance indicators, e.g., coverage probability, network throughput power consumption, EE, delay and offloaded traffic are studied. Both the theoretical and numerical results show that the proposed information caching strategy for cyber social computing can achieve high coverage probability, throughput, EE and delay by optimizing STF threshold, VIBS coverage and D2D communication radius.

INDEX TERMS Information caching strategy, social cyberspaces, D2D communication

## I. INTRODUCTION

Nowadays, more and more people surf on the Internet via various smart mobile terminal devices such as phones, iPads, laptops, etc, and people take most of the entertainment on cyber such as watching videos, reading news, playing games, chatting with friends, etc. Therefore, the amount of traffic data in mobile cellular networks increases exponentially.

To satisfy the increasing traffic requirement, improving the network throughput needs to be considered preferentially [1], [2]. Among all the solutions, deploying intelligent caching and computing at the mobile edge is efficient and able to cope with the demand [3]. By deploying cache at BSs, users can quickly obtain the information they required. However, the static information caching strategies are not suitable

2168-6750 © 2017 IEEE. Translations and content mining are permitted for academic research only. Personal use is also permitted, but republication/redistribution requires IEEE permission. See http://www.ieee.org/publications\_standards/publications/rights/index.html for more information. 391 because of people's interests changing and the popularity of a certain content varies. Thus, studying the cyber users' social interest and behavior is necessary and meaningful.

Earlier, the social network refers to the social network sites (SNSs) like MySpace, Facebook, Twitter and Instagram where people connect with each other, share contents and disseminate information on cyber [4]. Therefore, understanding how users behave when they are connecting SNSs is more useful in studying social influences, improving the design of content distribution systems [7]. Some studies utilized the data of these SNSs to study the social relationship and impacts among users, the patterns of users' social interest and behavior are summarized [8]–[10]. In [8], the authors conceive a wireless virtual social network which describes the way people seeking information via social network. A model based on Indian Buffet Process is proposed to reflect the influences of one user's choice to the others and the distribution of contents in the users' online social networks (OSN) [9]. People's predictable social patterns are exploited to improve the content delivery performance and lower endto-end delay in time critical application in [10]. Thus, cyber social computing is significant to study the social ties among users, and how strong these ties are. As the users' behavior have great impacts on the variation of traffic [5], they are analyzed to achieve better performance of networks. Besides, D2D communication has emerged to support the transmission of contents between UEs, and become an underlay to cellular networks.

D2D communication underlays over cellular systems has become a promising technique to overcome the imminent wireless capacity crunch [6]. The majority of the traffic in cellular pertains to the download of popular content such as videos or mobile applications [11], and offloading these downloads to the D2D tier can reduce the load in the cellular network's infrastructure [8]. When two users are involving D2D communications, they should satisfy the following requirements: Strong social tie, high similarity of interest and are adjacent to each other [12]. Besides, the encounter duration for the two users in D2D communication must be long enough to transmit the contents. Many studies attempt to model the distribution of the call holding time, which exhibits the same property with encounter duration between individuals, and the gamma distribution has been shown to be an accurate model [13], [14].

Because the social interest and behavior of users influence the traffic fluctuation and cached contents of BSs, the social network of BSs is built to exploit the social characteristic and relationship between BSs [15]. In [16] the traffic fluctuation has already derived as an important social characteristic to indicate the similarity of traffic variation of BSs. By utilizing the social relationship between BSs, the cache can be appropriately deployed to improve the network performance.

In this paper, we propose an information caching strategy for a two-layer social cyberspace, which is illustrated in Figure 1. The top layer represents the BSSN, and the lines with different colors indicates the social relationship among



FIGURE 1. Two-layer social cyberspace.

BSs, BSs connected with green lines have stronger social-tie than the BSs connected with purple lines, and the BSs connected with pink lines have the strongest than other BSs. The social characteristic of BSs is exploited by utilizing the base station social network (BSSN) in our previous study [11], and the social relationship between BSs is modeled as the socialtie factor (STF) based on the data collected from practical network. The BSs are divided into three kinds: Very important base stations (VIBSs) are selected with the STF higher than the threshold, and the normal small cells are selected within the VIBSs coverage, all the rest BSs in the network are unique small cells (USCs). We assume the network is backhaul and cache capacity limited. As the VIBS has higher STF, it could represent the traffic variation of other BSs. The USC has less similarity with other BSs so that they cannot associate with other kinds of BSs, but while the NSCs can be served by VIBSs because of the physical location. Taking all these into consideration, the VIBSs and the NSCs share the limited cache and backhaul capacity together.

The other layer of the social cyberspace is the user layer which is reflected as the bottom layer of Figure 1. Different users have different interests, some might be interest in painting or reading while others are not. Users connected with lines in different colors symbolizes different characteristics

in social interests. To reflect the social characteristics of users, we adopt the Indian Buffet Model proposed in [9], the author has already proved the model perfectly fits the real data in the simulation. The users require the contents in order, and each user can require the old content which has been required by former users, or the new content which has no history of requirement. Each user's requirement is influenced by the former users' choice, which is similar with people choosing dishes when eating buffets. In our proposed information caching strategy, we assume that the D2D communication users can always get the old contents from their D2D partners. Other requirements of D2D communication are: The two users' encounter duration must be longer than the minimum time of content transmission and are adjacent to each other. When a user requires a content from the work, the BS will first identify whether the required content pertains to an old content or a new content. If the user requires an old content, it will try to find a D2D partner first if there exists one satisfying all the requirements, and he will take D2D communication, otherwise, the user gets the content from the cellular network. The main contributions of this paper are summarized as follows:

- A two-layer social cyberspace for both traffic correlation between BSs and the social relationship between UEs is constructed. A base station social network based on the STF between BSs and the Indian Buffet Model is used to model the social UEs' mutual influence. We also utilizes D2D communication for UEs who can share the locally stored content to reduce the traffic load at the base station. Specifically, the UEs will communicate with each other via D2D links only if certain favorable conditions are met. Otherwise, the UE shall obtain the required contents via cellular networks.
- We proposed an information caching strategy based on the two-layer social cyberspace which takes advantages of the features of two layers, and by cyber social computing, the most popular contents of the next moment can be predicted and the contents cached in BSs can be dynamically replaced. Taking the D2D communication as the underlay of cellular network, the traffic load at BSs can also be reduced by offloading it to the user layer.
- Key performance indicators, e.g., coverage probability, cache hitting probability, network throughput, power consumption, EE, network average delay and traffic offloaded by D2D communication are derived. The theoretical and numerical results show that our caching strategy can achieve high coverage probability, network throughput and energy efficiency by optimizing the STF threshold, VIBSs' cover radius and D2D communication radius.

The rest of this paper is organized as follows: Section II presents the BSSN model and Indian Buffet Model, and users encounter duration is modeled as Gamma distribution. The network model of our caching strategy is also presented and contents access situation of users is discussed. Key

#### II. SYSTEM MODEL

In this section, we will briefly present our previous study on BSSN and STF model. The Indian Buffet Model and the distribution of users encounter duration are also introduced. Later, the network model of our caching strategy is presented and the contents access situations of users are discussed.

## A. BSSN AND STF MODEL

In our previous work [17], the BSSN is constructed to visualize the hidden relationship between BSs by utilizing the theory of social network. The STF is modeled to indicate the strength of the relationship. The STF is defined as:

$$
\rho_{ij} = \frac{E\big((S_i - \mu(S_i))(S_j - \mu(S_j))\big)}{\sigma(S_i)\sigma(S_j)},
$$
\n(1)

where  $S_i(S_j)$  is the traffic volume series of BS  $i(j)\cdot \mu(S_i)$  is the mean of S,  $\sigma(S_i)$  is the standard deviation of S, and E is the mean of  $S_i$ ,  $\sigma(S_i)$  is the standard deviation of  $S_i$  and E is the expectation.  $\rho_{ii}$  varies between  $-1$  and  $+1$ , where 1 is total positive correlation, 0 is no correlation, and  $-1$  is total negative correlation [16]. The result of curve fitting application in MATLAB shows that the probability density function (PDF) of STF follows the Gaussian distribution with the goodness of fit:  $SSE = 6.215e - 0.5$ , mean value  $\mu = 0.2829$ , and the variance value  $\sigma^2 = 0.0655$ .

### B. USERS ENCOUNTER DURATION

Many studies have researched the users behavior and the moving track to predict the mobility of users. In [19], the authors identify that human mobility shows a very high degree of temporal and spatial regularity, and that each individual returns to a few highly frequented locations with a significant probability. The encounter duration among individuals follows a continuous distribution, and exhibits the same property with call holding time. Thus, some studies find out that the gamma distribution  $\Gamma(k, \theta)$  has shown to be an accurate model [9], [13], [14]. k and  $\theta$  are two parameters that define the shape of the distribution.

Assuming  $X_n$  is the contact duration of UE i and UE j, and  $N_{i,j}$  is the number of encounter times, the estimate of the expected contact duration length  $M_{i,j}$  is  $M_{i,j} = \sum_n X_n/N_{i,j}$ , and the variance  $I_{i,j}$ , which reflects the fluctuation is:  $I_{i,j}$ and the variance  $I_{i,j}$  which reflects the fluctuation is:  $I_{i,j} = \sum (X - M_{i,j})^2/N_i$ .  $\sum_{n} (X_n - M_{i,j})^2 / N_{i,j}.$  The encounter duri

The encounter duration distribution is derived as  $X \sim \Gamma$  $(k, \theta) = \Gamma(M_{i,j}^2/I_{i,j}, I_{i,j}/M_{i,j})$ , and the PDF is given

$$
f(x; k, \theta) = \frac{1}{\theta^k} \frac{1}{\Gamma(k)} x^{k-1} e^{-\frac{x}{\theta}}.
$$
 (2)



Thus, the probability of qualified contact duration is given by

$$
w_{i,j} = 1 - \int_0^{X_{\min}} f(u;k,\theta) du = 1 - \frac{\gamma(k,\frac{X_{\min}}{\theta})}{\Gamma(k)},
$$
 (3)

where  $X_{\text{min}}$  is the minimal contact duration required for transmitting one content data packet successfully [11], since our analysis of the network is more meticulous than traditional heterogeneous network that we can dig each user's interest in requiring content, so that the successful D2D communication requires D2D users transmitting at least one content data packet and the minimal contact duration must be considered in successful D2D communication.  $\gamma(k, \frac{X_{\min}}{\theta}) = \int_0^{\frac{X_{\min}}{\theta}} t^{k-1} e^{-t} dt$  is the lower incomplete Gamma function.

## C. INDIAN BUFFET MODEL

The Indian Buffet Model is based on the Indian Buffet Process (IBP) [18] which is important for learning the content popularity distribution and predicting the content that users may require. The IBP is a stochastic process which models a restaurant problem where each dinner sample is from some subset of an infinite selection of dishes on offer at a buffet [9]. The first customer will choose its preferred dishes equally as the dishes are all new to him. However, once the first customer complete the choice, the following customers will be influenced by the feedback of the first customer. Therefore, the probability of each dish being selected by the following customers are changed because of the previous customers' feedbacks.

The author in [9] utilizes the IBP to describe the users social influence and the circumstances that users select and require the contents just like of which they choosing the dishes at a buffet in the restaurant. Assuming there are  $N$  users in the networks, and  $K$  files to be required,  $K = K_h + K_0$ , where  $K_h$  represents the number of files that have been required by previous users, and  $K_0$  represents the number of files that do not have a required history. Users are ranked from 1 to  $N$ , the first user selects each file with equal probability of  $\varepsilon/K$  and ends up with the number of files following  $Poisson(\varepsilon)$  distribution, where  $\varepsilon$  is the parameter which determines the probability of whether the user chooses to select a content or not. For the subsequent users  $n = 2, \ldots, N$ , the probability of having file k already belongs to previous UEs is  $m_k^{n-1}/n$ , where  $m_k^{n-1}$  is the number of users prior to  $n$  who select dish  $k$  [20]. UE  $n$  will also require  $m_n^0$  new files which are not required by the previous users following  $Poisson(\varepsilon/n)$ , which is proved in the Appendix A of [9], so that the number of old files required by customer  $n$  is given as

$$
m_n^h = \sum_{k=1}^K \frac{m_k^{n-1}}{n} = m_n - m_n^0.
$$
 (4)

## D. NETWORK MODEL

As shown in Figure 2, the downlink transmission in this network is considered. By adopting the stochastic geometry theory, BSs are modeled as independent homogeneous Poisson Point Processes (PPPs) denoted as  $\Phi_B$ , with corresponding density of  $\lambda$ . Assuming the VIBSs, the NSCs and the USCs are all distributed as PPPs and will be explained in next section. The users are positioned with PPP  $\Phi_u$  with the density of  $\lambda_{UE}$ . A threshold of STF  $\rho$  is set to select VIBSs. A VIBS's cover radius is set to select NSCs which are located within the VIBSs' coverage. NSCs are linked to VIBSs with limited fronthaul while USCs and VIBSs occupy the limited backhaul to the core network. Users will get required contents from either D2D communication or cellular network which is depended on the judgement made by BSs. The standard path loss propagation model is used with path loss exponent  $\alpha > 2$ . All the links in this network are Rayleigh fading channels following exponential distribution with mean of 1:  $h_{b,i} \sim \exp(1)$ ,  $h_{j,i} \sim \exp(1)$ . We assume the network is an interference-limited scenario, so that the additive white Gaussian noise  $\sigma^2$  is neglected.

## E. CONTENT ACCESS

The D2D communication is taken as the underlay of the cellular network in our proposed information caching strategy. We assume the users require contents in the set order. Before user  $n$  get the required content, the serving BS judges whether the content has a history of requirement by previous users. If it belongs to the old contents, the user  $n$ will try D2D communication first. He will search the D2D partners within the range of a set radius, after that, the user  $n$  will select the best partner who has enough encounter duration within the range, and they become a D2D pair. At the same time, user  $n$  gets the old content from his D2D

partner. If user *n* required a new content or he could not find a D2D partner satisfied all the D2D communication requirement, he will obtain the content from cellular network. Thus, the content access cases are summarized as following:

- The user  $n (n \neq 1)$  obtains the old content from his D2D partner by taking D2D communication.
- The user *n* accesses to the VIBS, and obtain the old or new content from local caching space of the VIBS.
- The user associated with the VIBS, but the required content is not cached in the BS, so that the content will be fetched by the VIBS from the core network via backhaul links.
- The user accesses to an NSC, the request is sent to its corresponding VIBS, and the user gets the content from the cache in corresponding VIBS.
- The user accesses an NSC, but the required content is not cached in the corresponding VIBS, so that the user obtained the content from the core networks fetched by the VIBS via backhaul links.
- The user accesses to a USC and obtained the content from the USC's local cache.
- The user accesses to a USC, but the required content is not cached in the BS, so that the content will be fetched by the USC from the core network via backhaul links.

#### III. PERFORMANCE ANALYSIS

In this section, we will first analyze the probability of new and old contents the nth user may require and the proportion of different kinds of BSs. Some key performance indicators including coverage probability, the cache hitting probability, network throughput, traffic offloaded by the D2D layer, power consumption, average delay and EE will be derived.

## A. PROBABILITY OF REQUIRING NEW AND OLD **CONTENTS**

As is mentioned in Section II, the *nth* user requires  $m_n^0$ new files, and the  $m_n^0 \sim Poisson(\frac{\varepsilon}{n})$ , and the mean value<br>is  $\frac{\varepsilon}{n}$ . The total number of files required by user *n* denotes is  $\frac{\varepsilon}{n}$ . The total number of files required by user *n* denotes as  $m_n$ , and  $m_n \sim Poisson(\varepsilon)$ , the expectation value is  $\varepsilon$ , so that the expected number of old contents that the *nth* user requires is

$$
\bar{m}_n^h = E\{m_n^h\} = E\{m_n\} - E\{m_n^0\} = ((n-1)/n)\varepsilon. \tag{5}
$$

Based on the analysis of [9], we know that the number of old contents is the difference of two Poisson distribution and follows the Skellam distribution.

Although the Probability mass function (PMF) and the PDF of the number of old contents is given in [9], our priority of consideration in this paper is the cache deploying and replacing strategy, and how to improve the performance of the whole network. The probabilities of new and old contents required by users only have impacts on the proportion of the number of users taking D2D communication or associating with the



Successful D2D Communication

FIGURE 3. Requirements for successful D2D communication.

cellular network. Thus, we simplify the probabilities of the new contents and the old contents by utilizing the mean values of  $m_n^0$ ,  $m_n$  and  $m_n^h$ , which represent the average probability for the requirements of user  $n$ . The probability that the content required by user  $n$  is also required by previous users is

$$
P_{oc} = \frac{\bar{m}_n^h}{\bar{m}_n} = \frac{E\{m_n^h\}}{E\{m_n\}} = \frac{((n-1)/n)\varepsilon}{\varepsilon} = \frac{n-1}{n},\qquad(6)
$$

and the probability that the required content does not have a required history is

$$
P_{nc} = \frac{E\{m_n^0\}}{E\{m_n\}} = \frac{(1/n)\varepsilon}{\varepsilon} = \frac{1}{n}.
$$
 (7)

#### B. PROBABILITY OF D2D COMMUNICATION

In our network, the successful D2D communication requires similarity in social interest, adjacent physical location and enough encounter duration as is shown in Figure 3. The Indian Buffet Model gives the probability that two users require the same content which represents the similarity of users' social interest. As the locations of the users follow the PPP distribution with the density  $\lambda_{UE}$ , the probability of the typical user can find a potential D2D partner within the D2D communication distance is

$$
P_{UE} = 1 - e^{-\lambda_{UE}\pi r_{UE}^2},\tag{8}
$$

where  $r_{UE}$  is the distance between the typical user and any other users in the network, the PDF of  $r_{UE}$  is  $f_{r_{UE}}(r) =$  $2\pi\lambda_{UE}e^{-\pi\lambda_{UE}r^2}$ . The probability of qualified contact duration  $w_{i,j}$  is given in Section II, so that the probability of successful D2D communication is

$$
P_D = \left(1 - e^{-\lambda_{UE}\pi r_{UE}^2}\right) w_{i,j} P_{oc}
$$
 (9)

Similarly, the probability of the typical user obtains the required content from cellular network is:

$$
P_C = 1 - P_D \tag{10}
$$

$$
= \left(1 - \left(\left(1 - e^{-\lambda_{UE}\pi r_{UE}^2}\right)w_{i,j}\right)\right)P_{oc} + P_{nc}.\tag{11}
$$

#### C. PROPORTION OF DIFFERENT BSS

To deploy the cache capacity properly, we divide the BSs into three different kinds: The VIBS, the NSC and the USC, and the three kinds of BSs are distributed PPP respectively according to the feature of Poisson distribution. The threshold of STF  $\rho$  is the key parameter to select VIBSs. As the STF follows the Gaussian distribution with the mean value  $\mu$ and the variance value  $\sigma^2$ , the proportion of VIBSs is

$$
P_v = \frac{1}{2} erfc\left(\frac{\rho - \mu}{\sigma\sqrt{2}}\right).
$$
 (12)

The selected VIBSs have higher STF, which means they have stronger social ties with other BSs, and larger similarity of traffic variation with other BSs. Since the VIBS is more typical and representative, it can serve some BSs which is located in the range of a particular distance, these BSs are served by the corresponding VIBS and defined as NSCs without equipping cache, the NSCs can only link to the corresponding VIBS for meeting the limitation of backhaul. The proportion of NSCs is

$$
P_n = (1 - e^{-P_v \lambda \pi r_v^2})(1 - P_v), \tag{13}
$$

where  $r_V$  is the distence between the typical NSC and the corresponding VIBS, and the PDF of  $r_V$  is  $f_{rv}(r) =$  $2\pi\lambda e^{-\pi\lambda r^2}$ . All the rest BSs are sorted as USCs, the USCs are with lower STF than the threshold  $\rho$  and cannot be served by the VIBSs which should be equipped with cache and are able to link to the core networks via backhaul links. The proportion of USCs is

$$
P_u = e^{-P_v \lambda \pi r_v^2} (1 - P_v).
$$
 (14)

#### D. COVERAGE PROBABILITY

For the convenience of analysis, a typical user is chosen to be located at the origin, and the distances to the serving BS and the D2D partner are defined as  $r_1$  and  $r_2$ . Besides, the parameters of three kinds of BSs are exactly the same. The downlink signal-to interference ratio (SIR) are

$$
SIR_B = \frac{P_B h_{b_0,i} r_1^{-\alpha}}{\sum_{b \in \Phi B/b_0} P_B h_{b,i} r_{b,i}^{-\alpha} + \sum_{j \in \Phi J} \beta_{ji} P_{UE} h_{j,i} r_{j,i}^{-\alpha}}
$$
(15)

$$
SIR_D = \frac{P_{UE}h_{j_0,i}r_2^{-\alpha}}{\sum_{b \in \Phi B} P_B h_{b,i}r_{b,i}^{-\alpha} + \sum_{j \in \Phi J/j_0} \beta_{ji} P_{UE} h_{j,i}r_{j,i}^{-\alpha}}, \quad (16)
$$

where  $P_B$  and  $P_{UE}$  are the transmission power of BSs and terminal devices respectively.  $\beta_{ji}$  in (15) indicates the presence of interference from D2D communication to cellular communication,  $\beta_{ji}$  only takes the value of 0 or 1 which presents whether there exists an interference. For  $\beta_{ji}$  in (16) represents the interference from the other D2D pairs that share spectrum resources with user  $j$  and user  $i$  [9].

The coverage probability of cellular communication is

$$
P_{cover}^{C} = E_{r_1}[P[SIR_B > T|r_1]]
$$
  
=  $\int_{r_1>0} P[SIR_B > T|r_1] f_{r_1}(r) dr$   
=  $\int_{r_1>0} e^{-\pi \lambda r_1^2} P[h_{b,i} > \frac{r_1^{\alpha}}{P_B} T I_1|r_1] 2\pi \lambda r_1 dr_1$  (17)  
=  $\exp\left(-\sum_{g=1}^{2} p_{a,g} \hat{\lambda}_g \hat{P}_g^{\frac{2}{\alpha}} T^{\frac{2}{\alpha}} G_{\alpha}\left(\frac{1}{T^{\frac{2}{\alpha}}}\right)\right),$ 

where  $p_{a,1} = 1, p_{a,2} = \beta_{j,i}$  and  $\hat{\lambda}_1 = \lambda/\lambda = 1, \hat{\lambda}_2 = \lambda_{UE}/\lambda$ .<br>T is the SIR threshold for cellular communication. The  $T$  is the SIR threshold for cellular communication. The gamma function is defined as  $G_{\alpha}(y) = \int_{y}^{\infty} \frac{1}{1+x^2} dx, y \ge 0.$ 

Similarly, the coverage probability of D2D communication is

$$
P_{\text{cover}}^D = E_{r_2} [P[SIR_D > T | r_2]]
$$
  
= 
$$
\exp\left(-\sum_{g=1}^2 p_{a,g} \,\hat{\lambda}_g \,\hat{P}_g^{\frac{2}{\alpha}} T^{\frac{2}{\alpha}} G_\alpha \left(\frac{1}{T^{\frac{2}{\alpha}}}\right)\right),
$$
 (18)

where  $\hat{\lambda}_1 = \lambda / \lambda_{UE}, \hat{\lambda}_2 = \lambda_{UE} / \lambda_{UE} = 1.$ <br>The coverage probability of the netwo The coverage probability of the network is

$$
P_{\text{cover}} = P_C \cdot P_{\text{cover}}^C + P_D \cdot P_{\text{cover}}^D. \tag{19}
$$

#### E. CACHE HITTING PROBABILITY

Our proposed network is cache limited, the total number of cached files in the network is  $N_f$  and each file is of L length. The simulation in [9] shows that the IBP simulated trace accurately fits the read data and approximately follows the distribution. Thus we adopt the Zipf distribution to model the file popularity in the network, and the probability of the  $f - th$ ranked content requested by terminal users is  $p_f = (\delta - 1)f^{-\delta}$ ,<br>where  $f > 1$  and  $\delta > 1$  reflects the skew of the popularity where  $f > 1$  and  $\delta > 1$  reflects the skew of the popularity distribution. The cache capacity is shared by the VIBSs and the NSCs equally

$$
N_{\nu} = \frac{N_f}{(P_{\nu} + P_u) \cdot \lambda} \tag{20}
$$

$$
N_u = \frac{N_f - N_v \cdot P_v \lambda}{(P_v + P_u) \cdot \lambda}.
$$
\n(21)

When the typical user takes cellular communication and associated with the VIBS, the cache hitting probability and missing probability are

$$
P_h^{\nu} = P_{\nu} \cdot \int_1^{N_{\nu}} p_f \, \mathrm{d}f = \left(1 - N_{\nu}^{1-\delta}\right) P_{\nu} \tag{22}
$$

$$
P_m^{\nu} = P_{\nu} \cdot \left(1 - \int_1^{N_{\nu}} p_f \, df\right) = N_{\nu}^{1 - \delta} P_{\nu}.
$$
 (23)

When the typical user takes cellular communication and associated with the NSC the cache hitting probability and missing probability are

$$
P_h^n = P_n \cdot \int_1^{N_v} p_f \, \mathrm{d}f = \left(1 - N_v^{1-\delta}\right) P_n \tag{24}
$$

$$
P_m^n = P_n \cdot \left(1 - \int_1^{N_v} p_f \, df\right) = N_v^{1-\delta} P_n. \tag{25}
$$

When the typical user takes cellular communication and associated with the USC, the cache hitting probability and missing probability are

$$
P_h^u = P_u \int_1^{N_u} p_f \, \mathrm{d}f = \left(1 - N_u^{1-\delta}\right) P_u \tag{26}
$$

$$
P_m^u = P_u \cdot \left(1 - \int_1^{N_u} p_f \, \mathrm{d}f\right) = N_u^{1-\delta} P_u. \tag{27}
$$

# F. NETWORK THROUGHPUT AND OFFLOADED **TRAFFIC**

When the typical user  $n$  takes D2D communication, the data rate is given by

$$
R_D = W \log_2(1 + SIR_D),\tag{28}
$$

and the throughput of the D2D communication comes to

$$
T_D = P_D \cdot R_D. \tag{29}
$$

When the user takes cellular communication, the data rate depends on which kind of BSs the user associated with.

If the user  $n$  associates with the VIBS and hits the cache, the data rate will be

$$
R_h^B = W \log_2(1 + SIR_B),\tag{30}
$$

where *W* is the bandwidth of the network, and if the user did not get the required content from the local cache in VIBS, the data rate will be limited by the backhaul, which is

$$
R_m^B = \begin{cases} W \log_2(1 + SIR_B) & \text{if} \quad W \log_2(1 + SIR_B) \le C_{bh1} \\ C_{bh1} & \text{if} \quad W \log_2(1 + SIR_B) \ge C_{bh1}, \end{cases}
$$
(31)

where

$$
C_{bh1} = C_{bh2} = \frac{C_1}{(P_v + P_m^n + P_m^u)\lambda},
$$
 (32)

 $C_1$  is the total backhaul limitation of core network. The fronthaul is shared with both the NSCs and the USCs

$$
C_{fh1} = \min\left\{\frac{C_2}{(1 - P_v)/P_v}, C_2\right\},\tag{33}
$$

where  $C_2$  is the fronthaul limitation of VIBS, and  $C_{fh1} > C_{bh1}$ .

The throughput will be given as

$$
T_V = P_h^V \cdot \bar{R}_h^V + P_m^V \cdot \bar{R}_m^V, \tag{34}
$$

 $T_V = P_h^V \cdot \bar{R}_h^V + P_m^V \cdot \bar{R}_m^V$  (34)<br>where the average data rate is given below after derived and simplified

$$
\bar{R}_{h}^{V} = \int_{0}^{\infty} \frac{1}{1+\eta} \left(1 + \sum_{g=1}^{2} \widehat{\lambda}_{g} p_{a,g} \widehat{P_{g}^{a}} \eta^{\frac{2}{\alpha}} G_{\alpha} \left(\frac{1}{\eta^{\frac{2}{\alpha}}}\right)\right)^{-1} d\eta
$$
\n(35)

$$
\bar{R}_{m}^{V} = \int_{0}^{e^{C_{bh_1}-1}} \frac{1}{1+\eta} \left(1 + \sum_{g=1}^{2} \widehat{\lambda}_{g} p_{a,g} \widehat{P_{g}^{\alpha}} \eta^{\alpha} G_{\alpha} \left(\frac{1}{\eta^{\alpha}}\right)\right)^{-1} d\eta.
$$
\n(36)

Similarly, the throughput when the *nth* user associate with the NSC and USC are given

$$
T_n = P_h^n \cdot \int_0^{e^{C_{fh_1}} - 1} \frac{1}{1 + \eta} \left( 1 + \sum_{g=1}^2 \widehat{\lambda}_g p_{a,g} \widehat{P_g^g} \eta^{\widehat{a}} G_\alpha \left( \frac{1}{\eta^{\widehat{a}}} \right) \right)^{-1} d\eta
$$
  
+ 
$$
P_m^n \cdot \int_0^{e^{C_{bh_1}} - 1} \frac{1}{1 + \eta} \left( 1 + \sum_{g=1}^2 \widehat{\lambda}_g p_{a,g} \widehat{P_g^g} \eta^{\widehat{a}} G_\alpha \left( \frac{1}{\eta^{\widehat{a}}} \right) \right)^{-1} d\eta
$$
(37)

$$
T_{u} = P_{h}^{u} \cdot \int_{0}^{\infty} \frac{1}{1+\eta} \left( 1 + \sum_{g=1}^{2} \widehat{\lambda}_{g} p_{a,g} \widehat{P_{g}^{a}} \eta^{\frac{2}{\alpha}} G_{\alpha} \left( \frac{1}{\eta^{\frac{2}{\alpha}}} \right) \right)^{-1} d\eta
$$
  
+  $P_{m}^{u} \cdot \int_{0}^{e^{C_{bh_{1}}-1}} \frac{1}{1+\eta} \left( 1 + \sum_{g=1}^{2} \widehat{\lambda}_{g} p_{a,g} \widehat{P_{g}^{a}} \eta^{\frac{2}{\alpha}} G_{\alpha} \left( \frac{1}{\eta^{\frac{2}{\alpha}}} \right) \right)^{-1} d\eta.$  (38)

When the typical user  $n$  takes cellular communication, the throughput is denoted as

$$
T_c = P_V \cdot T_V + P_n \cdot T_n + P_u \cdot T_u. \tag{39}
$$

In our proposed network, different ranked users has different probabilities of selecting the contents, so the total network throughput is described as

$$
T = \sum_{n=1}^{N} P_{oc}(P_{D}T_{D} + P_{C}T_{c}) + P_{nc}T_{c}.
$$
 (40)

The traffic offloaded by D2D communication layer is denoted as

$$
T_{ol} = T' - P_{nc} \cdot T_c, \qquad (41)
$$

where  $T'$  represents the network throughput when there is no D2D layer, and is derived as

$$
T' = P_h^v \bar{R}_{\text{olh}}^v + P_h^n \bar{R}_{\text{olh}}^n + P_h^u \bar{R}_{\text{olh}}^u + P_h^u \bar{R}_{\text{olh}}^u + P_m^v \bar{R}_{\text{olm}}^v + P_m^u \bar{R}_{\text{olm}}^u
$$
\n
$$
(42)
$$



#### TABLE 1. Important variables.

The average data rate above are simplified as

$$
\bar{R}^{\nu}_{\text{olh}} = \bar{R}^{n}_{\text{olh}} = \lambda \int_0^\infty \frac{1}{1+\eta} \left(1 + \eta^{\frac{2}{\alpha}} G_\alpha \left(\frac{1}{\eta^{\frac{2}{\alpha}}}\right)\right)^{-1} d\eta
$$
\n
$$
\bar{R}^{\mu}_{\text{olh}} = \lambda \int_0^{e^{C_{\text{fh1}}-1}} \frac{1}{1+\eta} \left(1 + \eta^{\frac{2}{\alpha}} G_\alpha \left(\frac{1}{\eta^{\frac{2}{\alpha}}}\right)\right)^{-1} d\eta
$$
\n
$$
\bar{R}^{\nu}_{\text{olh}} = \bar{R}^{\mu}_{\text{olh}} = \bar{R}^{\mu}_{\text{olh}} \tag{43}
$$

$$
\bar{R}_{\text{olm}}^V = \bar{R}_{\text{olm}}^u = \bar{R}_{\text{olm}}^n
$$
\n
$$
= \lambda \int_0^{e^{C_{bh_1}}-1} \frac{1}{1+\eta} \left(1 + 1 p_{a,1} \eta^{\frac{2}{\alpha}} G_\alpha \left(\frac{1}{\eta^{\frac{2}{\alpha}}}\right)\right)^{-1} d\eta.
$$

# G. POWER CONSUMPTION AND ENERGY EFFICIENCY

The network power consumption is constructed of two parts, the D2D communication part and the cellular communication part. As the throughput is derived on the view of users, We will derive the network power consumption from users angle, and is derived as

$$
Pow = \sum_{n=1}^{N} (P_DPow_{D2D} + (1 - P_D)Pow_c), \qquad (44)
$$

where  $Pow<sub>D2D</sub>$  is the transmission power of terminal devices, and the  $Pow<sub>c</sub>$  is the power consumption which contains three kinds of BSs power consumption, the basic BS power consumption, caching power consumption and backhaul power consumption.

The expression of the EE of the network is

$$
EE = \frac{T}{P_{OW}},
$$
 (45)  
which is the ratio of total network throughout to the network

power consumption.

#### H. NETWORK AVERAGE DELAY

As an important KPI, the network delay has a huge influence on user's Quality of Experience (QoE). In our paper, the average network delay is denoted as

$$
\tau = P_c \cdot \underbrace{(P_h^V \cdot \tau_{1hd} + P_m^V \cdot 2\tau_{1bh})}_{get access to VIBSS}
$$
\n
$$
+ \underbrace{P_h^n \cdot (\tau_{1hd} + 2\tau_{fh}) + P_m^n \cdot (2\tau_{fh} + 2\tau_{1bh})}_{get access to NSCs}
$$
\n
$$
+ \underbrace{P_h^u \cdot \tau_{2hd} + P_m^u \cdot 2\tau_{2bh})}_{get access to USCs} + \underbrace{P_D \cdot \tau_D}_{D2D communication},
$$
\n(46)





which is the product of the delays of different conditions and the corresponding probabilities.  $\tau_{1hd}$  and  $\tau_{1bh}$  are the cache retrieve and backhaul delay for VIBSs,  $\tau_{2hd}$ ,  $\tau_{2bh}$  and  $\tau_{fh}$ are cache retrieve, backhaul and fronthaul delay for SCs, and  $\tau_{2bh} > \tau_{1bh} > \tau_{fh} > \tau_{2hd} > \tau_{1hd}$ . As the successful D2D partners are all local users within the edge of the network and are closed with each other, the delay of D2D communication  $\tau_D$  is short enough to neglect. Thus, the average network delay mainly depends on the delay of cellular network communication.

## IV. NUMERICAL RESULTS

In this section, we evaluate the performance of the caching strategy for two-layer social cyberspaces. Related simulation parameters are given in Table 2. The users' encounter duration related parameters are taken from [9], the power related parameters are from [20], [21].

The coverage probability of the network is shown in Figure 4. The different colors of lines denote the variation in the densities of terminal users and BSs. For the convenience of comparison, only the density of users is changed, as the coverage probability is related to the ratio of the density of users to the density of BSs. As is shown in Figure 4, the



FIGURE 4. Coverage probability.



FIGURE 5. Network throughput: (a) The impact of VIBS cover radius on throughput; (b) The impact of D2D communication radius on throughput; (c) The impact of social-tie factor (STF) threshold on throughput.

coverage probability goes down when the SIR threshold becomes higher, because more requirements could not meet the SIR threshold and are failed to sent to the BSs or to the D2D partners, and the coverage probability goes down quickly at first, when the threshold becomes larger and the slope turns small. The lines with color red, green and blue represent the ratios of users' density to the BSs' density are 5, 10 and 20 respectively. When the ratio is smaller, the coverage probability is much higher because of less interference among users, and each BS serves fewer users with fewer requirements at the same time, so that the channel quality is assured. When the threshold is higher, the coverage probability becomes lower when the ratio is smaller, because under the high STF threshold, D2D communication is easier taken than the cellular communication as the physical distance between two users is short and has less interference compared with cellular communication.

The numerical results of network throughput are shown in Figure 5. In Figure 5(a), The impact of VIBS cover radius on network throughput is reflected. The threshold of STF takes the values of 0,  $\mu$ , 0.4 and 0.6. The D2D communication radius takes the value of 20. As is shown in Figure 5(a), the network throughput decreases when the radius of VIBSs' cover range increases. The larger the radius is, VIBSs can serve more BSs, and more small cells turn into NSCs without caching and backhaul capacity. Thus, the throughput goes down. When the radius arrives at some specific value, network throughput will not change even the radius changes, because the total number of BSs is limited, when the radius is larger than a specific value, all the other small cells can be served by the VIBSs, and there is no USC exists. The proportion of VIBSs and the NSCs is a fixed value, and the throughput is no longer changing. When the STF threshold  $\rho$  increases, the network throughput decreases first and increases later. To further study the impact of  $\rho$  on the network throughput, we simulated the throughput with different values of STF threshold and the result is shown in Figure 5(c), and we will explain the variation later. Another obvious feature of Figure 5(a) is that the four different lines have crossings with others. The reason for this phenomenon is that the proportion of three different kinds of BSs is decided by both the STF threshold  $\rho$  and the

VIBSs' cover radius, so that the throughput of the network with lower value of  $\rho$  and larger VIBSs' cover radius may be equal with the network with higher value of  $\rho$  and smaller VIBSs' cover radius. By optimizing the STF threshold and VIBS cover radius jointly, the network throughput can achieve 44 percent gain than the lowest throughput.

Figure 5(b) shows the impact of D2D communication radius on the network throughput. The threshold of STF takes the values of 0,  $\mu$ , 0.4 and 0.6. The VIBSs' cover radius takes the value of 100. As is shown in the figure, the network throughput can achieve 60 percent gain by selecting the D2D communication radius properly. When the radius of maximum successful D2D communication increases, the network throughput increases at first and can reach the maximum of network throughput, when the radius is larger than 35 meter, the throughput is no longer changing, as when the radius increases, the probability of users taking D2D communication increases, but the interference from other D2D pairs will increase and will result in the failure of transmitting contents via D2D links. Besides, the requesting user will find a best D2D partner in the available physical range, so the throughput will be stable because the probability of successful D2D communication for the typical user is stable. When the STF threshold  $\rho$  increases, the network throughput decreases first and increases later, which reflects the exactly tend with the result in Figure 5(c).

To exploit the impact of STF threshold  $\rho$  on the network throughput, We take some values of radius of VIBSs' coverage and D2D communication distance in pairs. As is shown in Figure 5(c), the influence of  $\rho$  is much larger than that of both radius, because the proportion of VIBSs is mainly up to the value of  $\rho$ . Since the VIBS is equipped with cache and backhaul, and serves other BSs as well, it contributes to the network throughput most, so that the network throughput decreases at first when the number of VIBSs becomes less. As the USCs share limited caching and backhaul capacity, its number also has an obvious influence on the network throughput. When the threshold of STF becomes higher, the proportion of USCs increases and results in the increase of the network throughput. When the difference of the number of VIBSs and USCs achieves the maximum, the network throughput comes to the minimum as is shown in Figure 5(c).



FIGURE 6. Power consumption: (a) The impact of VIBS cover radius on power consumption; (b) The impact of D2D communication radius on power consumption.

The simulation results show that the tendency of network EE has similar properties with the network throughput for the same reason. The proportion of three BSs and the probability that whether the users take D2D communication or the cellular communication to obtain the required contents are the key elements of influencing the network EE.

Figure 6 shows the power consumption results with the changes of the VIBS cover radius and D2D communication radius. In Figure 6(a), the macro tend of the power consumption is increasing as the VIBS cover radius increases and the STF threshold  $\rho$  becomes higher. As the VIBS cover radius increases, VIBSs will serve more BSs, which results in the power consumption of backhaul and cache hitting rises. The USCs also contribute a lot to the power consumption as they are equipped with cache capacity and can directly link to the core network via backhaul. The higher the threshold  $\rho$  is, the larger number of USCs is in this network, and results in the rise of the network power consumption. As the number of USCs is up to both  $\rho$  and the VIBSs cover radius, the four lines have cross spots as expected.

As is shown in Figure 6(b), the results of network power consumption with different STF threshold have little difference. After magnified the figure, we can see that the four lines are not totally overlapped, which means the STF threshold has a less impact on power consumptions when comparing with the impact of D2D communication radius. As the cellular communication consumes much more powers than D2D



FIGURE 7. Network average delay: (a) The impact of VIBS cover radius on average delay; (b) The impact of D2D communication radius on average delay.

communication, the probability of users taking D2D communication influences the power consumption a lot. When the D2D communication radius increases, more users take D2D communication and the total power consumption goes down.

Figure 7 shows the impact of VIBS cover radius and D2D communication radius on network average delay. The threshold of STF takes the values of  $0, \mu, 0.4$  and 0.6. The D2D communication radius is 20 meter in Figure 7(a) and the VIBS cover radius is 100 meter in Figure 7(b). The results in Figure 7(a) show that when VIBS cover radius or  $\rho$  decreases, the network average delay decreases. When a user accesses to a VIBS to get the required contents, the delay is smaller than the user accesses to the NSC, and the delay of user accesses to the USC is the largest. Thus, the proportion of VIBS and NSC increase, and the probability of user accesses to VIBS or NSC increases, which results in the decrease of network average delay. In Figure 7(b), when the D2D communication radius increases, the network average delay decreases. In the proposed network, we assumed the delay of D2D communication is neglected. When the D2D communication radius increases, the probability of user taking D2D communication increases, and the network average delay decreases.

Figure 8 shows the result of the traffic offloaded by D2D communication with different STF thresholds. We adopt the difference of the throughput of all the users in our network and the network without D2D underlay to indicate the offloaded traffic amount. The impacts of the proportion of three



FIGURE 8. The traffic offloaded by D2D.

kinds of BSs are the key factors which determine the amount of offloaded traffic. When  $\rho$  rises, or the VIBS cover radius decreases, the amount of offloaded traffic increases.

The numerical results of coverage probability, network throughput and power consumption have shown that our caching strategy performs well by taking the social network of both base stations and terminal users into consideration, and is a promising way to cope with the exponentially increasing traffic in the future network.

#### V. CONCLUSION

In this paper, we proposed an information caching strategy for a two-layer social cyberspace by utilizing the social characteristics of BSs layer and users layer. On the basis of our previous study on BSSN, we proposed a new BS selecting policy and caching strategy by utilizing the social relationship and physical location of the BSs. In our proposed network, D2D communication is taken as the underlay to the cellular network to improve the network performance. Indian Buffet Model has been utilized to model the social influence among users. The contents cached in the BSs can be dynamically replaced by the lately popular contents predicted by taking the interest and behavior of cyber users into consideration. Besides, the traffic load on the cellular network can be efficiently reduced by offloading it to the D2D layer. The network coverage probability, the cache hitting probability, network throughput, power consumption, EE, average delay and the traffic offloaded by D2D are derived as key performance indicators. Theoretical and numerical results show that the proposed network achieves high coverage probability, and the network throughput can achieve the gain of 44 and 60 percent by optimizing the VIBS cover radius and the D2D communication radius respectively. Meanwhile, the results also show that a large amount of traffic can be offloaded by D2D layer in our two-layer social cyberspace. Therefore, the information caching strategy will be a promising approach to coping with the exponentially increasing traffic data in the future network.

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#### **IEEE TRANSACTIONS ON EMERGING TOPICS IN COMPUTING**



XING ZHANG is full professor with the School of Information and Communications Engineering, Beijing University of Posts and Telecommunications (BUPT), China. His research interests are mainly in 5G wireless communications and networks, green communications, cognitive radio and cooperative communications, big data and Internet of Things. He is the author/coauthor of two technical books and more than 100 papers in top journals and international conferences and filed more than 30 patents. He has served as general co-chairs of

the 3rd IEEE International Conference on Smart Data (SmartData-2017), as a TPC co-chair/TPC member for a number of major international conferences. He received the best paper awards in the 9th International Conference on Communications and Networking in China (Chinacom 2014), the 17th International Symposium on Wireless Personal Multimedia Communications (WPMC 2014), and the 8th IEEE International Conference on Wireless Communications and Signal Processing (IEEE WCSP 2016). He is a senior member of the IEEE and IEEE ComSoc, Member of CCF.



YONGJING LI received the BE degree in communication engineering from Beijing University of Posts and Telecommunications, Beijing, China, in 2015 and she is currently working toward the ME degree in the key laboratory of universal wireless communications, School of Information and Communication Engineering. Her research interests include green communication, 5G network architecture, and mobile edge computing technologies.



YAN ZHANG received the PhD degree in School of Electrical & Electronics Engineering, Nanyang Technological University, Singapore. He is fulltime full professor at University of Oslo, Norway. He is also chief scientist at Simula Research Laboratory, Norway. He is an associate editor or on the editorial board of a number of well-established scientific international journals. He is currently serving the book series editor-in-chief for the book series on "Wireless Networks and Mobile Communications" (CRC Press). He serves as organizing

committee chairs and technical program committee for many international conferences. He has received the 8 Best Paper Awards. His current research interests include: Wireless networks leading to 5G, and cyber-physical systems (e.g., smart grid, healthcare, transport). He is a senior member of the IEEE, IEEE ComSoc, Computer Society, PES and IEEE VTS. He is a fellow of IET.



JIAXIN ZHANG received the BE degree in information engineering from Beijing University of Posts and Telecommunications, Beijing, China, in 2012 and he is currently working toward the PhD degree in the Key Laboratory of Universal Wireless Communications, School of Information and Communication Engineering. His research interests include green communication, 5G network architecture, and mobile edge computing technologies.

HAILING LI received the MAEng degree in Chinese Academy of Sciences, and she is working toward the PhD degree in University of Chinese Academy of sciences and working in CNCERT/CC. Her research interests are in the areas of network behavior analysis, network security event monitoring and emergency responses.



SHUO WANG received the BE degree in information engineering from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2011 and received the ME degree in communication and information systems from China Academy of Space Technology, Beijing, China, in 2014. He is currently working toward the PhD degree in the key laboratory of universal wireless communications, School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing, China. His research interests

include 5G network technology, green communication, mobile edge caching and cloud computing.



DANYANG WANG received the BE degree in communication engineering from Beijing University of Posts and Telecommunications, Beijing, China, in 2016 and she is currently working toward the ME degree in the key laboratory of universal wireless communications, School of Information and Communication Engineering. Her research interests include green communication, 5G network architecture, and mobile edge computing technologies.