Social-Aware Data Caching Mechanism in D2D-Enabled Cellular Networks

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Abstract. In this paper, we investigate the problem of content caching in wireless cellular networks (CN) using device-to-device (D2D) transmission method to reduce subscriber's download delay. We focus on how to efficiently allocate files to the selected important nodes (INs), and propose a novel approach for minimizing the downloading latency. In particular, we first model the problem of minimizing delay as a matching game. Then we tackle this game by exploiting the popularity of contents as well as users' social properties to generate the utility functions of two-side players: INs and files. Based on the utility function, the preference lists of cache entities is developed. For solving this game, we design a user-file caching (UFC) algorithm to achieve a stable matching between INs and files. Simulation and analytical results show that the proposed mechanism is capable of offering a better delay performance than benchmarks, e.g., random caching and recent-used-file caching scheme.

Keywords: Cellular network · Content caching · D2D
Social property

1 Introduction

With the proliferation of smartphones and other derivative intelligent equipments, the network traffic has witnessed a trend of explosive growth. It is expected to increase by 40 fold over the next five years [1], due to mobile video stream and social network traffic. This increasing need for high rate transmission and low-cost power has impelled mobile operators to redesign and find more efficient techniques to meet the increase. In this respect, device-to-device (D2D) communication [2,3] has emerged as a promising technique to achieve high efficiency. User equipments can obtain data from other mobile devices or small base station rather than the cellular base station (BS) by employing D2D communications [4]. Although it is a promising technology for the next generation communication to meet unprecedented traffic demands, D2D has to overcome

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some challenges such as mutual interference and transmission distance limitation. However, most researches on D2D communications have focused on the physical layer. In fact, the social-aware networks among the D2D participators can be investigated to further increase the transmission rate.

Social network provides various platforms to users for the purpose of online content sharing with their friends, or searching someone who has common interests in the virtual network. Interestingly, the connection established in the virtual network actually is tightly associated with our offline life. For example, on campus our connected friends in Facebook, Twitter, Youtube, or Sina Blog, usually have a very close physical distance. The authors in [5] make a detailed summary and analysis to the features of social network and propose a social-aware D2D communication architecture. As shown in [5], the social network characteristics consist of ties, community, centrality and bridge. Moreover, eigenvector centrality, closeness centrality and betweenness centrality are commonly used in the identification of social importance. In [6], the authors present a novel approach utilizing eigenvector centrality to judge the relationship in social network. Recently, social network has been proposed to combine with the caching mechanism [7,8]. In [9], the placement of popular content is proposed considering the importance of nodes in social layer. However, how to efficiently match the contents with users remains a challenge.

Matching theory is an effective method for solving the combinatorial problem of matching players in two distinct sets. In [10], the classic classification of matching problem includes one to one matching, many to one matching and many to many matching. Specially, the many to one matching game is utilized in resources allocation, where two players have different preferences towards network resources [11]. Additionally, many to many has been widely applied to the resource and spectrum allocation in wireless network [12].

In this paper, we are inspired to research on the social-aware content allocation in wireless cellular networks (CN) using matching algorithm. Popular contents and important nodes (INs) are modeled as two sides of the matching game. To this end, we model the content allocation problem as a matching game. Our main contributions can be summarized as follows:

1. We present an framework of INs selecting where three social characteristics are considered.
2. We propose a many to one matching game to solve the content allocation problem. In this game, the two sides of players establish their preferences towards each other considering content popularity, social connection features, and the wireless physical layer metrics.
3. The stability of the proposed matching algorithm is proved. Simulation is carried out to evaluate the performance of the proposed algorithm.

The rest of this paper is organized as follows. In Sect. 2, we describe the system model in detail and present the content allocation problem. In Sect. 3, we propose the many to one matching framework. In addition, we design a novel matching algorithm and prove that the algorithm is stable. Simulation results are shown in Sect. 4, the performance of the proposed method is analysed. Finally, we draw the conclusions in Sect. 5.

2 System Model and Problem Formulation

We focus our attention on a cellular network consisting of one BS and an amount of mobile users randomly located in the cellular area. Mobile users would like to acquire some interested files that belong to content providers, such as YouTube and Youku. A sample model of combination of social network and D2D communication is shown in Fig. 1. Such a system can be divided into two layers: the physical layer and social layer and each node in social layer can be projected onto a real user equipment in physical layer. In the social layer, the virtual connections between social users can reflect their offline activities [13]. Thus, we can infer the close degree of user's relationship by observing their behaviors in social network platform. Besides, in the physical layer, users can access to the cellular network or establish D2D connection to obtain required files. Taking the social characteristics of D2D communication pairs into account, we can select INs for caching popular files. For example, in physical layer of Fig. 1, if V_6 and V_9 are active in social layer, the popular files can be downloaded within their storage capacity for disseminating to their linked users. The problem of how to select INs will be introduced in the following. However, there exists some difference between social layer and physical layer. For example, node V_6 has social link with node V_8, but in physical layer the D2D link does not exist between them due to the faraway distance. Also, In physical layer, V_1 and V_3 have close distance, but they don't have a social link.

In this paper, we construct the network model considering both the social layer and physical layer [14]. If the D2D link and social link exist simultaneously between two users, we say that the two users are connected, which means that if the connection exists, the connecting users are not only within the transmission range but also have certain social relationship. We denote the set of M user equipments by $\mathcal{V} = \{V_1, \cdots, V_m, \cdots, V_M\}$, where V_m, $m \in \{1, 2, 3, \cdots, M\}$ represents the mth user equipment. Moreover, the set of INs is $\mathcal{M}_c = \{1, 2, \cdots, m_c\}$, which is chosen by BS for sake of proactive caching within their storage. The set of $\mathcal{M}_d = \{1, 2, \cdots, m_d\}$ represents the general users. In addition, $\mathcal{F} = \{f_1, f_2, \cdots, f_L\}$ denotes requesting file set controlled by content provider.

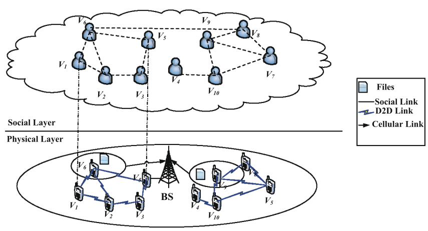

Fig. 1. A detailed description of combination of social network and D2D communication.

2.1 System Description

We suppose that the probability of content requests p_q obeys the Zipf distribution

$$p_q = \frac{1/q^{\alpha}}{\sum_{i=1}^{L} 1/i^{\alpha}}, \quad \text{for} \quad q = 1, \cdots, L \tag{1}$$

where α characterizes the skewness of the distribution, reflecting different content popularity. However, generally speaking, people usually have different preference towards files. Thus, The content popularity matrix for all users is given by $\mathbf{P} \in R^{M \times L}$ where each entry P_{m,f_i} represents the probability that the mth user requests the ith file f_i. The relation between $P_{m,i}$ and p_q is illustrated in [15] in detail.

Here, we use $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ to denote a social relationship graph, in which $\mathcal{V} = \mathcal{M}_c \cup \mathcal{M}_d$ represents the set of all nodes and $\mathcal{E}$ is the set of edges connecting $\mathcal{M}_c$ and $\mathcal{M}_d$. Adjacent nodes (m_c, m_d) are connected by a bidirectional edge $e(m_c, m_d) \in \mathcal{E}$, where $m_c \in \mathcal{M}_c$ and $m_d \in \mathcal{M}_d$. For simplicity, $e(m_c, m_d) = 1$ represents the connection between m_c and m_d, while $e(m_c, m_d) = 0$ represents the disconnection.

We suppose that a dedicated frequency band of bandwidth W is allocated to the downlink channels. The wireless channels with path-loss is considered here. For the purpose of offloading data from BS, we assume that each user will firstly try to download data from its connected INs. If a user cannot find its requested files from INs, it will then turn to BS for help. The cellular BS contains the whole content library and can serve all user terminals in the system. Moreover, the channels of D2D connection and cellular connection is assumed to be orthogonal in the frequency domain.

In general, BS is far away from the mobile users. Therefore, the download rate supported by the base station is generally lower than that supported by the D2D link. It will not only encourage the users to download from the D2D transmission first, but also effectively reduce the data traffic of BS imposed by files downloading. In addition, general users can only communication with INs that the connection exists between them.

According to the CN model, the transmission rates of directly cellular network and D2D connections can be expressed as

$$R_{b,V_m} = W \log_2 \left(1 + \frac{P_{b,V_m} G_{b,V_m}^2}{\sigma^2} \right), \tag{2}$$

and

$$R_{m_c,m_d} = W \log_2 \left(1 + \frac{P_{m_c,m_d} G_{m_c,m_d}^2}{\sum_{m'_d \in \mathcal{M}_d} P_{m_c,m'_d} G_{m_c,m'_d}^2 + \sigma^2} \right), \tag{3}$$

respectively [9], where P_{m_c,m_d}, and P_{b,V_m} denote the transmission powers by the m_cth IN and BS, respectively. G_{m_c,m_d} is the D2D channel gain and G_{b,V_m} is BS's the channel gain, and σ^2 is the noise variance.

2.2 Social Importance Analysis

Taking social importance and battery capacity into account, to choose the INs, we define the following importance measurement matrix $\mathbf{X}$

$$\mathbf{X} = \mu\mathbf{B} + \nu\mathbf{S} + \upsilon\mathbf{C}, \tag{4}$$

where $\mathbf{B} = \{b_{j,k}\}$, $\mathbf{S} = \{s_{j,k}\}$, and $\mathbf{C}$ denote the matrices of betweenness centrality, similarity, and battery capacity, respectively, and μ, ν and υ are adjustable parameters with constraint $\mu + \nu + \upsilon = 1$. $b_{j,k}$ is the edge betweenness of the link between nodes j and k, and $s_{j,k}$ is the degree of similarity between j and k. Betweenness centrality is one commonly used way to measure the nodes centrality property. The betweenness centrality of node i can be calculated as

$$b_{j,k} = \sum_{j,k\in\mathcal{V}} \frac{d_{jk}(i)}{d_{jk}}, \tag{5}$$

according to [16]. In this equation above, d_{jk} is the number of shortest distance paths of connecting from node j to node k, and $d_{jk}(i)$ is the number of geodesic paths including node i. In order to facilitate the calculation, a normalized element (j, k) of matrix $\mathbf{B}$ is as follows

$$B(j,k) = \frac{b_{j,k}}{(M-1)^2}. \tag{6}$$

Similarity Matrix: in [9], for a pair of nodes, (j, k), their similarity matrix is defined as

$$s_{j,k} = \begin{cases} \sum_{z\in M(j)\cap M(k)} \frac{1}{k(z)} & \text{if } j \text{ is connected with } k, \\ 0 & \text{otherwise,} \end{cases} \tag{7}$$

where $M(j)$ is the set of neighbors of j, $z \in M(j) \cap M(k)$ denotes the set of the common neighbors between node j and k. $k(z)$ is the number of nodes connected with z. Similarly, in order to facilitate the calculation, the simple additive weighting (SAW) method is considered. Also, the normalized entries of $\mathbf{S}$ are

$$S(j,k) = \frac{s_{j,k}}{\max s_j}, \tag{8}$$

where s_j denotes the jth row of $\mathbf{S}$. In the Eq. (4), because of the adjustability of parameters, we formulate a constraint on the value as shown below

$$\sum_{n=1}^{h} R_{m,n} \geq \gamma, \tag{9}$$

where $n \in \mathbf{\Theta} \triangleq \{1, 2, \cdots, h\}$ denotes the nodes connected with node m, and γ represents the predefined minimum sum-rate threshold according to network performance. In this case, if the node m is selected as IN, it transmission should meet the limitation.

Through analysis and calculation of the centrality of all nodes, we sort the element of $\mathbf{X}$ in a descending order and then choose top $|\mathcal{M}_c|$ as INs. A number of vital users in our cellular network are selected. Thus, these nodes can be exploited for proactive caching. We will elaborate on the problem of content allocation to the INs and will focus on this issue in the next subsection.

2.3 Problem Formulation

To formulate the allocation problem between files and INs, we set up a file distribution matrix $\mathbf{A}^{|\mathcal{M}_c|\times L}$, where L is the total number of files cached. The entry $\lambda_{m_c,f_i} \in \{0,1\}$ in $\mathbf{A}^{|\mathcal{M}_c|\times L}$ indicates whether f_i is cached by the m_cth IN or not as follows

$$\lambda_{m_c,f_i} = \begin{cases} 1, & \text{if } f_i \text{ is cached by } m_c\text{th IN}, \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

In the CN, the strategy of D2D users is selecting caching files for sake of minimizing the transmission delay by optimizing the matrix $\mathbf{A}^{|\mathcal{M}_c|\times L}$. According to the consideration, the delay of downloading the file f_i by user n can be calculated as

$$T_{n,f_i} = \begin{cases} \frac{Y}{\max_{\{R_{m_c,n}\}}}, & \exists\lambda_{m_c,f_i} \neq 0,\, e(m_c,n)=1, \\ \infty, & \exists\lambda_{m_c,f_i} \neq 0,\, e(m_c,n)=0, \\ \frac{Y}{R_{b,n}}, & \text{otherwise,} \end{cases} \tag{11}$$

where Y denotes the size of the requested file f_i. In this case, If general users request the INs that have no connection between them, we suggest that the delay is infinite. Based on the request probability of each file, the delay for user n to download a file from $\mathcal{F}$ can be written as

$$T_n = P_{n,f_i} \cdot T_{n,f_i} \quad \text{for } f_i \in \mathcal{F}, \tag{12}$$

where $f_i \in \mathcal{F}$ and $P_{n,f_i} \in \mathbf{P}$. Thus, the content allocation strategy can be solved by the following optimization problem

$$\begin{aligned} &\min_{A} \sum_{n\in\mathcal{M}_d} \sum_{m_c\in\mathcal{M}_c} \sum_{i=1}^{L} \lambda_{m_c,f_i} T_n, \\ \text{s.t.}\quad & ① \sum_{i=1}^{L} \lambda_{m_c,f_i} \leq 1, \quad m_c \in \mathcal{M}_c, \\ & ② \ \lambda_{m_c,f_i} \in \{0,1\}, \\ & ③ \sum_{m_c=1}^{|\mathcal{M}_c|} \lambda_{m_c,f_i} \leq Q, \quad f_i \in \mathcal{F}. \end{aligned} \tag{13}$$

In the above optimization, constraint ① states that a maximum number 1 of files can be matched for an IN, and condition ② guarantees that λ_{m_c,f_i} is a binary variable. Also, condition ③ denotes a maximum number Q of nodes that can be selected for caching by file f_i. The optimization problem (13) is a NP-hard combinatorial binary optimization problem [17]. However, since (13) contains only one binary variable, it can be modeled as a matching problem. Thus, in the next section, we propose a matching algorithm to solve the optimization problem.

3 Matching Algorithm

Caching files in INs can make other users to require files directly from the caching nodes rather than from the cellular network. In this section, we propose a novel content allocation method of utilizing matching game in allocating files.

3.1 Matching Related Definitions

We first introduce some notations to facilitate the solving process. There are two non-intersect sets of participants: $\mathcal{M} = \{\mathcal{M}_i\}_{i=1}^{I}$ and $F = \{F_j\}_{j=1}^{J}$. Here $\succ_{\mathcal{M}} = \{\succ_{\mathcal{M}_i}\}$ and $\succ_F = \{\succ_{F_j}\}$ denote, respectively, the set of preference relations of two players.

Definition 1. *A matching relationship Φ is defined as a function from the set $\mathcal{M} \cup \mathcal{F}$ based on the preference list.*

Let $V_m(\cdot)$ and $U_f(\cdot)$ denote the utility function of user m and pre-cached file f, respectively. Given these utilities, we can get the following instructions

$$V_m(f_i) > V_m(f_j) \Leftrightarrow f_i \succ_m f_j, \tag{14}$$

Above shows that a user m prefers file f_i to f_j. Similarly, a pre-cached file f prefers user m_i to m_j can be expressed as

$$U_f(m_i) > U_f(m_j) \Leftrightarrow m_i \succ_f m_j. \tag{15}$$

Consequently, we denote this matching function Φ:$(\mathcal{M}_c, \mathcal{F}, Q)$, where $(\mathcal{M}_c, \mathcal{F})$ is the set of matching pairs and Q denotes the maximum number of INs that per file can be cached in.

3.2 Proposed Matching Algorithms

User-file caching (UFC) problem is further comprised of two types of game players including D2D users and files regulated by BS. The matching problem that we elaborate on is a many-to-one game. Based on the above definition, in the system model, limited by the storage capacity of mobile users, an IN can save only one file set but one file can be stored many times at INs of D2D links.

The strategy of both D2D users and BS is to maximize their respective profits in matching algorithm based on the preference over opposite sets. On the other hand, BS makes its content allocation decision based on its local information without relying on a central coordination. So the UFC matching algorithm attend to solve the optimization problem in (13). To design the algorithm, we first design an algorithm for allocating files for one BS. Denote by $\mathcal{H}_{m_c} = \{H_{m1}, H_{m2}, \cdots, H_{mh}\}$ the index set of nodes connected with IN m_c.

Based on this consideration, D2D utility function over the file f_i is defined as

$$V_{m_c}(f_i) = \frac{1}{|\mathcal{H}_{m_c}|} \sum_{n \in \mathcal{H}_{m_c}} P_{n,f_i}, \tag{16}$$

where P_{n,f_i} represents the connected node n's preference degree to the file f_i and the above equation illustrates that the INs' preference over files is ranked based on the degree of content popularity. Furthermore, the favourite file can be obtained by sorting the utility function in a descending order. Similarly, the utility for file $f_i \in \mathcal{F}$ to be matched with the m_cth IN can be written as

$$U_{f_i}(m_c) = \frac{1}{|\mathcal{H}_{m_c}|} \sum_{n \in \mathcal{H}_{m_c}} P_{n,f_i} T_{n,f_i}. \tag{17}$$

The utility function over D2D users is affected by the average transmission delay and social network structure. Besides, by sorting the utility function in a ascending order, we can obtain the preference list.

The matching problem proposed in this paper is not a traditional matching game, since the preference lists of files and INs depend not solely on the information available locally but on the character of social-layer architecture. Our proposed matching problem exhibits externality such as peer effects, which means that the users and files may change their preferences during the game, due to the constantly updated social relationship among users. Nevertheless, traditional matching game algorithm may not be able to converge to a stable matching, especially when the game has peer effects [3]. Therefore, we need to develop a new algorithm to find a stable solution of this problem in this paper.

Let $\mathbb{A}(\mathcal{M}_c, \mathcal{F})$ denotes the set of ultimate matching pairs, and $\eta(m, f)$ denotes the subset of $\mathbb{A}(\mathcal{M}_c, \mathcal{F})$, where (m, f) are matched. Thus, the concept of blocking pair and stability is introduced as follows.

Definition 2. *A matching $\eta^*(m, f') \nsubseteq \mathbb{A}(\mathcal{M}_c, \mathcal{F})$, but comparing with the matching pair $\eta(m, f)$, there exists relation that $\eta^* \succ_m \eta$, that it to say, the current matching does not maximize the utility. We define this matching pair $\eta^*(m, f')$ as the blocking pair. If and only if there is no blocking pair, the proposed matching algorithm is stable.*

The UFC matching algorithm considers one BS, and is the solution to the problem in (13). The algorithm is displayed in Table 1. In the following, we describe the process of the algorithm briefly. The preferences are calculated by INs and files, respectively. Then, INs make proposals to the most prefer files, and in turn, the content provider's files decide to accept or reject these proposals based on their preference lists. For a particular user, if it requests for the top of file f_i within the set $\mathcal{F}$, the file f_i updates its utility and accepts the request if the action do not yield a degradation of its utility.

Table 1. Proposed UFC matching algorithm

Algorithm 1 :

Input: **B**, **S**, **C**, **X**, Q;
Output: $\mathbb{A}(\mathcal{M}_c, \mathcal{F})$;
Steps:

1: **for** $q = 1$ to L **do**
2: $\quad p_q = \frac{1/q^{\alpha}}{\sum_{i=1}^{L} 1/i^{\alpha}}$;
3: $\quad P_{m,f_i}$;
4: **end for**
5: Calculate the $V_{m_c}(\cdot)$ based on the equation (16);
6: $V_{m_c}(\cdot)$ are sorted in descending way;
7: Set all INs request the most preference file and create request matrix R;
8: Then, the requested file make decision to choose the optimal $U_{f_i}(\cdot)$ based on the equation (17);
9: **while** quota<Q **do**
10: The most popular file is cached by the optimal IN, and quota=quota+1. In addition, $U_{f_i}(m_c)$ of remove the selected IN is set 0;
11: Return step 7;
12: **end while**
13: **if** quota==Q **do**
14: Select the second most popular and repeat the step 8;
15: **end if**
16: Then according to the next popular ranking, the files are allocated to their prefer INs;
17: Obtain the optimal matching pairs;

We prove the stability of the algorithm proposed in Table 1. Here, we merely discuss the situation in a stable community, which means all the nodes may not readily add or remove any connections established between them. This condition guarantees that the peer effects cannot make any change in community. Observing from our algorithm, the preference is strictly monotone and subjects to (13). In this case, the blocking pairs can not exist because all the players select their matching pairs based on the preference. Moreover, the number of storage is finite and our matching pair selecting method always adheres to the utility maximum principle. Accordingly, under the situation of a stable community, our proposed algorithm is stable.

4 Simulation Results

In this section, we study a wireless network consisting of one BS. This BS is designed as a regulator with 300 meters coverage. And in this range, $M = 20$

and user equipments are randomly distributed in the community. The relationship among them considers both the social online connections and their off-line physical locations.

In this simulation, we set the path-loss exponent $\beta = 4$, noise power $\sigma^2 = 10^{-10}$ and transmission power of BS $P_{b,V_m} = 20$W and D2D transmission power $P_{m_c,m_d} = 2$W. In addition, we assume that there are $L = 10$ files and the distance between equipments and BS is randomly generated within a certain range, besides, $Q = 2$, the tunable variables μ, v and ν are set to $1/3$.

In this simulation, we compare the proposed UFC matching algorithm with random file allocation (randomly choosing files), RUC (caching most recent used files) [18], and no caching algorithms. In the random allocation algorithm, we assign the files randomly to the INs. In the RUC algorithm, the recently used files are allocated to the INs. Figure 2 shows the average download delay for different caching strategies varying with the number of INs. It can be seen that as the INs number increases, all the three algorithms employing caching mechanism show a declining trend. While the download delay of no caching algorithm is fixed at 15 units, due to the reason that no caching method acquires files only through the BS. However, it is clear that the proposed UFC algorithm yields significant performance improvements compared with other methods.

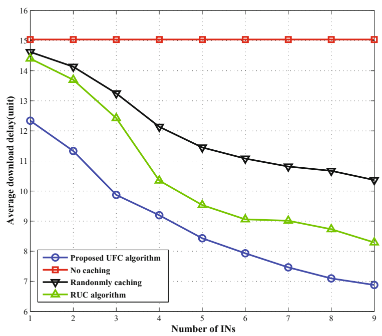

Fig. 2. Average download delay vs. the number of INs

In the file allocation stage, it is critical to choose the INs. Figure 3 depicts the differences between the proposed algorithm and the random file allocation algorithm. As we expected, the proposed algorithm taking the social importance into consideration can bring prominent improvement than the random file allocation algorithm. It can be seen from Fig. 3, when the number of INs is 6, the proposed algorithm's average transmission delay is 8.47 units, while the random file allocation algorithm is 9.24 units.

Figure 4 illustrates that the quota value has a great impact on the transmission delay. We set the quotas to be 1 and 2, respectively. It inspires us that we need to make full use of the storage space of user equipments for the purpose of gaining low transmission delay.

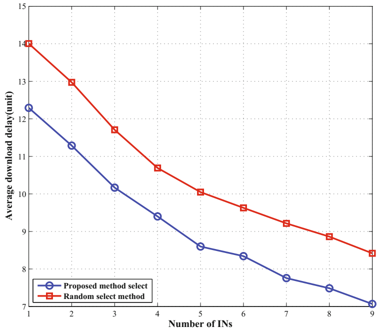

Fig. 3. Average download delay vs. different selecting method of INs

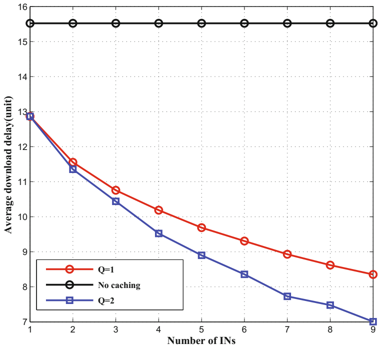

Fig. 4. Average download delay vs. different matching games

5 Conclusion

In this paper, we design a novel distributed caching optimization algorithm to solve the cache allocation problem in D2D underlaid cellular networks. We formulate a many to one matching game combining the social relationship with physical locations in order to minimize the average transmission delay. To solve the D2D transmission problem, we propose a UFC matching algorithm. Also, we prove the stability of the proposed algorithm. At last, the simulation results are provided to demonstrate the validity of this algorithm that considering the social importance can greatly reduce the transmission delay. Furthermore, increasing the quota of files can also reduce the transmission delay.

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References

1. Cisco: Cisco visual networking index: global mobile data traffic forecast update, 2013–2018. http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white_paper_c11-520862.pdf
2. Doppler, K., Rinne, M., Wijting, C., Ribeiro, C.B., Hugl, K.: Device-to-device communication as an underlay to lte-advanced networks. IEEE Commun. Mag. **47**, 42–49 (2009)
3. Hakola, S., Chen, T., Lehtomaki, J., Koskela, T.: Device-to-device communication in cellular network - performance analysis of optimum and practical communication mode selection. In: 2010 IEEE Wireless Communication and Networking Conference, pp. 1–6 (2010)
4. Zhang, H., Liu, H., Jiang, C., Chu, X., Nallanathan, A., Wen, X.: A practical semidynamic clustering scheme using affinity propagation in cooperative picocells. IEEE Trans. Veh. Technol. **64**(9), 4372–4377 (2015)
5. Li, Y., Wu, T., Hui, P., Jin, D., Chen, S.: Social-aware D2D communications: qualitative insights and quantitative analysis. IEEE Commun. Mag. **52**(6), 150–158 (2014)
6. Hu, J., Yang, L.L., Poor, H.V., Hanzo, L.: Bridging the social and wireless networking divide: Information dissemination in integrated cellular and opportunistic networks. IEEE Access **3**, 1809–1848 (2015)
7. Shanmugam, K., Golrezaei, N., Dimakis, A.G., Molisch, A.F., Caire, G.: Femtocaching: wireless content delivery through distributed caching helpers. IEEE Trans. Inf. Theory **59**(12), 8402–8413 (2013)
8. Li, J., Chen, Y., Lin, Z., Chen, W., Vucetic, B., Hanzo, L.: Distributed caching for data dissemination in the downlink of heterogeneous networks. IEEE Trans. Commun. **63**(10), 3553–3568 (2015)
9. Ma, C., Lin, Z., Marini, L., Li, J., Vucetic, B.: Learning automaton based distributed caching for mobile social networks. In: 2016 IEEE Wireless Communications and Networking Conference, pp. 1–6 (2016)
10. Gu, Y., Saad, W., Bennis, M., Debbah, M., Han, Z.: Matching theory for future wireless networks: fundamentals and applications. IEEE Commun. Mag. **53**(5), 52–59 (2015)
11. Semiari, O., Saad, W., Valentin, S., Bennis, M., Poor, H.V.: Context-aware small cell networks: how social metrics improve wireless resource allocation. IEEE Trans. Wireless Commun. **14**(11), 5927–5940 (2015)
12. Jiang, L., Cai, H., Chen, Y., Zhang, J., Li, B.: Many-to-many matching for combinatorial spectrum trading. In: 2016 IEEE International Conference on Communications (ICC), pp. 1–6 (2016)
13. Boyd, D.M., Ellison, N.B.: Social network sites: definition, history, and scholarship. IEEE Eng. Manage. Rev. **38**, 16–31 (2010). Third
14. Wang, L., Wu, H., Wang, W., Chen, K.C.: Socially enabled wireless networks: resource allocation via bipartite graph matching. IEEE Commun. Mag. **53**, 128–135 (2015)

15. Chang, Z., Gu, Y., Han, Z., Chen, X., Ristaniemi, T.: Context-aware data caching for 5G heterogeneous small cells networks. In: 2016 IEEE International Conference on Communications (ICC), pp. 1–6 (2016)
16. Ashraf, M.I., Bennis, M., Saad, W., Katz, M.: Exploring social networks for optimized user association in wireless small cell networks with device-to-device communications. In: 2014 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), pp. 224–229 (2014)
17. Gale, D.: College admissions and the stability of marriage. Am. Math. Mon. **69**(1), 9–15 (1962)
18. Gu, J., Wang, W., Huang, A., Shan, H., Zhang, Z.: Distributed cache replacement for caching-enable base stations in cellular networks. In: 2014 IEEE International Conference on Communications (ICC), pp. 2648–2653, June 2014