Cache Resource Allocation in D2D Multi-layer Social Network

Xianglin Kong[1], Pingping Chen[1], Zhijian Lin[1](✉), Ying Wang[1], and Yongcheng Yang[2]

[1] Fuzhou University, Fuzhou 350116, Fujian Province, China
zlin@fzu.edu.cn
[2] Jimei University, Xiamen 361000, Fujian Province, China

Abstract. In cache-enabled device-to-device (D2D) cellular networks, efficient utilization of mobile terminal cache storage reduces peak traffic demands and has a substantial impact on network performance. The combined impact of centrality value and cache memory size of user equipment (UE) are two crucial factors in D2D network, which are ignored in the existing researches. In this paper, an optimization algorithm is proposed to calculate the value of effect centrality (EC) to maximize the cache storage utilization considering various locations and preference of UEs. Firstly, users are clustered according to location, and users in the cluster form a multi-layer social network according to the preference of the requested content. Then based on the user's location, the effect centrality value is calculated, and the general mathematical expressions for the optimization of cache storage utilization with the constraints of effect centrality value and total cache storage is obtained. Subsequently, a Cache Storage Allocation (CSA) algorithm is proposed to obtain the cache storage utilization by taking the value of effect centrality as a variable. Simulation results show that the size of the effect centrality value will affect the utilization of the user's cache storage. Compared with the other two traditional methods, the proposed CSA can achieve the highest cache storage utilization.

Keywords: Cache storage · Centrality value · D2D · Social-aware · Edge caching

1 Introduction

With the widespread popularity of smart devices, a large number of emerging multimedia services are also booming. And services small video, live broadcast and other services meet most of the needs of mobile users for learning and entertainment. It is estimated that by 2020, a person will need more than 5 million years to watch the amount of video flowing through the global IP network every month [1]. Users have higher and higher requirements for video quality. At present, in the personal video on demand traffic, the percentage of ultra high definition (UDP) to IP video on demand (VOD) will rise from 1.6% in 2015 to 20.7%. The traditional wireless network architecture has great limitations, with the development of the times, it has been insufficient to meet the user's requirements for low latency and high reliability. With

B. Li et al. (Eds.): IoTaaS 2020, LNICST 346, pp. 207–221, 2021.
https://doi.org/10.1007/978-3-030-67514-1_17

the maturing 4G standardization, technological research on 5G network is underway in both academia and the industrial community [2].

One method proposed by the researchers is to improve the coding and communication technologies related to the transmission of information [3], in order to save wireless resources in a coding manner for communication. In this way, the utilization of wireless resources has been improved, but it still cannot meet the rapidly increasing demand for wireless traffic in the future. One promising technology adopted by the fifth-generation cellular network is edge caching. Cache files that users may request to the edge of the network, when users request files, they can be obtained directly without going through the server, saving a lot of network resources [4]. Perino D et al. studied the system evaluation of the applicability of existing routers for network-supported caching [5]. Popular content is cached in the router, when the user requests the file, the file can be directly obtained from the router, which can save the backhaul link. In practice, caching content in routers requires a lot of cost. A router with flash memory capacity and a cache space of 10 TB will cost $ 300,000. and the power of the router is also very large. Cooperative caching in D2D networks is an effective solution to the problem of expensive hardware [6]. Cooperative caching network is a promising technology that can meet the rapidly growing demand for mobile data traffic.

D2D communication allows neighboring devices to communicate directly with each other, and smart caching strategies need to be developed in mobile cellular networks[7–9], thereby promoting proximity services with high-speed requirements, so that data can be provided through nearby content Providers visit, which can help improve resource utilization and network capacity, for example, content sharing and distribution. In [10], D2D communication is regarded as a major technology to overcome the upcoming shortage of wireless capacity and achieve novel application services, jointly considering the attributes of the physical layer and the social layer, and constructing the content of the user's online social network according to the Indian Buffet Process. In [11], the author studied the problem of data offload in cache-enabled network, based on the machine learning framework, a novel algorithm for predicting file caching was proposed to solve the problem of active caching in the network. In [12], C. Yen et al. Studied the problem of collaborative caching in ultra-dense cellular networks, where the limited cache space is considered, predicting the popularity of unknown content. In [13], the author proposed a novel method of calculating the centrality value to reflect the importance of the node, and then based on the centrality value, a cache space allocation scheme was proposed, the allocated cache space size was proportional to the centrality value. In a cache-enabled network, how to use the effective cache space of the user terminal more efficiently is called one of the main challenges of whether the caching network is feasible in the future.

In a community, we can use the centrality attribute to select the user node to cache the content. The centrality of a node indicates how close a node is to other nodes in the network, and also indicates the importance of the node in the network. In [14], Z. C. Song et al. proposes a new measure of centrality based on the topology of the path of information transmission between nodes in the network, called "load centrality", because it focuses on the load the nodes bear in the network. The authors briefly reviewed the complex network concept and concentration. Four widely used measures of centrality, the degree centrality, the closeness centrality, the betweenness centrality, and information centrality, are introduced [15], K. Zhang et al. studied the calculation method of closeness centrality in complex networks, which is expressed by the total reciprocal of the sum of the path distances from a certain node to other nodes in the network. In [16], the author proposed the concept of K-hop centrality to represent the importance of nodes in a multi-hop D2D network. It can be calculated locally by adjusting the maximum multi-hop K value in the network, thereby reducing the complexity greatly increases the feasibility. In the pioneer work, many researches are based on the four measures of centrality earlier, David A. Bader [17] proposed a parallel algorithm for network centrality measurement, which is optimized for scale-free sparse graphs.

Recently, the measurement method of centrality of multi-layer social networks means that users form multiple social layer networks according to different request preferences, and the user node preferences in the same social layer are highly the same. In this work, a new metric named EC is defined to reflect the importance of the node. Then the caching performance of multi-layer social network has been carried out with consideration on the size of individual mobile user terminal. Finally, the cache storage quota allocated to user terminal is further optimized based on CSA algorithm, rather than proportional to the centrality value.

Based on the weights between nodes, we proposes an EC for D2D multi-layer social networks. With this EC, the centrality of each node in a multi-layer social network can be measured. Next, we propose a CSA based on the EC value. This is a fundamental outlook of our proposed methodology, which we will further discuss in Sect. 3. In order to verify the proposed method, we simulate it in a multi-layer social network and compared the performance with other two commonly used cache storage allocation methods.

The rest of this paper is organized as follows: Sect. 2 presents the definition of EC. In Sect. 3, we analyses the EC and applied CSA algorithm to allocate cache space. In Sect. 4, the evaluation results are provided. We conclude the paper with future work in Sect. 5.

2 System Model

2.1 Social Layer Model

In recent years, the social attributes of users in the network have attracted extensive attention from researchers in various fields [18, 19]. D2D social network refers to the social network established by users of terminal devices with different social attributes based on supporting D2D communication. In the world, all mobile devices are related to each other in many ways. Users with similar request preferences constitute the same layer of social network, and the attributes of the social network are also constituted by the social attributes of the users. User nodes often have multiple social attributes, and multiple users establish communication at different social layers, called cross-layer social networks or multi-layer social networks. Simple social networks assume that users have only one social attribute, but for the real world, this assumption ignores a lot of valid information. Practically, social network presents different levels due to its sociability, such as layer of interests and hobbies. For instance, in a social network, common node interacts with others through sports program, comedy, technology channel and so on in a social network.

2.2 User Distribution Model

In this section, we first introduce two-tiered caching system illustrated in Fig. 1. As shown in the figure, the physical layer distribution and social network layer distribution of nodes are divided into two layers of social networks according to the social attributes between nodes. Red users belong to social-layer1, blue users belong to social-layer2, black users have two social attributes and belong to a common-layer. Nodes with the same social attributes can communicate with each other, while nodes with different social attributes cannot directly establish D2D links. The nodes that exist in common-layer are the black dots in the figure above, which are also the bridges between the two layers of social networks.

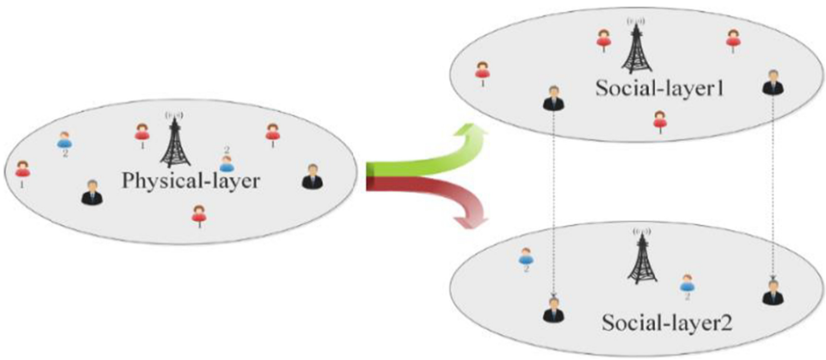

Fig. 1. Example of a multi-layer social network. Red users belong to social-layer1, blue users belong to social-layer2, and black users belong to common-layer at the same time. (Color figure online)

When requesting a file, the user first searches whether other users in the cluster have cached target files. If so, you can directly establish a D2D link between nodes for communication without going through the base station. If not, the user requests the target file from the base station.

2.3 Several Common Calculation Methods of Centrality

This section gives a simple review of the measures of centrality. In [14], four basic centrality calculation methods are introduced. The EC proposed in this paper is mainly combined with the shortest path-based measures of centrality, that is, closeness centrality and betweenness centrality, which will be briefly introduced next.

Closeness Centrality. Closeness centrality was originally proposed by Sabidussi [20] in 1996. The key factor affecting the data transmission volume and speed in the network system is the distance between the data provider and the data requester. Closeness centrality holds that the closer the nodes are, the faster they can reach other nodes.

$$C_i^C = \frac{N-1}{\sum\limits_{j \in N, j \neq i} d_{ij}}. \tag{1}$$

In this expression, $N-1$ represents the number of nodes other than itself in the network, and d represents the distance between two nodes. The closer the distance between the nodes, the greater the calculated centrality value.

Betweenness Centrality. The number of communication paths between any two nodes in the network passes through a certain node, which is expressed as the betweenness centrality value of the node. It emphasizes the importance of nodes when connecting other nodes [21]. The betweenness centrality of a node i can be defined as:

$$C_i^B = \frac{\sum\limits_{\substack{j,k \in N \\ j \neq k; j,k \neq i}} \frac{n_{jk}(i)}{n_{jk}}}{(N-1)(N-2)}. \tag{2}$$

The network assumes that the nodes communicate with each other along the shortest path. The centrality value of the nodes in the network is obtained by accumulating the number of paths through the changed nodes, and the value is divided by $(N-1)(N-2)$ to normalize the process to facilitate comparison of centrality values.

The commonly used measures of centrality in topology diagrams are directed or undirected, weighted or unweighted. However, the social network environment in this paper is D2D communication, which is different from the previous network topology. Under the same layer of network, two nodes are connected to each other, and the nodes of different layers communicate through common nodes. Combined with the characteristics of centrality measure, the EC is proposed in this paper. The EC value of a node is obtained by accumulating the value of closeness centrality between the nodes at the same layer and the betweenness value between nodes across layers. Details of which are shown in 3.1 of Sect. 3.

3 Cache Storage Allocation Based on the Value of Effect Centrality

In this section, we discussed the definition and detailed calculation steps of EC and CSA algorithm in multi-layer social networks.

3.1 Node Importance Metric: Effect Centrality

The EC measure of nodes gives the influential power of the points in a given network. If the centrality of a node is large, it indicates that the node can transmit information to other nodes along a closer path, and can be used more efficiently of the cache space. Social network presents different layers due to its sociability, such as stratification by interest [22]. In D2D communication network, the cache storage of mobile devices is limited. By combining the cache storage size, offline social relations, user interests and hobbies, etc., the size and type of cache contents can be determined by automatically calculating the utility index. In this paper, the social network is divided into different layers according to the types, and an important direction for calculating the nodes with the optimal influence in a given D2D communication network is provided. In this section, we first describe a cache problem in social-aware network. Then a new metric named EC is defined for measuring the value of node importance along the content delivery path by the request.

Now researchers have defined many methods to calculate the central value of a single-layer network based on information such as topology, but the centrality of computing nodes in multi-layer social networks has not been solved yet. In this article, A new centrality measurement method is presented. Compared with other centrality calculation methods, EC is more suitable for computing multi-layer social network scenarios. It is used to measure the importance of nodes in the network and is called “effect centrality”, which calculates the node’s closeness degree to other nodes in the multi-layer network, because this method takes into account the influence of same-layer nodes and cross-layer nodes.

Weight Value. In [23], when studying channel coding, it is assumed that in a block-fading channel, the fading gain during each symbol block in the codeword remains constant, while it remains a random variable on different blocks. In this paper, inspired by [23], the fading weight value between users is defined as a constant within the same fading gain range, a simulation environment is built under the coverage of a base station (BS), and D2D communication users are distributed under the coverage of a BS according to poisson point process (PPPs). Since D2D is a short-distance communication, the maximum communication distance of D2D users is set to be 30 m, and the adopted D2D path loss model is:

$$PL(dB) = 79 + 40\log(d) + 30\log(f_c). \tag{3}$$

In the above equation, d is the distance between D2D users, f_c is the carrier frequency of the system, which is set as the default value of 3.3GHZ in this paper.

As the distance between nodes increases, the path loss increases, but the weight value between nodes decreases. As shown in Fig. 2, U_1 and U_2 represent users. Calculate the loss value PL_{sum} from U_1 to the communication radius and divide it into 9 equal parts, denoted as PL_{ave}. The distance of each fading PL_{ave}, as shown in $R_1 \sim R_9$, which is correspondingly weighted from near to far 0.9 $\sim$ 0.1. For example, the node whose distance from U_1 is within R_1 has a weight of 0.9, the weight between U_1 and U_2 is 0.6.

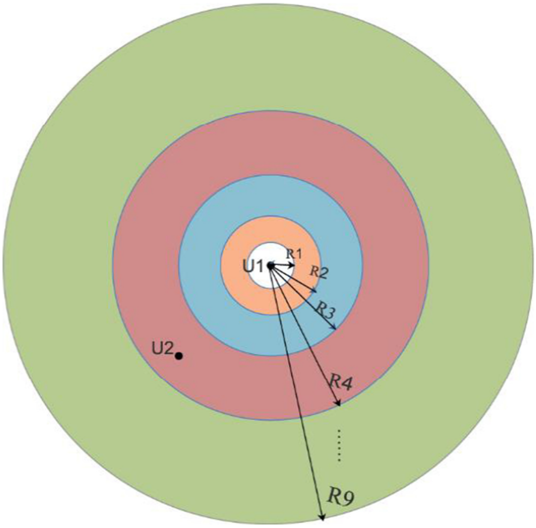

Fig. 2. Schematic diagram of defining weight values according to path loss.

Effect Centrality Algorithm. As far as we know a variety of algorithms have been proposed for finding out the centrality in a single layer social network, our work focused on calculating the centrality value in multi-layer network. The algorithm calculates the centrality level of nodes in D2D social networks. The general formula for closeness centrality is given as follow:

$$C_i^E = \sum_{\substack{j=1 \\ j \neq i}}^{n} W_{ij} \tag{4}$$

Where C_i^E is the EC of node i and $\sum_{\substack{j=1 \\ j \neq i}}^{n} W_{ij}$ is the sum of the weight between nodes. For a multi-layer social network in this paper, the formula is slightly changed.

In a D2D multi-layer social network, it is assumed that cross-layer nodes cannot communicate with each other directly, they are able to communicate with each other through common nodes. If node j and node i are not in the same layer, an optimal common node k is needed to be a relay between node j and i.

Algorithm 1 Pseudocode of effect centrality algorithm

Input: Coordinate matrix of nodes within the cluster, $N_1 \in layer1, N_2 \in layer2, N_3 \in common-layer$
Output: Value of effect centrality C_i^E

for each $i \in N_1$ **do**
  for each $j \in N_1$ **do**
    if $j \neq i$ **then**
      $d = \sqrt{(i_x - j_y)^2 + (i_y - j_y)^2}$
      $w = weight(d)$: (The weight value w is given by the defined weight function according to the distance d)
      $C_i^1 = C_i^1 + w$
    end if
  end for
  for each $j \in N_3$ **do**
      $d = \sqrt{(i_x - j_x)^2 + (i_y - j_y)^2}$
      $w = weight(d)$
      $C_i^3 = C_i^3 + w$
  end for
  for each $j \in N_2$ **do**
    for each $k \in N_3$ **do**
      calculate d_{ik} and d_{jk}, and get w_{ik} and w_{jk}
      $w_{ij}(k) = w_{ik} * w_{jk}$
    end for
    $w = \min [w_{ij}]$
    $C_i^2 = C_i^2 + w$
  end for
  $C_i^E = \frac{N_1}{N_1+N_2+N_3} * C_i^1 + \frac{N_2}{N_1+N_2+N_3} * C_i^2 + \frac{N_3}{N_1+N_2+N_3} * C_i^3$
end for
return C_i^E
Similarly, the centrality value of each node in other layers is calculated

The formulation for cross layer EC is given as:

$$C_i^E = \gamma \sum_{\substack{j \in N_1 \\ j \neq i}} W_{ij} + \beta \sum_{k \in N_3} W_{ik} + (1 - \gamma - \beta) \sum_{n \in N_2} W_{in}, \quad (5)$$

where C_i^E gives the cross-layer EC value of node i. W_{ij} is the weight of the node i to node j which belongs to social-layer1, W_{ik} is the weight of the node i to node k that belongs to common node, and W_{in} is the weight of the node i to node n that belongs to social-layer2. γ and β is a tuning parameter, which balances the importance of edge within the layer or across the layer. The formulas are as follows:

$$\gamma = \frac{N_1}{N_1 + N_2 + N_3}, \tag{6}$$

$$\beta = \frac{N_3}{N_1 + N_2 + N_3}, \tag{7}$$

$$1 - \gamma - \beta = \frac{N_2}{N_1 + N_2 + N_3}, \tag{8}$$

where N_1 is the number of nodes in the social-layer1, N_2 and N_3 represent the number of nodes in the social-layer2 and the common-layer, respectively.

Algorithm 1 gives the detailed calculation process of EC, which is mainly divided into two steps. First, calculate the weight value between nodes, and then calculate the EC value through the cumulative weight value.

3.2 Cache Storage Allocation Algorithm

In order to allocate users' cache storage more efficiently and reasonably, our goal is to maximize the cache storage utility function. Therefore, we first proposed the CSA algorithm of the basic water-filling algorithm, and then proposed the cache storage utility function of the D2D multi-layer social network, which represents the gain of the cache space used by the node to cache files to the system performance.

Cache Storage Value Function. The cache storage value indicates the system performance that the node can achieve. The optimal CSA that maximizes the cache storage utility function for a multi-layer social networks can be formulated as:

$$\max E_u = \sum_{n=1}^{N} \log(1 + \frac{s_n(c_n)^2}{N_0}), \tag{9}$$

$$s.t. \sum_{n=1}^{N} S_n = S_{sum},\ n = 1, 2, \ldots, N. \tag{10}$$

Where E_u represents the total cache storage value of the system, N represents the number of nodes that need to be allocated cache storage, S_n represents the cache storage allocated for the n_{th} node, C_n represents the EC value of the n_{th} node, N_0 represents the adjustment parameter, and S_{sum} represents the total cache storage requested by the system.

The optimization problem is a convex optimization problem, and the global optimal solution can be obtained by Lagrange multiplier method.

$$\zeta(\lambda, S_1, S_2, \ldots, S_N) = \sum_{n=1}^{N} \log(1 + \frac{S_n (C_n)^2}{N_0}) + \lambda(\sum_{n=1}^{N} S_n - S_{sum}), \tag{11}$$

if

$$\frac{\partial \zeta}{\partial S_n} = \frac{\partial \zeta}{\partial \lambda} = 0, \tag{12}$$

the optimal storage allocation scheme of the solution is:

$$S_n^* = (\frac{1}{\lambda} - \frac{N_0}{|C_n|^2}). \tag{13}$$

In terms of constraints $\sum_{n=1}^{N} S_n - S_{sum}$, we can get:

$$\lambda = \frac{N}{S_{sum} + \sum_{n=1}^{N} \frac{1}{C_n}}. \tag{14}$$

Then substitute the calculated value back into Eq. (13), the optimal cache storage allocation is:

$$S_n^* = (\frac{1}{\lambda} - \frac{N_0}{|C_n|^2})^+, \tag{15}$$

where $(\bullet)^+$ means non-negative.

We observe that the importance of nodes is measured by the EC value in the D2D multi-layer social network. Important nodes are allocated more cache space to achieve higher practical value of cache storage. Less data is sent through the cellular network, thus saving a lot of network communication resources.

4 Simulations

In this section, we provide some numerical results to verify our analysis and compare the performance with other two baselines, which are average allocation and equal proportion allocation. Parameter settings are described in Table 1.

Table 1. Default parameter setting

Parameters	Value
D2D communication range	30(m)
Base station transmission range:	200(m)
The density of node in social-layer1:	0.05
The density of node in social-layer2:	0.01
The density of node in common-layer:	0.005
The total cache storage:	0.1T/0.5T/1T/3T/10T

As shown in the Fig. 3, the social-layer1 nodes, social-layer2 and common-layer nodes, nodes are spatially distributed according to three mutually independent homogeneous PPPs with density λ_1, λ_2 and λ_3, respectively.

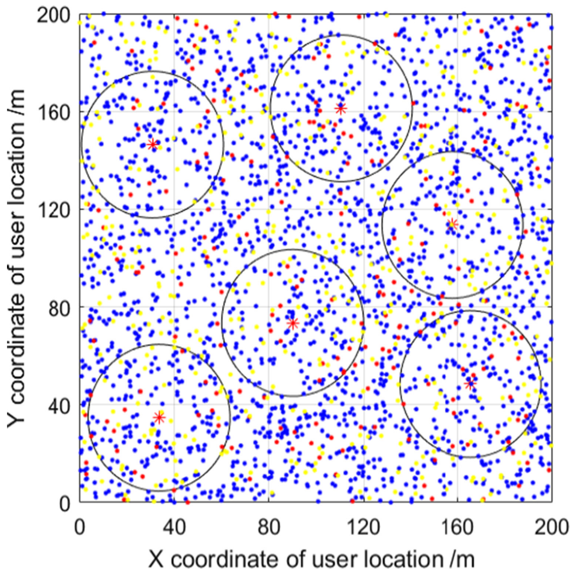

Fig. 3. Node distribution diagram. (Color figure online)

The points in Fig. 3 are the location of user's devices. There are three colored points, namely blue, red and yellow. The blue points represent the nodes in social-layer1, the yellow points represent the nodes in social-layer2, and the red points represent the common nodes in the system.

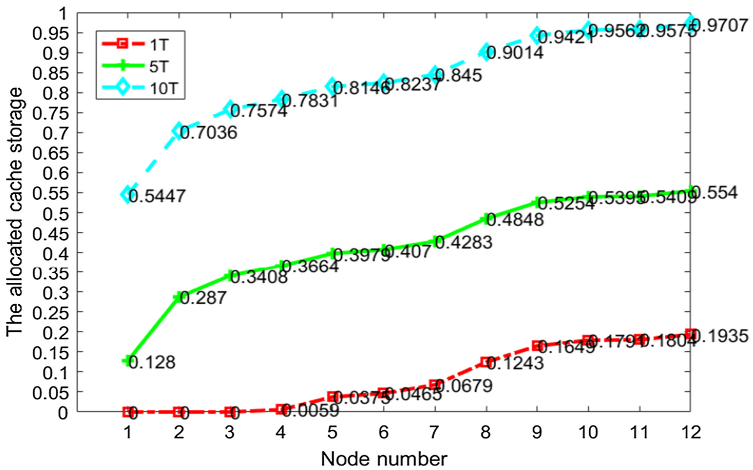

Fig. 4. The cache storage allocation results obtained by CSA algorithm. (Color figure online)

Figure 4 shows the CSA results using the CSA algorithm under different total cache spaces. The blue line at the top represents the total cache space of 10T. the green line represents the total cache storage of 5T, and the red line represents the total cache storage of 1T. Through the proposed allocation algorithm, each node is allocated according to the size of its EC value. The three curves show the same trend. The larger the EC value is, the larger allocated cache storage is, and vice versa.

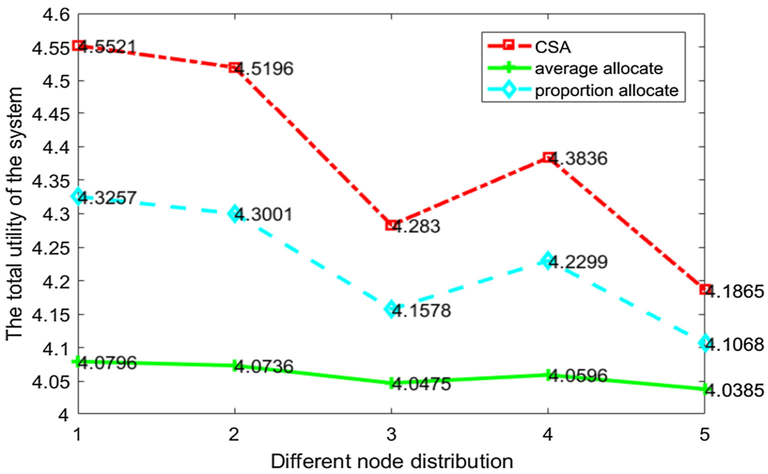

Fig. 5. Cache storage utility values obtained by three allocation algorithms. (Color figure online)

In this section, allocation algorithm numerical results are presented to verify our analysis and performance comparisons among the proposed allocation algorithm with average allocation and proportion allocation. As shown in Fig. 5, three curves represent the cache storage utility value obtained by different algorithms. The blue line represents the value allocated by CSA algorithm, the value on the red line in the middle represents the value allocated by proportion allocation, and the green line below represents the average allocation. The five points on each curve represent five different system node distributions. It can be seen from the figure that CSA algorithm outperforms two other existing methods. The cache storage utility value of CSA algorithm is about 11% higher than that of average allocation and 7% higher than that of proportional allocation.

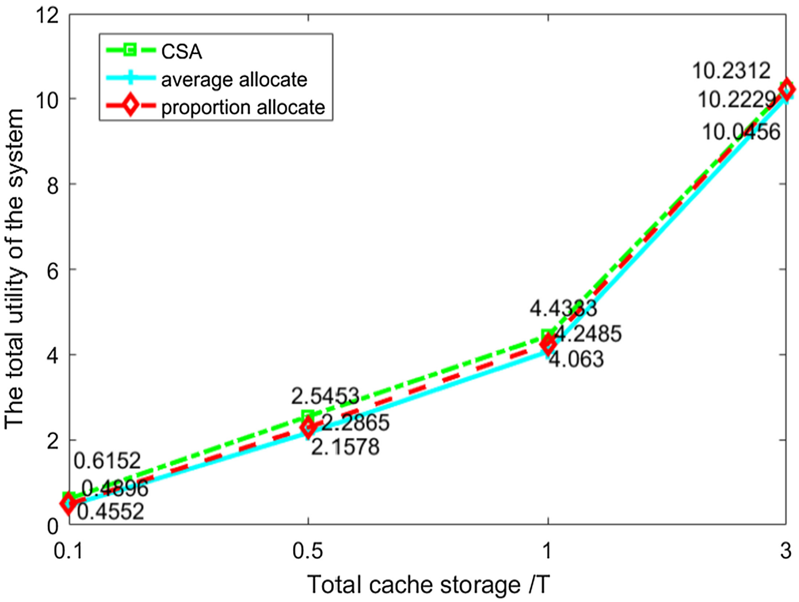

Fig. 6. Cache storage utility values for different total cache storage.

Figure 6 shows the performance implementation and comparisons of the proposed allocation algorithm. The graph shows the cache storage utility value function curves of the three allocation methods under the condition of the same user distribution and different total cache storage, the x-axis indicates that the total cache storage is 0.1T, 0.5T, 1T and 3T from left to right. In addition, we see that when the curve is at the positions of 0.1T and 3T, the cache storage utility value functions achieved by the three distribution methods are relatively close, while the curve is at the position of 0.5T and 1T, the three cache storage utility value are quite different. When the cache storage is moderate, our proposed algorithm achieved improved performance compared with the other two methods; on the contrary, the performance gain is correspondingly small. The CSA proposed in this paper allocates cache storage based on the EC value of the node. The higher the EC value, the more important the node is in the network and the closer it is to other nodes. Compared with the two basic allocation algorithms of average allocation and proportional allocation, CSA can allocate more cache storage to important nodes to achieve higher system performance.

5 Conclusion

In this paper, we first propose a new method to calculate the importance of nodes, named EC. In addition, an optimal CSA approach is proposed to optimize the performance of D2D multi-layer social network. Specifically, the CSA problem for the social network is formulated as a difference of convex (DC) problem and solved by the DC programming. Simulation results show that the nodes with larger centrality value will share more cache storage, while the nodes with smaller centrality value will share less space. By exploiting CSA algorithm for allocation, numerical results show that cache storage utility functions are 11% and 7% higher than that of average and proportional respectively.

Our future work is to extend this algorithm to more complex networks, not only to take into account the location of the node consider other factors in the network, such as the size of the node's own cache storage, the remaining power and the similarity between users, etc. Another line of investigation is the joint optimization of cooperation between clusters, multi-hop communication and scheduling techniques. In the case of mobility, smarter mechanisms are needed to balance computational complexity and content sharing. Also, we are planning to keep our aim to other structural properties of multi-layer networks.

References

1. San Jose: Mobile Video Delivery With Hybrid ICN, Cisco, CA, USA, pp. 1–14 (2017)
2. Lin, Z., Du, X., Chen, H., Ai, B., Chen, Z., Wu, D.: Millimeter-wave propagation modeling and measurements for 5G mobile networks. IEEE Wirel. Commun. **26**(1), 72–77 (2019)
3. Chen, P., Xie, Z., Fang, Y., Chen, Z., Mumtaz, S., Rodrigues, J.P.C.: Physical-layer network coding: an efficient technique for wireless communications. IEEE Netw. **34**(2), 270–276 (2020)
4. Ding, Q., Pang, H., Sun, L.: SAM: cache space allocation in collaborative edge-caching network. In: IEEE International Conference on Communications (ICC), pp. 1–6. IEEE, Paris (2017)
5. Perino, D., Varvello, M.: A reality check for content centric networking. In: ACM SIGCOMM Workshop Information-Centric Networking, pp. 44–49. Association for Computing Machinery, Toronto (2011)
6. Zhang, M., Chen, X., Zhang, J.: Social-aware relay selection for cooperative networking: an optimal stopping approach. In: IEEE International Conference on Communications (ICC), pp. 2257–2262. IEEE, Sydney (2014)
7. Wang, L., Wu, H., Wang, W., Chen, K.: Socially enabled wireless networks: resource allocation via bipartite graph matching. IEEE Commun. Maga. **53**(10), 128–135 (2015)

8. Ma, C., Lin, Z., Marini, L., Li, J., Vucetic, B.: Learning automaton based distributed caching for mobile social networks. In: IEEE Wireless Communications and Networking Conference, pp. 1–6. IEEE, Doha (2016)
9. Zhu, K., Zhi, W., Zhang, L., Chen, X., Fu, X.: Social-aware incentivized caching for D2D communications. IEEE Access **4**, 7585–7593 (2016)
10. Zhang, Y., Song, L., Saad, W., Dawy, Z., Han, Z.: Exploring social ties for enhanced device-to-device communications in wireless networks. In: IEEE Global Communications Conference (GLOBECOM), pp. 4597–4602. IEEE, Atlanta (2013)
11. Baştuğ, E., Bennis, M., Debbah, M.: Social and spatial proactive caching for mobile data offloading. In: IEEE International Conference on Communications Workshops (ICC), pp. 581–586. IEEE, Sydney (2014)
12. Yen, C., Chien, F., Chang, M.: Cooperative online caching in small cell networks with limited cache size and unknown content popularity. In: 3rd International Conference on Computer and Communication Systems (ICCCS), pp. 173–177. IEEE, Nagoya (2018)
13. Cui, X., Liu, J., Huang, T., Chen, J., Liu, Y.: A novel metric for cache size allocation scheme in content centric networking. In: National Doctoral Academic Forum on Information and Communications Technology 2013, pp. 1–6. IEEE, Beijing (2013)
14. Song, Z., Duan, H., Ge, Y., Qiu, X.: A novel measure of centrality based on betweenness. In: Chinese Automation Congress (CAC), pp. 174–178. IEEE, Wuhan (2015)
15. Zhang, K., Li, H., Qin, L., Wu, M.: Closeness centrality on BBS reply network. In: International Conference of Information Technology, Computer Engineering and Management Sciences, pp. 80–82. ITM, Nanjing (2011)
16. Niu, J., Fan, J., Wang, L. Stojinenovic, M.: K-hop centrality metric for identifying influential spreaders in dynamic large-scale social networks. In: IEEE Global Communications Conference, pp. 2954–2959. IEEE, Austin (2014)
17. Bader, D.A., Madduri, K.: Parallel algorithms for evaluating centrality indices in real-world networks. In: International Conference on Parallel Processing (ICPP'06), pp. 539–550. ACM, Columbus (2006)
18. 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 (2006)
19. Rao, J., Feng, H., Yang, C., Chen, Z., Xia, B.: Optimal caching placement for D2D assisted wireless caching networks. In: IEEE International Conference on Communications (ICC), pp. 1–6. IEEE, Kuala (2016)
20. Sabidussi, G.: The centrality index of a graph. Psychometrika **31**(4), 581–603 (1966)
21. Freeman, L.C.: A set of measures of centrality based on betweenness. Sociometry **40**(1), 35–41 (1977)
22. Mittal, R., Bhatia, M.P.S.: Analyzing the structures of clusters in multi-layer biological networks. In: First International Conference on Secure Cyber Computing and Communication (ICSCCC), pp. 502–507. IEEE, Jalandhar (2018)
23. Fang, Y., Chen, P., Cai, G., Lau, F.C.M., Liew, S.C., Han, G.: Outage-limit-approaching channel coding for future wireless communications: root-protograph low-density parity-check codes. IEEE Veh. Technol. Mag. **14**(2), 85–93 (2019)