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Cooperative caching game based on social trust for D2D communication networks

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Summary

Content sharing via device-to-device (D2D) communications has become a promising method to increase system throughput and reduce traffic load. Due to the characteristic of spectrum sharing in D2D network, confidentiality is becoming a key issue in content transmission. Secure communication in D2D networks is generally guaranteed by a physical-layer security mechanism. However, this method sacrifices the system transmission rate while ensuring security. Since mobile devices are carried by humans, we can leverage their trust relations to enhance the security of communications. As much, considering the psychology structure and social attributes of mobile users, we build a multidimensional trust evaluation mechanism to evaluate the trust relationship between users, and we pick out the trusted users based on the decision-theoretic rough sets. By sharing content only between trust users, we can enhance the security of content transmissions without relying on physical-layer security measures. Meanwhile, content caching is now widely used to improve accessing efficiency and reduce traffic load on cellular networks. However, caching content for other users incurs additional cost, which results in selfish and noncooperative behavior in users. Considering such selfishness, we introduce a cooperative caching game based on multidimensional trust relations to motivate users to cache contents for other devices. In this game, the trust relations and physical distance between two users are considered to formulate the cost function. Furthermore, we introduce an incentive caching algorithm based on social trust to minimize the total cost in the D2D network.

KEYWORDS
cooperative game, D2D communications, incentive caching, social trust

1 | INTRODUCTION

In order to cater to the rapid growth of multimedia services and the effective use of network resources, device-to-device (D2D) communication is proposed to enable peer-to-peer communication between two users, which not only greatly reduces the load of base stations (BS)[1, 2] but also improves radio frequency spectrum utilization and network throughput. In the D2D network, mobile users can share content when they are in proximity, and the content they request can be transmitted directly by establishing a D2D link.[3] Confidentiality now has become a key issue in content transmission for the characteristic of spectrum sharing in D2D network. In order to protect the shared content from eavesdropping, physical-layer security mechanisms are currently used to prevent unauthorized users from accessing the content.[4] However, this method will lead to a low transmission rate of the system.[5] Considering that there is a stable social structure among mobile users, and social trust is an important factor to build social groups[6] We believe that closer trust relationships can help reduce the number of potential eavesdroppers in the network and enhance the security of content delivery without relying on physical-layer security measures. By sharing content only in trusted groups, we can guarantee the reliability of communications between users.

Caching content in a cooperative way now is a promising way to improve system performance by choosing some users to cache the content that may be of interest to other users.[7, 8] However, both the cache user and other users need to pay an additional cost when they perform cooperative caching, where the cost mainly includes the cache placement and the accessing cost. Each user intends to obtain more contents from the nodes with a closer physical distance or a closer social relationship, and they may behave selfishly and may be unwilling to cooperate due to the additional cost.[9, 10]

In this paper, we investigate these two fundamental problems and build a multidimensional trust evaluation mechanism by analyzing historical interactions and content requests. According to the decision-theoretic rough sets based on Naive Bayes, we divide neighboring users into three categories, named reliable users, observed users, and unreliable users. Furthermore, a cooperative cache game is proposed to incentivize users to participate in caching. In the caching game, we consider the trust relationships and physical distance between users as the factors to formulate the caching cost. Finally, a heuristic cache incentive algorithm is designed to minimize the total cost for all users to obtain content in the network. The major contributions in this paper are summarized as follows:

- We establish a multidimensional trust evaluation mechanism by evaluating the cooperative capacity, preference similarity, and social reciprocity between users to effectively select reliable users from neighboring users as cooperative partners for caching. Meanwhile, trust recording and computing are provided by the user-side and BS-side, which makes the evaluation results more accurate.
- We pick up the reliable user set from neighboring users by combining the decision-theoretic rough set theory in the Naive Bayes. The neighboring users can be divided into three categories, named reliable users, observed users, and unreliable users.
- To analyze the cost of accessing content in the D2D network, we combine the trust relations with physical distance between two users to formulate the cost function and propose a cooperative caching game to motivate content caching. Moreover, we introduce an incentive caching algorithm to obtain the optimal solution.

The rest of the paper is organized as follows. We review the related work in the Section 2. Section 3 presents the system model, and Section 4 describes the trust evaluation based on the hybrid trust model. Section 5 describes the problem in detail, analyzes the caching game, proves that Nash equilibrium exists in our game, and then outlines the incentive caching algorithm based on social trust. Simulation results are analyzed in Section 6. Finally, our work is concluded in Section 7.

2 | RELATED WORK

Many works have focused on D2D cooperative caching.[11–14] However, these works all ignore the selfish nature of users and the incentives for content caching. As mentioned before, social attributes strongly influence collaborative communication between D2D users. Some works have studied incentive cooperation through game theory based on social consciousness.[15–19] Chen et al[15] developed a framework for maximizing the utility of social groups in collaborative wireless networks that takes into account physical and social relationships by using game theory to maximize the utility of social groups. Chen et al[16] used social connections to promote effective collaboration between devices in a D2D network. Chen et al[18] proposed a preference-aware cache deployment algorithm, which caches specific content that matches user preferences, and users in nearby areas may also be interested in these contents. Previous works have established a contact-based incentive cache model, but social attributes have not been fully considered. In addition, these works did not explicitly consider the security issues.

Ometov et al proposed a trust-based D2D transmission survey,[20] and Wang et al[21] claim that they were the first to study the impact of selfishness on the underlying cellular network of D2D through the relationship between incoming and outgoing flows in user buffers. In Zhang et al,[22] a green cooperative D2D communication is designed to avoid non-cooperative behavior by adopting the social-aware cooperative D2D MAC protocol. Wu et al[23] proposed a user-centric video transmission mechanism by considering user sharing willingness, user location distribution, and user quality of experience (QoE) requirements. These works have established some reliable D2D cooperative communication mechanisms based on objective factors rather than social factors. Different from other works, this paper constructs a relationship evaluation mechanism based on a variety of social factors. For this reason, more D2D users will be motivated to participate in content caching.

3 | SYSTEM MODEL

In this paper, we consider a D2D cooperative communication scenario in Figure 1, where D2D users carrying mobile devices are distributed randomly in a single-cell cellular network, and the BS can be reached from any user in this cell. And there is no co-channel interference between D2D links since D2D communication uses orthogonal frequencies.[2] Both the D2D users and BS can be considered as content providers. If a copy of the requested content exists in the user's own cache space, the request can be completed immediately without establishing a connection. Otherwise, the user can request the content from other neighboring users within its D2D transmission range; if the requested content is cached by its neighboring users, the user can obtain the content by establishing a D2D link. Otherwise, the user needs to download the content from BS through a backhaul link.

When mobile users participate in content sharing, they prefer to choose the user with a close relationship as partner. As shown in Figure 1, we can divide the neighboring users within D2D communication coverage into three different types. The unreliable users are alienated from the current user and may be potential eavesdroppers, the observed users are the users with uncertain reliability, and they may be trustworthy or a potential threat, and the reliable users are trustworthy and have close relationships with the current user. Obviously, mobile users are willing to cooperate with those trustworthy users because it can not only protect the content from being accessed by eavesdroppers but also deepen the social relationships between them.

Moreover, due to the consumption content transmission and storage space, users may behave selfishly, which make them unwilling to cache contents for other users. And each user intends to get contents from the cache user with a lower cost. As mentioned, social relationship has a great impact on the cooperative behavior between users. A closer relationship between users means higher willingness to help each other. Instead, users may exhibit noncooperative behaviors that have a significant impact on system performance. In this model, based on the proposed trust evaluation

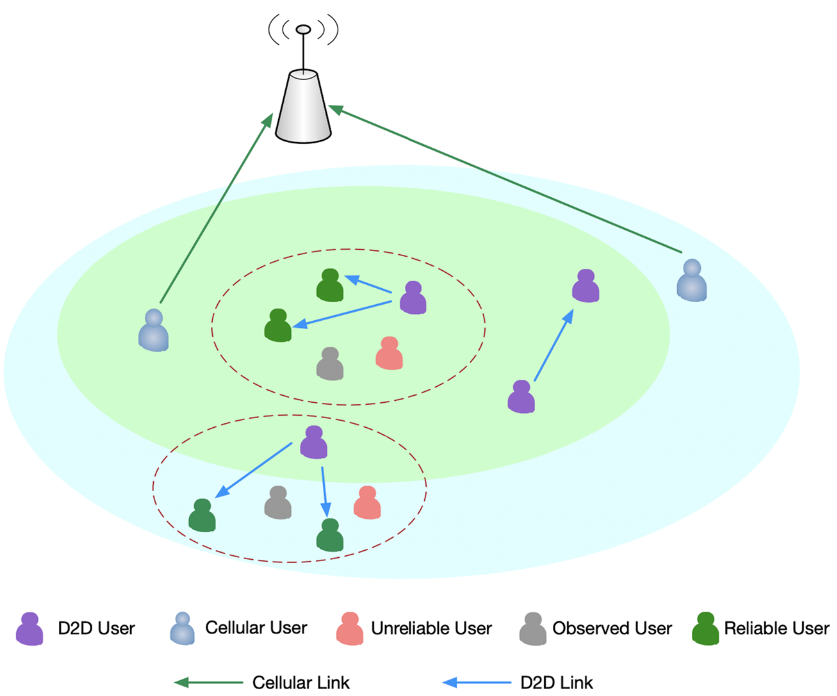

FIGURE 1 D2D caching network

mechanism, we can divide nearby users into three categories, and each D2D user is willing to choose partners from the trust user set. Therefore, if collaborative behavior occurs only between trusted users, the security of content transmission can be indirectly guaranteed. A list of the key mathematical notations used in this paper is given in Table 1.

4 | TRUST EVALUATION MECHANISM

In this part, we propose a multidimensional trust evaluation mechanism to evaluate the trust relationship between users by mining historical interactions between users and historical content requests. As shown in Figure 2, the trust model is composed of trust record, trust computation, and trust decision. Social trust relationship between users are subjective, abstract, and virtual. The trust record mainly analyzes and stores the data of user interactions, including the historical cooperative behaviors, interest sets of requested content, and reciprocal behaviors between users. Based on these records, we calculate the trust value of each dimension by evaluating cooperative capacity, preference similarity, and social reciprocity between two D2D users. After obtaining multidimensional trust relations between D2D users, trust decision makes the final decision and divides the nearby users into three categories based on the rough set of naive Bayesian decision theory. Then, we will clearly describe the evaluation in each dimension between users.

4.1 | Cooperative capacity

Cooperative capacity is an evaluation of the cooperative ability and reliability of mobile users. If users never collaborate with others to share their cached content, they will not be trusted by other users. Cooperative ability can be achieved

TABLE 1 List of key notations

Notations	Description
$DC_{i,j}^t$	Capacity of direct collaboration between users
$IC_{i,j}^t$	Capacity of indirect collaboration between users
$T_{i,j}^t$	Number of interactions between users at time t
$C_{i,j}^t$	The total capacity of collaboration between users
M	The complete set of content
U	The D2D user set
K	The cache capacity of each mobile device
w_k	Theme of content
$Pro(m, w_k)$	Property function of content m under the theme w_k
$f_{u_i}^{w_k}(t)$	Preference degree of u_i for theme w_k
$q_{i,m}^t$	Preference degree of u_i for content m
$P_{i,j}^t$	Preference similarity between users
$t_{i,j}^{\overline{\text{circle}}}$	Average reciprocity interval between users
$R_{i,j}^t$	Social reciprocity between users
$S_{i,j}$	Final decision whether u_i chooses u_j as its trusted partner
$d(i,j)$	Physical distance between users
$s(i,j)$	Social distance between users
$\phi_{i,j}$	Total distance between users
α_m	The placement cost of content m
$c_{i,m}$	The cost function for u_i to obtain content m
G	Cooperative caching game
P_*	Nash equilibrium strategy
U_c	Caching user set

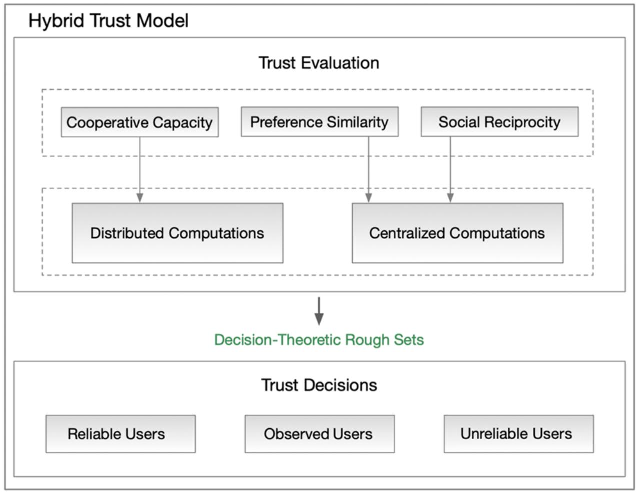

FIGURE 2 Hybrid trust model

according to the content forwarding behavior between D2D users, which can be obtained through the users' historical interaction. When D2D users meet each other, they will update the cooperative information to each other, such as the proportion of assisting users in delivering content. Having higher content sharing rate means that users have greater willingness to cooperate and indicates a greater cooperative ability for them.

The ability to collaborate can be achieved through direct and indirect collaborative behavior between two users. We represent the capacity of collaboration from user u_i to u_j as the ratio of u_j assisting other users in forwarding contents, and then the capacity of direct collaboration $DC_{i,j}^t$ based on the interactive information between u_i and u_j at time t can be defined as

$$DC_{i,j}^t = \sum_{X=0}^{t} F_{i,j}^X / \sum_{X=0}^{t} R_{i,j}^X, \tag{1}$$

where $\sum_{X=0}^{t} R_{i,j}^X$ is the number of contents which is requested by u_i to u_j, and $\sum_{X=0}^{t} F_{i,j}^X$ represents the number of contents which u_j has delivered for u_i.

When there is not enough interaction between u_i and u_j, the ability to collaborate can be obtained through interaction information between u_j and other users. Obviously, the relationship between u_j and other users will affect the accuracy of the capacity of cooperation. The stronger the relationship between u_j and other users, the more reliable the interaction information is. Therefore, we choose the users who have a cooperative ability greater than DC_j as the auxiliary users, where DC_j represents the average ability of user u_j to directly cooperate with other users, so we set the auxiliary user set to

$$\Pi(u_j) = \{u_x \in U | DC_{x,j} \geq DC_j\}. \tag{2}$$

When u_i meets the auxiliary user u_λ, u_λ forwards the interaction information between u_λ and u_j to user u_i at time t. Considering there are h such auxiliary users, the indirect cooperative ability $IC_{i,j}^t$ from u_i to u_j can be defined as

$$IC_{i,j}^t = \sum_{k=1}^{h} \frac{\sum_{X=0}^{t} F_{\lambda,j}^X / \sum_{X=0}^{t} R_{\lambda,j}^X}{h}. \tag{3}$$

Obviously, the difference between these two types of capacity is the number of historical interactions. When there is no interaction between user u_i and user u_j, the capacity of direct collaboration between u_i and u_j is 0. When the number of interactions increases, other users can more accurately feedback the collaborative behavior of u_j. We quantify social trust regarding cooperative behavior by considering both direct and indirect collaborative behavior; then, we have

$$C_{i,j}^t = \omega DC_{i,j}^t + \omega_i IC_{i,j}^t, \tag{4}$$

where $\omega + \omega_i = 1$, $\omega = 1 - \mathrm{e}^{-T_{i,j}^t}$, and $T_{i,j}^t$ denotes the number of interactions between the users at time t.

4.2 | Preference similarity

Preference similarity reflects the degree of interest relevance between two users. Assuming a D2D user u_i has p_i interest contents, $M_i = \left(m_i^1, m_i^2, m_i^3 \cdots m_i^{p_i}\right)$, respectively, and different users have different content sets, and their content sets may overlap. The complete set of content can be expressed as $M = M_1 \cup M_2 \cdots \cup M_i \cdots \cup M_n = \{m_1, m_2, \cdots, m_M\}$.

The user's preferences are closely related to the theme that a content contains. We consider that each content has K themes in the network, and $w = (w_1, w_2, \cdots, W_G)$ is the theme set for all contents. We define the property function of content m under the theme w_k as $Pro(m, w_k)$; $Pro(m, w_k) = 1$ means content m contains the theme w_k, otherwise $Pro(m, w_k) = 0$. Meanwhile, users have their own preference for each theme, and we define the preference function $f_{u_i}^{m_k}(t)$ to represent the preference of the theme w_k to u_i at time t. Then, we use mutual information to represent the user's preference function in this paper,[24] which can be calculated as

$$f_{u_i}^{w_k}(t) = I(X(w_k); H_{u_i}) = \log \frac{p(X(w_k)|H_{u_i})}{p(X(w_k))}, \tag{5}$$

where $I(X(w_k); H_{u_i})$ is the mutual information and $X(w_k)$ is the set containing all the contents of theme w_k. $p(X(w_k))$ is the unconditional theme probability, which represents the probability that the content with theme w_k is included in the entire content set. $p(X(w_k)|H_{u_i})$ is the conditional theme probability which means the probability that the content contains theme w_k is included in the historical information H_{u_i} of u_i.

We use cousin theory to define the preference of user u_i to the content m, that is,

$$q_{i,m}^t = \frac{\sum_{k=1}^{K} f_{u_i}^{w_k}(t) Pro(m, w_k)}{\sqrt{\sum_{k=1}^{K} f_{u_i}^{w_k}(t)} \sqrt{\sum_{k=1}^{K} Pro(m, w_k)}}. \tag{6}$$

Obviously, the more similar $Pro(m, w_k)$ and $f_{u_i}^{w_k}(t)$ are, the higher $f_{u_i}^{w_k}(t)$ is. The preference degree to all contents of u_i in time t is defined as $\mathbf{q}_i^t = \left[q_{i,m_1}^t, q_{i,m_2}^t, q_{i,m_3}^t \cdots, q_{i,m_{p_i}}^t\right]$, where constraints hold as shown:

$$\begin{cases} 0 \le q_{i,m_z}^t \le 1 (1 \le z \le p_i), \\ \sum_{z=1}^{p_i} q_{i,m_z}^t = 1. \end{cases} \tag{7}$$

The preference of u_i and u_j for a given content m in time t are $\mathrm{q}_{i,m}^t$ and $\mathrm{q}_{j,m}^t$. We define the preference similarity of two users based on the cosine similarity concept in collaborative filtering,[25] which is frequently used to reflect the similarity level of preferences between two users; then, we have

$$P_{i,j}^t = sim\left(\mathbf{q}_i^t, \mathbf{q}_j^t\right) = \frac{\sum_{m=1}^{M} q_{i,m}^t q_{j,m}^t}{\sum_{m=1}^{M} \left(q_{i,m}^t\right)^2 \sum_{m=1}^{M} \left(q_{j,m}^t\right)^2}. \tag{8}$$

According to the above method, BS can construct the initial similarity based on the difference of interest between two users. Obviously, the themes of the content shared between D2D users have a great impact on preference similarity. Specifically, when users cache and share content that other users are interested in, other users will also show higher willingness to share, thereby deepening the similarity of preferences between cache users and other users.

4.3 | Social reciprocity

Social reciprocity is a powerful mechanism to facilitate mutual beneficial cooperation in the absence of social trust, which does not need a strong social connection between two users.[26] For example, when D2D users have no friends in the network, they may help nearby strangers to improve the network performance by providing relay assistance or other services; then, they may also get help due to the mutual psychology of strangers. Generally, we can divide social reciprocity into direct and indirect reciprocity, as shown in Figure 3. Direct reciprocity means two users exchange altruistic behaviors so they both can gain benefits. Indirect reciprocity means a group of users exchanging altruistic behavior so that each of them can have a better experience.

When a user helps others transmit content via the D2D link, there must be a directional connection between them. Therefore, the BS can build a reciprocal relationship between two users.[23] But the reciprocal relationship described in Li et al[27] ignores temporal characteristics such as the reciprocity interval between users. Generally, in a given time, the shorter the reciprocity interval, the higher the trust between two users.[26] Considering the reciprocity interval, we define the trust relation of social reciprocity between two users as

$$\mathrm{R}_{i,j}^{t} = \begin{cases} \dfrac{2}{\pi}\operatorname{arccot} \overline{t_{i,j}^{\text{circle}}}, & \text{direct or indirect mutual aid,} \\ 0, & \text{other,} \end{cases} \tag{9}$$

where $\overline{t_{i,j}^{\text{circle}}}$ represents the average reciprocity interval between two users.

4.4 | Trust decision

The cooperative capacity, preference similarity, and social reciprocity were established in the aforementioned part, but the trust relation between users is a kind of fuzzy set—we still cannot find trusted partners. In order to pick up reliable partners, we apply the decision-theoretic rough sets based on Naive Bayes. According to this theory, we can transform a fuzzy relation set into definable sets, which are generally expressed as positive regions, negative regions, and boundary regions.[28] When the trust calculation is complete, the trust decision between u_i and u_j is required. We record the trust decisions in Table 2; $S_{i,j}$ represents the final decision whether u_i chooses u_j as its trusted partner.

We introduce the Naive Bayesian method into decision rough sets to find the trusted set from all D2D users. In particular, the conditional probability that u_j can be trusted at time t is calculated as

$$\begin{aligned} &P\left(S_{i,j} \middle| \left[C_{i,j}, P_{i,j}, R_{i,j}\right]\right) \\ &\quad = \frac{P\left(\left[C_{i,j}, P_{i,j}, R_{i,j}\right] \middle| S_{i,j}\right) P\left(S_{i,j}\right)}{P\left(C_{i,j}, P_{i,j}, R_{i,j}\right)}. \end{aligned} \tag{10}$$

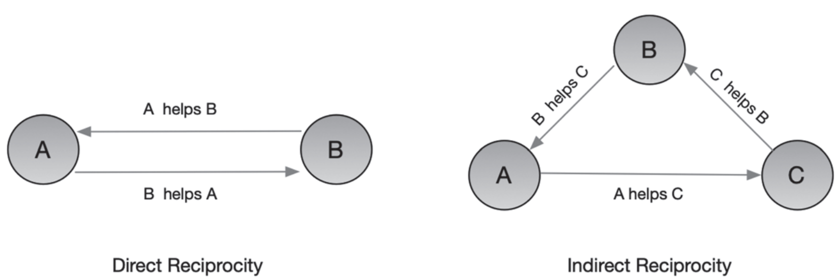

FIGURE 3 Two types of reciprocal behavior

TABLE 2 Trust decision table

T	$C_{i,j}$	$P_{i,j}$	$R_{i,j}$	$S_{i,j}$
1				
2				
3				
4	…	…	…	…
…	…	…	…	…

$P(S_{i,j}|\,[C_{i,j}, P_{i,j}, R_{i,j}])$ is the posterior probability, which represents the probability that u_i chooses u_j as its trusted partner based on the trust relations at time *t*. $P(S_{i,j})$ is the prior probability, which represents the probability that u_i chooses u_j as its trusted partner before *t*. $P([C_{i,j}, P_{i,j}, R_{i,j}]|\, S_{i,j})$ is the likelihood function, which means the probability of trust events when u_j is regarded as a trusted partner of u_i.

Specially, cooperative capacity is evaluated by historical interaction information. Preference similarity is calculated based on users' degree of similarity in contents with different themes, and social reciprocity is established by mutual aid action. In addition, the trust relations of all dimensions are independent of each other. Hence, $P([C_{i,j}, P_{i,j}, R_{i,j}]|\, S_{i,j})$ can be expressed as

$$\begin{aligned} &P\left(\left[C_{i,j},P_{i,j},R_{i,j}\right]|S_{i,j}\right) \\ &\quad = P\left(\left[C_{i,j}\right]|S_{i,j}\right)\cdot P\left(\left[P_{i,j}\right]|S_{i,j}\right)\cdot P\left(\left[R_{i,j}\right]|S_{i,j}\right). \end{aligned} \tag{11}$$

Similarly, $P\left(\left[C_{i,j},P_{i,j},R_{i,j}\right]|S^c_{i,j}\right)$ can be expressed as

$$\begin{aligned} &P\left(\left[C_{i,j},P_{i,j},R_{i,j}\right]|S^c_{i,j}\right) \\ &\quad = P\left(\left[C_{i,j}\right]|S^c_{i,j}\right)\cdot P\left(\left[P_{i,j}\right]|S^c_{i,j}\right)\cdot P\left(\left[R_{i,j}\right]|S^c_{i,j}\right). \end{aligned} \tag{12}$$

Then, we translate the estimation of conditional probability $P(S_{i,j}|\,[C_{i,j}, P_{i,j}, R_{i,j}])$ into the ratio of likelihoods based on the odds form and logarithms; then, we have

$$\begin{aligned} &\log\left(O\left(P\left(S_{i,j}|\left[C_{i,j},P_{i,j},R_{i,j}\right]\right)\right)\right) \\ &\quad = \log\left(\frac{P\left[C_{i,j},P_{i,j},R_{i,j}\right]|S_{i,j}\right)}{P\left(\left[C_{i,j},P_{i,j},R_{i,j}\right]|S^c_{i,j}\right)}\right) + \log\left(\frac{P\left(S_{i,j}\right)}{P\left(S^c_{i,j}\right)}\right). \end{aligned} \tag{13}$$

The positive boundary is defined as α, namely, $P(S_{i,j}|\,[C_{i,j}, P_{i,j}, R_{i,j}]) > \alpha$; according to Equation 13, we have

$$\log\left(\frac{P\left(\left[C_{i,j},P_{i,j},R_{i,j}\right]|S_{i,j}\right)}{P\left(\left[C_{i,j},P_{i,j},R_{i,j}\right]|S^c_{i,j}\right)}\right) \geq \log\left(\frac{P\left(S^c_{i,j}\right)}{P\left(S_{i,j}\right)}\right) + \log\frac{\alpha}{1-\alpha}. \tag{14}$$

According to the above process, we can also get the boundary of negative region β. Therefore, we can obtain the user decision set at time *t* as

$$\begin{cases} \mathrm{POS}_{i,j} = \left\{\left(C_{i,j},P_{i,j},R_{i,j}\right)|\mathrm{L}\geq\alpha'\right\}, \\ \mathrm{NEG}_{i,j} = \left\{\left(C_{i,j},P_{i,j},R_{i,j}\right)|\mathrm{L}\leq\beta'\right\}, \\ \mathrm{BAD}_{i,j} = \left\{\left(C_{i,j},P_{i,j},R_{i,j}\right)|\beta'<\mathrm{L}<\alpha'\right\}, \end{cases} \tag{15}$$

where

$$\begin{cases} \alpha' = \log\left(\dfrac{\mathrm{P}\left(S_{i,j}^{c}\right)}{\mathrm{P}\left(S_{i,j}\right)}\right) + \log\dfrac{\alpha}{1-\alpha}, \\ \beta' = \log\left(\dfrac{\mathrm{P}\left(S_{i,j}^{c}\right)}{\mathrm{P}\left(S_{i,j}\right)}\right) + \log\dfrac{\beta}{1-\beta}, \\ \mathrm{L} = \log\left(\dfrac{\mathrm{P}\left(\left[C_{i,j}, P_{i,j}, R_{i,j}\right]|S_{i,j}\right)}{\mathrm{P}\left(\left[C_{i,j}, P_{i,j}, R_{i,j}\right]|S_{i,j}^{c}\right)}\right). \end{cases} \tag{16}$$

Combining Equation 16, the neighboring users can be classified into three categories. Therefore, the trust relationship between all users can be obtained by trust decision. In order to show the trust relationship intuitively, we construct a trust matrix $T^{U \times U}$, which is shown below. t_{ij} indicates the trust relationship between u_i and u_j, $t_{ij} = 1$ indicates u_i trusts u_j, $t_{ij} = -1$ indicates that u_j is still in observation of u_i, and $t_{ij} = 0$ indicates that u_i does not trust u_j.

$$T^{U\times U} = \begin{bmatrix} t_{11} & \dots & t_{1j} & \dots & t_{1U} \\ \vdots & & \vdots & & \vdots \\ t_{i1} & \dots & t_{ij} & \dots & t_{iU} \\ \vdots & & \vdots & & \vdots \\ t_{U1} & \dots & t_{Uj} & \cdots & t_{UU} \end{bmatrix}. \tag{17}$$

5 | COOPERATIVE CACHING GAME BASED ON SOCIAL TRUST

5.1 | Problem formulation

In a D2D cache network, each user needs to pay a cost during the content accessing process. Such costs mainly contain the cache placement and the accessing cost. Obviously, each user cares about their own benefits and wants to maximize their benefits, which leads to selfishness in choosing their caching strategy. In this paper, we consider that the cost is affected by the probability that the user requests for the content and the distance between two users. Particularly, the distance between users includes both physical meaning and social meaning due to the fact that closer physical distance means a lower accessing cost and closer social relationship can motivate users to cache content for others. Therefore, we formulate the distance between users based on these two factors. The physical distance between u_i and u_j is represented as $d(i,j)$. The social distance $s(i,j)$ is defined on multidimensional trust relations, which calculated as

$$s(i,j) = \frac{C_{i,j}^{t}}{C_0}\cdot W_1 + \frac{P_{i,j}^{t}}{P_0}\cdot W_2 + \frac{R_{i,j}^{t}}{R_0}\cdot W_3. \tag{18}$$

C_0, P_0, and R_0 are the standard values of each evaluation index, which are taken as the average value of all end-to-end trust relationships between mobile users in different dimensions, respectively. W_1, W_2, and W_3 are corresponding weights for different indexes. We consider that the trust relationships in each dimension are equally important and set each weight to one third in this paper.

Combining the physical distance and the social relationships, the distance $\varphi_{i,j}$ between u_i and u_j is defined as

$$\varphi_{i,j} = \frac{d(i,j)}{s(i,j)}. \tag{19}$$

According to the above distance, we define the cost function $\mathrm{c}_{i,m}$ of u_i to obtain content m as follows:

$$c_{i,m} = \alpha_m x_{i,m} + q_{i,m}\varphi_{i,j}(1 - x_{i,m}), \tag{20}$$

where α_m is the placement cost of content m. $q_{i,m}$ is the probability that u_i requests for m. u_j is the counterpart cache user of the content. Obviously, the farther the distance $\varphi_{i,j}$, the higher the accessing cost. $x_i \in [0,1]$ is the cache indicator of u_i. $x_i = 1$ means u_i caches the content and needs to pay a cache placement cost α_m. Otherwise, the content is cached by other users such as u_j, and an accessing cost $q_{i,m}\varphi_{i,j}$ will be needed. Mathematically, u_j is selected by $j = \text{argmin}_k\{\varphi_{i,k} : x_k = 1\}$.

Therefore, we define the following optimization problem to minimum total cost, that is,

$$\begin{aligned} \min_{x_{i,m}} \quad & \sum_m \sum_i \left(\alpha_m x_{i,m} + q_{i,m}\varphi_{i,j}(1 - x_{i,m})\right) \\ \text{s.t.} \quad & C1 : x_{i,m} \in [0,1] \\ & C2 : \sum_m q_{i,m} \le 1 \\ & C3 : 1 \le i \le N, 1 \le m \le M. \end{aligned} \tag{21}$$

The minimum cost caching problem has been proven to be an NP-hard problem.[29] Therefore, we propose the following cooperative caching game based on trust relations to solve this problem. In the game, each D2D user can be a player and cache the content by themselves or obtain content from nearby reliable players. Their payoff is influenced by the probability $q_{i,m}$ that u_i requests for m and the distance $\varphi_{i,j}$ between two players.

5.2 | Definition of cooperative caching game

In this paper, we define the cooperative caching game $G = \{S_1, ..., S_n : u_1, ...u_n\}$, where $\{u_1, ..., u_n\}$ represents the player set and $\{S_1, ..., S_n\}$ represents the strategy set of all players. The payoff function is defined by the cost function in Equation 20. $P^k = \left\{s_1^k, ..., s_n^k\right\}$ presents a strategy instance, and s_i is a policy rule of player i. Policy rule indicates not only whether the player is a cache node but also the player cache for whom and who to get content from. It's easy to see that s_i is different from $x_{i,m}$; $x_{i,m}$ only suggests whether the user serves as a cache node or not but cannot convey which users should serve for caching. Furthermore, we define $P^* = \left(s_1^*, ..., s_n^*\right)$ as the Nash equilibrium strategy in this game. The cost of P^* is always lower than that of P^k for any k in the strategy space. In the Nash equilibrium strategy, no player has any incentive to deviate since no player can unilaterally benefit by changing strategy. The following part proves the existence of Nash equilibrium solution in the cooperative games.

5.3 | Nash equilibrium solution

Considering selfishness, each user wants to minimize its own cost. We assume U is the initial user set and U_c is the cache user set. For a specific content m, we pick a player $y \in U$ such that $q_{y,m} \ge q_{x,m}$ for all x in U. Considering y as a cache user and defining $Z(y)$ as the accessing user set, the user in $Z(y)$ can obtain the content from y within the cost α_m, thus we have

$$Z(y) = \left\{Z : q_{z,m}\varphi_{z,y} \le \alpha_m, t_{zy} > 0, z \in U\right\}. \tag{22}$$

Then, we remove y and $Z(y)$ from U; let $N = N \cup Z(y)$ and $U_c = U_c \cup y$. Repeat the above process until U is empty. After that, find the cheapest D2D link for each non-cache user in N and clear Z. For any two users h and l in U_c, there are $q_{h,m}\varphi_{h,l} \le \alpha_m$ and $q_{l,m}\varphi_{l,h} \le \alpha_m$, which means no user can benefit by changing its role because it will lead to a higher cost compared to the placement cost. Meanwhile, the users in N are the accessing users which obtain the content from cache users; they have already chosen the cheapest and most reliable link to obtain the content. Once they change their strategy, the cost will be higher compared to their previous strategy. Therefore, no user has any incentive to deviate its strategy since no player can unilaterally benefit. Thus, a Nash equilibrium strategy exists in this game, and the solution is the optimum configuration.

5.4 | Incentive caching algorithm based on social trust

In this part, we propose a heuristic cache decision algorithm to obtain the optimal cache scheme. As shown in Algorithm 1, cooperative capacity, preference similarity, and social reciprocity among users are calculated based on BS statistics and user statistics. Then, by using the decision-theoretic rough sets based on Naive Bayes, we can pick out the trusted partners of each user and obtain the trust matrix between users. In the cache decision phase, the cache node is determined by comparing the cost of content placement with the cost of content accessing. When the placement cost is lower than the cost of content accessing, the user chooses to be a cache node and the trusted users within its communication range can get the cached content by establishing a D2D link. Otherwise, the user will choose to get the content from the trusted user with the lowest cost. In addition, when there is no trusted partner around, the user chooses to retrieve content from the BS via a backhaul link. Finally, the algorithm updates the cache policy of all users to minimize the total cost.

Algorithm 1 *Incentive Caching Algorithm Based on Social Trust*

Require:
The number of contents is M and the cache space capacity of each user is K
U is the initial user set and U_c is the cached user set
The caching cost of the specific content m is α_m
The demand of user $i \in U$ for the content m is $q_{i,m}$ and the distance between user i and j is $\varphi_{i,j}$
Ensure:
Making trust evaluation and calculate $C_{i,j}^{t}$, $P_{i,j}^{t}$ and $R_{i,j}^{t}$ at time t
Making trust decisions and initialize the trust matrix $T^{U \times U}$
Remove all users with zero demand for m from U
while $U \,!= \emptyset$ **do**
 pick a user y in U such that $q_{y,m} \geq q_{x,m}$ for all x in U
 If $K > 0$ **then**
  let $Z(y) = \{Z : q_{z,m}\varphi_{z,y} \leq \alpha_m, t_{zy} > 0, z \in U\}$
  mark y as a cache node and then remove y and all Z from U
  let $U_c = U_c \cup y, N = N \cup Z(y)$
 else
  remove y from U and let $N = N \cup y$
 end if
end while
for each node i in N **do**
 $j = \text{argmin}_{k \in U_c, t_{ik} > 0}\{q_{i,m}\varphi_{i,k}\}$
 $Z(j) = Z(j) \cup i$
end for
$t = t+1$
Update the basic information with time t
Repeat 5
End

In this algorithm, trust evaluation is performed periodically to update the trust matrix between users. During the cache decision phase, each loop has n iterations at most, and each iteration has n calculations at most. Accordingly, the complexity of this algorithm is $n-1, n-2, \ldots, 1, 0$, respectively. In the first loop, the complexity is $O\left(\frac{(n-1)n}{2}\right)$ at most. And in the last two loops, the complexity will not exceed n for there are n users in the network. Overall, the algorithm complexity is $O\left(\frac{(n-1)n}{2}+n\right)=O\left(\frac{n^2+n}{2}\right)$ at most. For any cache node i, its placement cost is α_m, and we have $\varphi_{i,j} * min\{q_{i,m}, q_{j,m}\} > \alpha_m$ according to Algorithm 1. If i changes its strategy to be a non-cache node and obtains the content from node j, its cost will be $q_{i,m} * \varphi_{i,j}$, which is higher than the previous cost α_m. Therefore, no cache node will deviate its strategy, and Algorithm 1 reaches Nash equilibrium.

6 | EXPERIMENTAL EVALUATION

6.1 | Simulation setup

In the simulation, a macro BS is deployed in the center of the cell, and N users are distributed uniformly in the cell. We assume that there are M contents and that each content has the same size. Each user device has the same capacity of cache space and can cache up to K contents. The system bandwidth of D2D communication is 10 MHz uplink and 10 MHz downlink for the frequency division duplex, and the indoor-to-indoor channel model is used as defined in the Technical Report of 3GPP, including the pathloss, shadowing, and the fast fading. The detailed parameters are shown in Table 3.

In order to implement the trust evaluation mechanism, we use the experimental dataset gathered by the MobiClique application at SIGCOMM 2009 conference in Barcelona, Spain. Specifically, the dataset contains the profiles of participants, interest groups, friends, proximity, and messages lists, and we use these social information and interactive records to initialize the trust relationships among different users. Meanwhile, to enable the simulation of our incentive algorithm, we assume the probability that each user requests the content conforms Poisson distribution and the BS has all contents the users requested. In the experiment, we compare our proposed caching algorithm with the following two caching schemes to show the performance advantage of our algorithm.

1. *Random Cache:* The users cache content randomly, and the other users obtain the copy from a random neighboring cache node or BS. The nodes choose their strategies randomly in this scheme, and they all care about their own benefit and behave selfishly.
2. *Selfish Cache*: The users ignore their social relationship and behave selfishly in this scheme. They merely consider whether to cache content or get content from the cache user with the nearest distance, and their strategies only depend on which way is cheaper.

In this paper, we use the following metrics to evaluate each caching algorithm. The definitions are given as following.

1. *Total cost* is defined as the total cost of contents access within the simulation period of all users in the D2D network. According to Equation 20, the total cost can be calculated as

$$c = \sum_i \sum_m \left(\alpha_m x_{i,m} + q_{i,m} \varphi_{i,j} (1 - x_{i,m}) \right), \tag{23}$$

TABLE 3 Simulation parameters

Parameters	Values
Carrier frequency	2 GHz
Intercell distance	500 m
Transmit power of D2D	30 dBm
Maximum transmit power of the BS	46 dBm
Noise power	−174 dBm/Hz
System bandwidth of uplink D2D	10 MHz
System bandwidth of downlink D2D	10 MHz
Minimum distance between UEs	5 m
Minimum distance between UE and BS	35 m

where $x_{i,m}$ indicates that the user requested content m or not, $q_{i,m}$ represents the probability of user i requesting content m, and α_m represents the placement cost of content m.

2. *Cache hit ratio* is defined as the percentage of interesting content that users obtained from their own cache space or their neighboring users via D2D links. Cache hit ratio reflects the efficiency of the cache strategy, which can be calculated as

$$r = \frac{\sum_i \sum_m \left(1 - e^{-d^2}\right) q_{i,m} x_{i,m}}{\sum_i \sum_m q_{i,m}}, \tag{24}$$

where d represents the communication range of user i, $x_{i,m}$ indicates that the user requested content m or not, and $q_{i,m}$ represents the probability of user i requesting content m.

3. *Average access delay* is defined as the average service delay of the total content requests of all users during the simulation; it has a great effect on the user experience. The average delay can be calculated as

$$\tau = \frac{1}{MN} \sum_{i}^{N} \sum_{m}^{M} \left(\frac{q_{i,m} v_m}{R_{i\_j} x_{i,m} + R_{i\_\mathrm{BS}} (1 - x_{i,m})} \right), \tag{25}$$

where M represents the total number of requested content during the simulation and N is the total number of users in the network, and v_m is the volume of the content m. R_{i_j} and R_{i_BS} respectively represent the transmission rate between users i and j and user i and the BS.

6.2 | Evaluation results

In this paper, we use MATLAB to run the simulation. Each simulation is run for 100 times, and we take the average value as the simulation results.

6.2.1 | Impact of the selfish users

In this part, we consider the impact of selfish users on system performance in the network. We make the percentage of selfish users vary from 0 to 1 in the network, and other users are completely selfless. In the experiment, the capacity of cache space of each device is set as $K = 10$, the number of mobile users is set as $N = 50$, and the number of contents is set as $M = 200$.

Firstly, we take the total cost as a function of the selfish percentage, as shown in Figure 4A. The total cost increases as the percentage of selfish users increases, and the total cost of our scheme is much lower compared to that of other schemes. Moreover, although selfish caching can help reduce total costs, it is not as good as our scheme. Due to the full consideration of the noncooperative behaviors caused by selfishness, our scheme greatly reduces the total cost.

Figure 4B shows the cache hit ratio varying by percentage of selfish users. The cache hit ratio of the three schemes all decrease as the percentage of selfish users increases. The reason is that as the increase of selfish users results in more users that are unwilling to cache content for other users and directly obtain content from the BS each time, the cache hit ratio naturally decreases. The cache hit rate of our scheme is higher than those of the other three schemes because we take into account the selfishness of users and motivate users to cache content for each other through social relationships. In addition, our scheme always selects the most suitable user as the cache node.

The average delay of the three schemes are shown in Figure 4C. As the percentage of selfish user increases, the average content access delay of all schemes gradually increases. The reason is that when the number of selfish user increases, the number of cache nodes will decrease, and then users need to obtain content from the remote BS. In

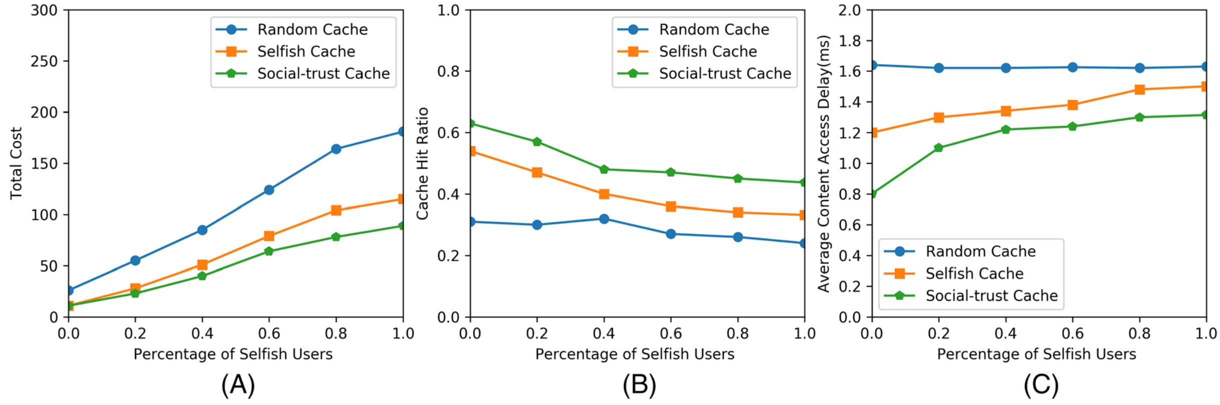

FIGURE 4 Performance comparison with varying percentage of selfish users

particular, the average access delay of the random scheme remains almost unchanged as the percentage of selfish user increases. The result shows that our scheme has a great advantage compared to other schemes, and when the percentage of selfish users exceeds half, the average access delay does not change much. This is due the fact that the amount of cached content is constantly increasing, and the cache users cannot cache all the requested content, causing users' need to request more content from BS.

6.2.2 | Impact of the placement cost

In this part, we give the simulation results of the impact of the placement cost on the total cost, average content access delay, and cache hit ratio when the percentage of selfish users is 0.5. In the experiment, the placement cost varies from 1 to 10, the number of mobile users is set as $N = 50$, and the number of contents is set as $M = 200$.

The total cost as a function of placement cost is given in Figure 5A. The total cost of all three schemes increased as the number of contents increased. This is due to the fact that higher the cost of placement, the smaller the number of cached nodes, leading to the higher total cost of the entire network. Furthermore, the total cost of the proposed scheme is always lower than that of random scheme and selfish scheme since we consider the user's preference and the social relationship between users.

Figure 5B shows how the cache hit ratio of random cache, selfish cache, and proposed scheme varies with the cost of placement. The cache hit ratio of all three schemes decreases with the increase of placement cost, while the random strategy has no significant change. This is because the higher the cost of placement, the smaller the number of cached nodes, resulting in the smaller amount of cached content. Besides, as the amount of content increases, the user cannot cache all the content in the limited cache space. Since our proposed scheme takes into account the cost of obtaining

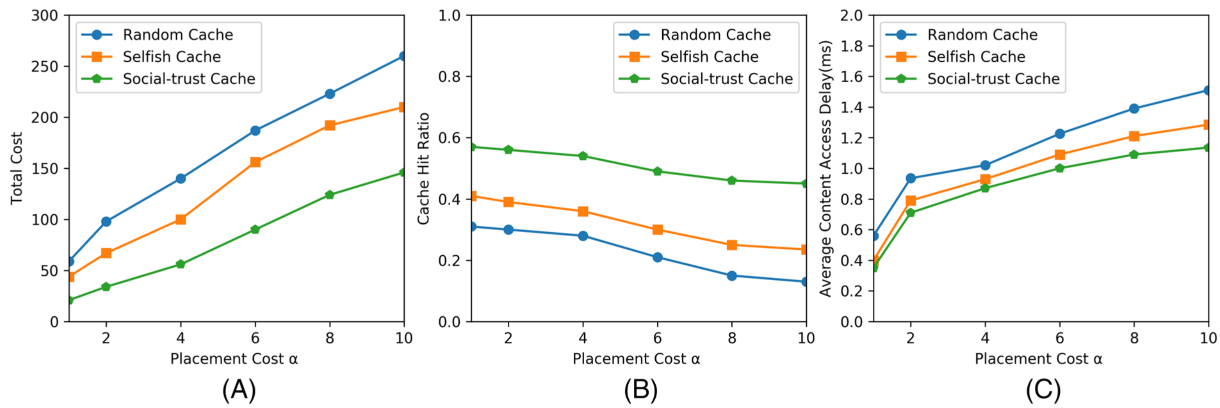

FIGURE 5 Performance comparison with varying placement cost

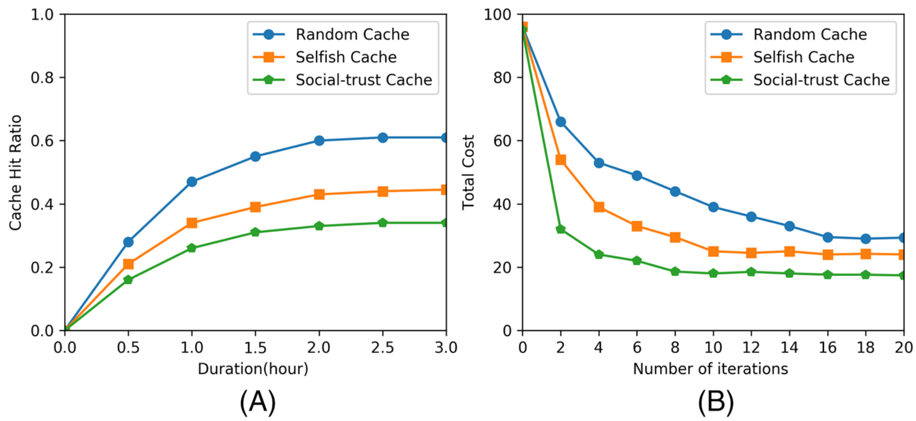

FIGURE 6 The evaluation comparison with varying duration and iterations

content and always chooses the most appropriate node as the cache node between users, the proposed scheme has performance advantages over random cache and selfish cache.

As we can see from Figure 5C, the proposed scheme achieves significant gains in terms of lower average content access delay compared to random scheme and selfish scheme. As the cost of placement increases, the average content access delay of our proposed scheme increases; this is due to the fact that the number of users of cached content decreases as the cost of placement increases, requiring users to obtain content from the remote BS. In addition, the access delay also increases as the number of content increases, since mobile devices with limited cache space cannot cache all the content requested by nearby users, which leads the user to request more content from the remote BS.

6.2.3 | Impact of duration and iteration

The cache hit ratio in a time duration of 3 h are shown in Figure 6A. In this group of experiments, the percentage of selfish users is set to 0.5 and the placement cost is set to 2. From Figure 6A, we can see that the cache hit ratio increases with time, and the proposed incentive caching scheme has better performance during all the time compared to the other two schemes. Meanwhile, the proposed scheme has no significant change in cache hit rate after 1.5 h and gradually stabilizes at 0.6.

Finally, we evaluate the impact of iterations for random caching, selfish caching, and our proposed caching with respect to the total cost variation after different numbers of iterations. In the simulation, the number of users is $N = 50$, the capacity of cache space is set as $K = 10$, and the number of contents is $M = 100$. Figure 6B shows the total cost variation as a function of the number of iterations when the placement cost is 5. It can be observed that our scheme can converge to the approximate optimal solution within 10 iterations while random caching needs 12 iterations and selfish caching needs 16 iterations. Furthermore, it also presents that the total cost decreases after each iteration. In each iteration, our caching scheme has lower total cost than both selfish caching scheme and random caching scheme.

7 | CONCLUSION

In this paper, we propose a trust evaluation mechanism between mobile users to ensure reliable content sharing by evaluating the cooperative capacity, preference similarity, and social reciprocity between them. Furthermore, we consider the incentive problem in content caching and introduce a cooperative caching game based on social trust. Then, we prove the existence of Nash equilibrium strategy in this game. We formulate the caching cost by combining trust relations with physical distance and propose an incentive caching algorithm to minimize the total cost in the D2D network. The simulation result shows that our caching algorithm can not only significantly reduce the total cost but also increases the cache hit ratio in the network.

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