IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 16, 2018, accepted April 7, 2018, date of publication April 11, 2018, date of current version January 7, 2019.

Digital Object Identifier 10.1109/ACCESS.2018.2825244

Time-Varying Social-Aware Resource Allocation for Device-to-Device Communication

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This work was supported by the Creative Research Group of China from NSFC under Grant 61421061.

ABSTRACT With the rapid development of wireless mobile communication, local content sharing has become the emerging demand for users who are geographically close. Device-to-device (D2D) communication allows two users to communicate directly with each other. In order to achieve more effective content distribution and content spread by allocating better spectrum resources to users with better social networking and content diffusion capabilities, we propose an optimization scheme for resource allocation of the D2D communication by utilizing the potential social relations that are embedded in the communication devices. The degree of intimacy between users is abstracted from the call records to quantify social-relation strengths. Considering the time-varying property of social relations, the auto-regressive integrated moving average model is applied to map the call records into time sequence to predict users' social relations. Besides, instead of individual utility or the overall network utility, each user aims to maximize its social-community utility which takes other social related D2D users into consideration. Potential game is utilized to solve the social-community utility maximization problem of resource allocation for the D2D communication due to its outstanding mapping nature and always has the Nash equilibrium. Finally, a social-aware distributed resource allocation algorithm is proposed, and the algorithm achieves convergence and stability. Numerical results show that our proposed scheme increases the overall utility over 30% compared with coalition game scheme, and over 50% compared with random selection scheme without loss of the fairness.

INDEX TERMS Device-to-device communication, time-varying, social relations, resource allocation, potential game.

I. INTRODUCTION

WITH the rapid spread of intelligent terminals and the explosive growth of network capacity, great challenges have been brought to wireless mobile communication [1]. Local content sharing has become the emerging demand for users who are geographically close. Mobile devices can act as caching servers and send content to other devices through short -distance communication [2]. As an example of short-distance communication, device-to-device (D2D) communication allows users to communicate directly by multiplexing cellular spectrum resources, which can improve the spectral efficiency and enlarge the system capacity [3], [4]. On the other hand, D2D communication as one of the wireless mobile communication, the most important feature is mobile communication devices are carried and operated by people [5], [6]. Their behaviors are regular and predictable to some extent in the interaction process. Social relations between people can be reflected by social behaviors, personal interests, type of activities, intimate relationships [7]. If social relations between people can be applied in D2D communication, not only can system performance be improved, the user experience (UE) can be improved too. In addition, D2D communication is a high-speed and low-power communication between users at short range [8]. Thus, the performance of D2D communication depends on the meeting frequency of users whose locations are near, and the frequency at which they require online communication or content sharing. In other words, the performance of D2D communication in cellular network is highly dependent on the behavior of the nodes. So taking social relations between D2D users into account is significant in D2D communication research. Through the consideration of social-aware resource allocation, effective content distribution and content spread can be achieved among users. Users with better social networks have better content diffusion capabilities. If better spectrum resources are allocated to them, the goal of efficient content distribution for users can be achieved in the process of resource allocation with considering the social attributes and the potential social fluctuations.

There are some researches focused on social-aware resource allocation for D2D communication. Some schemes are proposed to model social relations between users. Yang *et al.* [9] exploited social ties with delivery willingness of content owner to enhance D2D resource sharing and further proposed a social aware resource allocation framework. In this paper, social information is considered static. Wu *et al.* [10] proposed a social-aware cluster-based game theoretical scheme for resource allocation in which clusters are formatted based on the new defined weighted social interference degree and the physical interference graph. They utilized a new asymmetric social weighted graph to study the problem of resource allocation for D2D wireless social networks. Sun *et al.* [11] presented a novel approach to formulate the social relationships for the offline mobiles by comparing the similarity of mobile users' social activities with the Bayesian model. In these papers, the social relations between users are modeled by specific formulas or weighted graph based on the user's interests, common friends and other factors of social relations into the unresolved problems. Whether there is interaction between users are not considered. Moreover, as D2D environment and social relations among the users vary from time to time, social-relation models for D2D communication should be adaptive in nature. There is no current research considering the changes in social relations over time.

Current researches on social-aware D2D communication considered mainly four factors of social relations: social bond, social links, social community, social centrality [15]. The social communities are based on social relationships among people who have the same social behaviors or interests. There are also some researches about social-community-aware resource allocation for D2D communications. Fang *et al.* [13] exploited social ties in human-formed social networks to enhance D2D resource sharing and further proposed a social-community-aware D2D resource allocation framework, where cellular users would like to share their channels with D2D communications in the same community formed by a group of people with close social ties. Zhao *et al.* [14] considered the small size social communities formed by people with similar interests and exploited them to optimize the resource allocation of the communities. In this paper, social relations are normalized by physical-social graph methods. Ahmed *et al.* [15] proposed a novel social-community-aware LLs establishment strategy, which exploited the interplay between social network features and communication domain constraints. To evaluate the impact of social community on physical network, the users in a community care only about the average path length (APL) of the same community. In these papers, social community is utilized, but there is no explanation of how to get the social relations between users and how to obtain communities based on social relationships.

On the other hand, D2D users usually choose to multiplex cellular user's spectrum resource to increase the resource utilization, which improves the spectrum utilization, but also causes strong interference between D2D users and cellular users. In order to maximize the system data rate, an effective resource allocation approach is needed to manage the interference between users. Bai *et al.* [16] formulated the resource allocation into a social awareness and social blind optimization problem. In order to optimize the network utility and resource utilization, linear programming is utilized to solve the optimization problem. The advantage of using linear programming to solve the problem is there is a unified algorithm and any linear programming problem has a solution. The disadvantage is that the demand of data accuracy is high and the calculating amount is quite large. Bastug *et al.* [17] analyzed the influence of considering social relations for D2D communication in the downlink OFDMA network and modeled the resource allocation problem into mixed integer nonlinear programming (MINLP) problem. The solution multiplexes the downlink cellular subscriber resources, greatly increasing the available spectrum bandwidth. However, it also requires highly complex and expensive equipment. Jiang *et al.* [18] designed SoCast, which is a social video multicast system for D2D communication based on social trust and social reciprocity. They proposed a distributed algorithm based on cooperative game. The problem is solved by game theory, which simplifies the optimization process to some extent, but it is one-sided for cooperative game to assume that users are altogether altruistic.

Based on the above analysis, in this paper, the intimacy degree of users is presented based on the user's call records for quantifying social relations, then we map the call-log data into time sequence and use Auto-Regressive Integrated Moving Average (ARIMA) model to predict the social relations. This can model the user's interactive behavior based on the actual call records, and social relations among users vary from time to time, ARIMA model for resource allocation in D2D communication can be adaptive. In addition, assuming that all users are completely altruistic or selfish represents two extreme user relationships. The social relationships between D2D users are more complex than the two cases. In this paper users are divided into naturally formed groups called social communities. Social communities are based on social relationships among people who have the same social behaviors or interests. Instead of maximizing D2D users' individual utility or the overall network utility, each user aims to maximize its social-community utility with consideration of other D2D users who have social relations with it, which has distributed characteristics of the optimization problem. In [16] and [17] linear programming or MINLP are utilized to solve the optimization problem, which require massive computation and highly complicated equipment. Due to the distributed nature of the problem and in order to simplify the computational process, potential game [19] is used to solve the social-community utility maximization problem of resource allocation for D2D communication. Potential game

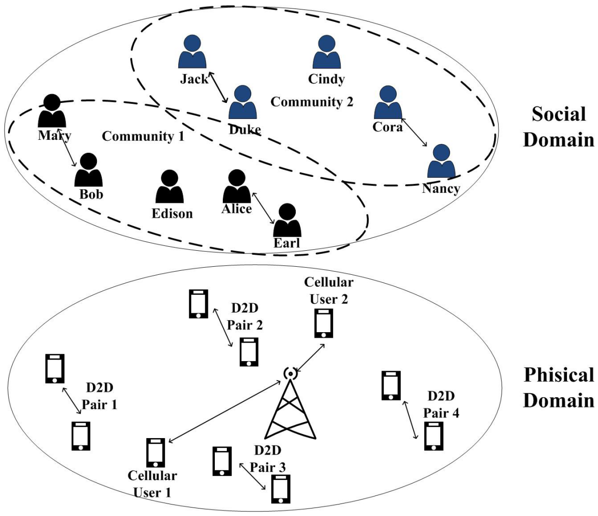

FIGURE 1. **Illustration of two-domain architecture for social-aware resource allocation in D2D communication, where there are 2 cellular users and 3 D2D pairs.**

is a useful tool to analyze the optimization problem, since the incentives of all players can be mapped into one function, and pure Nash Equilibrium can be found by potential function. Finally, a social-aware distributed resource allocation algorithm is proposed, and the algorithm achieves convergence and stability.

The rest of this article is organized as follows. The system model including physical domain and social domain and basic assumptions are established in Section II. In Section III, potential game is used to solve the social-community utility maximization problem and a social-aware distributed resource allocation algorithm is presented. The performance evaluation is given in Section IV. Finally, Section V concludes the paper.

II. SYSTEM MODEL

Since the performance of D2D communication in cellular network is highly dependent on users' behaviors, in order to achieve effective content distribution and content spread, social relations are applied in this paper. We consider a two-domain system model, which consist of physical domain and social domain, as shown in Figure 1. The physical domain describes the physical relations between users, and the social domain quantifies the social relations between mobile users derived from ARIMA model. In the social domain, mobile users in D2D communication are divided into different communities based on social behaviors or interests and users in the same community who have the same backgrounds and interests may be interested in similar contents.

A. PHYSICAL DOMAIN

In order to present every D2D user's social-community utility, the user's physical relations need to be proposed first.

In physical domain, it is assumed that cellular users share their uplink resources with D2D users to maximize spectrum efficiencies. Research scenarios are located in public areas such as office buildings and shopping malls. The users' density is much higher than that of other locations. The users' demands for data transmission are great and the propagation environment has a high path-loss exponent. But in order to avoid severe interference caused by D2D communication, one D2D user can share at most one resource block of a cellular user at a time. And the transmission powers of the cellular users and D2D users are constant.

Suppose a set of D2D users $M = \{M_1, M_2, \ldots, M_i, \ldots, M_j, \ldots, M_m\}$, share the upstream spectrum resources with a set of cellular users $N = \{N_1, N_2, \ldots, N_i, \ldots N_n\}$.

When D2D user M_i receives data from D2D user M_j and share the upstream spectrum resources with cellular user N_i, the data rate of user M_i can be given as:

$$R_{M_i} = W \log_2 \left(1 + \frac{P_{M_j} g_{M_i,M_j}}{P_{int} + N_0}\right) \tag{1}$$

Where W is the channel bandwidth, which is a constant. $P_{M_j} g_{M_i,M_j}$ is the received power from user M_j. P_{M_j} is the transmit power of user M_j. g_{M_i,M_j} is the channel gain between user M_i and M_j of D2D link. N_0 is the additive Gaussian white noise. P_{int} is the interference between users and can be denoted by

$$P_{\text{int}} = \sum\nolimits_{N_i \in N} \alpha_{N_i,M_i} P_{N_i} g_{M_i,N_i} + \sum\nolimits_{M_k \in M \setminus \{M_i,M_j\}} \alpha_{M_i,M_k} P_{M_k} g_{M_i,M_k} \tag{2}$$

Where $\sum_{N_i \in N} \alpha_{N_i,M_i} P_{N_i} g_{M_i,N_i}$ is the aggregated interference caused by cellular users, P_{N_i} is the transmit power of user N_i, g_{M_i,N_i} is the channel gain between D2D user M_i and cellular user N_i. α_{N_i,M_i} is a binary decision variable, where $\alpha_{N_i,M_i} = 1$ indicates D2D user M_i share the spectrum resources with cellular user N_i and the interference between them exits. Otherwise $\alpha_{N_i,M_i} = 0$. $\sum_{M_k \in M \setminus \{M_i,M_j\}} \alpha_{M_i,M_k} P_{M_k} g_{M_i,M_k}$ is the aggregated interference caused by other D2D users, P_{M_k} is the transmit power of user M_k. g_{M_i,M_k} is the channel gain between D2D user M_i and M_k. α_{M_i,M_k} is also an indicator variable, $\alpha_{M_i,M_k} = 1$ indicates there is interference between D2D user M_i and M_k, otherwise $\alpha_{M_i,M_k} = 0$.

B. SOCIAL DOMAIN

In this section, the degree of intimacy between users is quantified for social relation strengths based on mobile phone-call detail records. Then auto-regressive integrated moving average (ARIMA) model is applied to map the call-log data into time sequence and the users' predictions of social relations are made by the ARIMA model.

1) DEGREE OF INTIMACY

A vector of normalized frequencies of calls $P^{ab} = \{p_{in}^{ab}, p_{out}^{ab}, p_{\text{inter}}^{ab}\}$ is utilized to describe the degree of intimacy between any two users a and b. p_{in}^{ab} denotes the frequency of that user a receives calls from b, p_{out}^{ab} denotes the frequency of a calls b, p_{inter}^{ab} denotes the frequency of that a gives b a call then b calls back. p_{inter}^{ab} is a very important index, it can indicate the degree of interaction between user a and b. $P^{ab} = \{p_{in}^{ab}, p_{out}^{ab}, p_{\text{inter}}^{ab}\}$ can be calculated as follows:

The number of phone calls follows a Poisson distribution [20]. Suppose the arrival rate of user a receives calls from user b is λ_{in}^{ab}. The total arrival rate of user a *is* $\sum_{k\neq a} \lambda_{in}^{ka}$. Then user a's received number of calls from b in the interval $[0,t_j]$ is $C_{in}^{ab} = \lambda_{in}^{ab} t_j$, the total incoming number of calls of user a is $C_{in}^{a} = \sum_{k\neq a} \lambda_{in}^{ka} t_j$, so

$$p_{in}^{ab} = \frac{C_{in}^{ab}}{C_{in}^{a}} = \frac{\lambda_{in}^{ab} t_j}{\sum\limits_{k\neq a} \lambda_{in}^{ka} t_j} = \frac{\lambda_{in}^{ab}}{\sum\limits_{k\neq a} \lambda_{in}^{ka}} \tag{3}$$

Similarly, p_{out}^{ab} can be denoted as

$$p_{out}^{ab} = \frac{C_{out}^{ab}}{C_{out}^{a}} = \frac{\lambda_{out}^{ab} t_j}{\sum\limits_{k\neq a} \lambda_{out}^{ka} t_j} = \frac{\lambda_{out}^{ab}}{\sum\limits_{k\neq a} \lambda_{out}^{ka}} \tag{4}$$

Where λ_{out}^{ab} is the arrival rate of user a calls b, $\sum_{k\neq a} \lambda_{out}^{ka}$ is the total arrival rate of other users receives calls from user a. C_{out}^{ab} denotes the number of calls that a calls b, C_{out}^{a} denotes the total outgoing number of calls of user a.

p_{inter}^{ab} is calculated as follows. Due to the number of phone calls follows a Poisson distribution, the probability of no arrival calls in the interval [0, t] is $P(\tau > t) = e^{-\lambda t}$, where λ is the arrival rate and τ is inter-arrival time. The probability of at least one call arrivals in the interval [0, t] is $P(\tau > t) = 1 - e^{-\lambda t}$. The rate of user a calls user b in $[0,t_i]$ is $\lambda_{out}^{ab} t_i$. After a period of time user b calls user a back in $[t_i, t_j]$ with rate $\lambda_{in}^{ab}(t_j - t_i)$. According to [21],

$$\begin{aligned} &P(a \text{ calls } b \text{ and } b \text{ calls } a \text{ back}) \\ &= P(a \text{ calls } b)P(b \text{ calls } a \text{ ,when it is know that } a \text{ calls } b) \\ &= P(a \text{ calls } b)[P(b \text{ calls } a) + p_{\text{inter}}^{ab} P(b \text{ does not call } a)] \\ &= (1 - e^{-\lambda_{out}^{ab} t_i})[(1 - e^{-\lambda_{in}^{ab}(t_j - t_i)}) + p_{\text{inter}}^{ab} e^{-\lambda_{in}^{ab}(t_j - t_i)}] \end{aligned}$$

The factor $P(b$ calls a, when it is know that a calls $b)$ is the conditional probability. The factor is denoted as the prior probability that b calls a plus a fraction of the probability that b does not call a [22]. Then the fraction is p_{inter}^{ab}, which present the possibility of interaction between user a and b. It is obvious that p_{inter}^{ab} is zero when there is no tendency to reciprocate and unity when the tendency is maximal.

The number of calls from user a to b is denoted by C_{out}^{ab} as mentioned above, then the expected value of the number of calls describing the interaction between user a and user b, can be denoted by $E(C_{\text{inter}}^{ab})$, as

$$\begin{aligned} &E(C_{\text{inter}}^{ab}) \\ &\quad = C_{out}^{ab}(1 - e^{-\lambda_{out}^{ab} t_i})[(1 - e^{-\lambda_{in}^{ab}(t_j - t_i)}) + p_{\text{inter}}^{ab} e^{-\lambda_{in}^{ab}(t_j - t_i)}] \end{aligned} \tag{5}$$

After rearranging, p_{inter}^{ab} can be denoted by

$$p_{\text{inter}}^{ab} = \frac{C_{\text{inter}}^{ab} - C_{out}^{ab}(1 - e^{-\lambda_{out}^{ab} t_i})(1 - e^{-\lambda_{in}^{ab}(t_j - t_i)})}{C_{out}^{ab}(1 - e^{-\lambda_{out}^{ab} t_i}) e^{-\lambda_{in}^{ab}(t_j - t_i)}} \tag{6}$$

Where C_{inter}^{ab} is observed number of interaction calls.

After the calculation of $P^{ab} = \{p_{in}^{ab}, p_{out}^{ab}, p_{\text{inter}}^{ab}\}$ for the past few moments, ARIMA model is applied to predict the value of P^{ab}.

2) PREDICTION OF SOCIAL RELATIONS

The above method is used to calculate the past value of P^{ab}. The call-log data between any two user a and b are mapped into time sequence denoted by $(P_{t-1}^{ab}, P_{t-2}^{ab}, \ldots)$, which can be utilized to predict P_t^{ab} by ARIMA model. Auto-Regressive Integrated Moving Average (ARIMA) model integrates Auto-Regressive (AR), Integrated (I), and Moving Average (MA) into a general comprehensive time sequence model.

Before using the ARIMA model to predict P_t^{ab}, it is necessary to determine the type and parameters of the model. Firstly possible models need to be selected from the general models and then check the selected model based on historical data to see if the sequence is accurately described. If the residuals are small, the selected model is appropriate. It consists of the following three steps.

Step 1: The first step is model recognition. For convenience, we will abbreviate P_t^{ab} as P_t. First, it is necessary to determine whether P_t is stable. If the sequence is stable, it can be expressed by ARMA (r, s). i.e.

$$\begin{aligned} P_t &= \pi_1 P_{t-1} + \pi_2 P_{t-2} + \cdots + \pi_r P_{t-r} \\ &\quad + e_t - \psi_1 e_{t-1} - \psi_2 e_{t-2} - \cdots - \psi_s e_{t-s} \end{aligned} \tag{7}$$

Where $(P_{t-1}, P_{t-2}, \ldots, P_{t-r})$ is the past values of P_t. $(e_t, e_{t-1}, \ldots, e_{t-s})$ is the disturbance sequence that drives the system, which is a sequence of irrelevant random variables whose mean is zero and variance is constant. π_i, $i = 1, 2, \ldots, r$ and $\psi_j, j = 1, 2, \ldots, s$ are coefficients to be estimated.

By using the backshift linear operator B defined by $BP_t = P_{t-1}$, $B^i P_t = P_{t-i}$ for any integer i, ARMA(r, s) model can be written in backshift linear operator form

$$\begin{aligned} &(1 - \pi_1 B - \pi_2 B^2 - \ldots - \pi_r B^r) P_t \\ &\qquad = (1 - \psi_1 B - \psi_2 B^2 - \ldots - \psi_s B^s) e_t \end{aligned} \tag{8}$$

That is,

$$\pi_r(B) P_t = \psi_s(B) e_t \tag{9}$$

Where $\pi_r(B)$ is defined by $\pi_r(B) = 1 - \pi_1 B - \pi_2 B^2 - \ldots - \pi_r B^r$, $\psi_s(B)$ is defined by $\psi_s(B) = 1 - \psi_1 B - \psi_2 B^2 - \ldots - \psi_s B^s$.

If $\{\tilde{P}_t\}$ is an unstable time sequence, ARMA(r, s) model can be extended to ARIMA(r, d, s) model. Considering the difference linear operator Δ defined by $\Delta \tilde{P}_t = \tilde{P}_t - \tilde{P}_{t-1} = \tilde{P}_t - B\tilde{P}_t = (1 - B)\tilde{P}_t$, the stable time sequence $\{P_t\}$ can be obtained by the d^{th} difference Δ^d of unstable time sequence $\{\tilde{P}_t\}$, i.e. $P_t = \Delta^d \tilde{P}_t = (1 - B)^d \tilde{P}_t$, so the *ARIMA(r, d, s)* model can be denoted as

$$\pi_r(B) \Delta^d \tilde{P}_t = \psi_s(B) e_t \tag{10}$$

The main tool of model recognition is the autocorrelation function and partial correlation function of $\{P_t^{ab}\}$. If the autocorrelation function of $\left\{P_t^{ab}\right\}$ decays slowly, $\left\{P_t^{ab}\right\}$ is unstable and can be fitted with the ARIMA(r, d, s) model. Otherwise it is a stable sequence and ARMA(r, s) model is used to fit the sequence.

Step 2: The second step is model estimation. If the previous judgment of $\left\{P_t^{ab}\right\}$ is unstable, $\left\{P_t^{ab}\right\}$ is subjected to a sufficient number of differentials to be stable and the number of times of difference is d. That is, d is the difference order required to achieve stabilization. $\Pi = \{\pi_1, \pi_2, \ldots \pi_r\}$ and $\Psi = \{\psi_1, \psi_2, \ldots \psi_s\}$ need to be estimated by linear least squares iteration or Bayes principle [23].

Step 3: The third step is model validation. After the model is identified and estimated, the model is subjected to diagnostic tests. An effective method to test the model is "overfitting", that is, comparing the variance of ARIMA (r, d, s) with ARIMA (r+1, d, s) and ARIMA (r, d, s+1). If the variance of ARIMA (r, d, s) is the smallest, the model is fitted successfully. Otherwise, the coefficients need to be re-estimated and re-validation until the condition is satisfied.

According to [24], a large number of tests on the actual call records is done, the model of the actual call records is ARIMA(r, 0, s), i.e.

$$P_t = \pi_1 P_{t-1} + \pi_2 P_{t-2} + \ldots + \pi_r P_{t-r} + e_t - \psi_1 e_{t-1} - \psi_2 e_{t-2} - \ldots - \psi_s e_{t-s} \tag{11}$$

The parameters $\Pi=\{\pi_1, \pi_2, \ldots \pi_r\}$, $\Psi = \{\psi_1, \psi_2, \ldots \psi_s\}$ can be determined by the three steps above.

So As long as $\{P_{t-1}, P_{t-2}, \ldots P_{t-r}\}$ is calculated based on the call records observed before, the user's degree of intimacy at time t can be predicted, expressed as

$$P_t^{ab} = \{p_{t_{in}}^{ab}, p_{t_{out}}^{ab}, p_{t_{\text{inter}}}^{ab}\} \tag{12}$$

The vector $P_t^{ab} = \{p_{t_{in}}^{ab}, p_{t_{out}}^{ab}, p_{t_{\text{inter}}}^{ab}\}$ can be combined into a parameter ω_{ab}^t. For a pair of users a and b who have social relations between them, the strength of social relation at time t can be described as

$$\omega_{ab}^t = \frac{1}{3}p_{t_{in}}^{ab} + \frac{1}{3}p_{t_{out}}^{ab} + \frac{1}{3}p_{t_{\text{inter}}}^{ab} \tag{13}$$

$\omega_{ab}^t \in [0, 1]$, which is obtained by ARIMA model. $\omega_{ab}^t = 1$ means the strongest relations between user a and b while $\omega_{ab}^t = 0$ means the weakest relations between them.

III. SOCIAL-AWARE POTENTIAL GAME APPROACH

In order to achieve effective content distribution and content spread with consideration of social networks among users, that is, better spectrum resources are given to users who have better social networks and content diffusion capabilities. In order to achieve this goal, we aim at maximizing the social-community utility by potential game in the process of resource allocation for D2D communication. Potential game is utilized due to its outstanding mapping nature and always has the Nash Equilibrium. Finally, a social-aware distributed resource allocation algorithm is proposed, and the algorithm achieves convergence and stability.

A. GAME FORMULATION

Due to the distributed nature of the problem, game theory is utilized to solve the social-community utility maximization problem, which can effectively reduce the computational complexity.

The game of resource allocation for D2D communication can be defined as $G = \left\{M, \{X_{M_i}\}_{M_i \in M}, \{U_{M_i}\}_{M_i \in M}\right\}$, where $M = \{M_1, M_2, \ldots, M_i, \ldots, M_m\}$ is the set of D2D users, that is, game players. $\{X_{M_i}\}_{M_i \in M}$ is the set of resource allocation strategies for each D2D user M_i. $\{U_{M_i}\}_{M_i \in M}$ is the payoff function for each D2D user M_i.

In this paper, $\{U_{M_i}\}_{M_i \in M}$ is the social-community utility of user M_i. The social-community utility for any D2D user $M_i \in M$, can be defined as

$$U_{M_i}(x) = R_{M_i} + \sum\nolimits_{M_i \neq M_j} \omega_{M_i,M_j} R_{M_j} \tag{14}$$

Where $x = (x_{M_1}, x_{M_2}, \ldots x_{M_m}) \in \Pi_{M_1}^{M_m} X_{M_i}$ is the strategy profile of all users, x_{M_i} is the strategy of D2D user M_i and $x_{M_i} \in X_{M_i}$, $X_{M_i} = \{N_1, N_2, \ldots, N_n\}$ is all possible strategies for D2D user M_i. The social-community utility consists of 2 parts: its own data rate R_{M_i}, and the weight sum of other D2D users' data rate who have social relations with it. The strength of social relations ω_{M_i,M_j} is utilized in user's utility. When a D2D user has more social-related users and stronger social-tie strengths, it has a better content diffusion capability, and its social-community utility gets higher. In this case, the D2D user can be assigned to better spectrum resources to achieve more efficient content distribution.

Let $x_{-M_i} = (x_{M_1}, x_{M_2}, \ldots x_{M_{i-1}}, x_{M_{i+1}}, \ldots x_{M_m})$ be the set of chosen strategies for other D2D users except user M_i. Then $x = (x_{M_1}, x_{M_2}, \ldots x_{M_m}) = (x_{M_i}, x_{-M_i})$ is the set of all the strategies selected by the users. Given the strategies x_{-M_i} of other users, the user M_i needs to choose a strategy x_{M_i} to maximize its own social-community utility. i.e.

$$\max_{x_{M_i} \in X_{M_i}} U_{M_i}(x_{M_i}, x_{-M_i}), \quad \forall M_i \in M \tag{15}$$

We can prove that the optimization problem of resource allocation for D2D communication can be solved by potential game. First the definition of potential game is given. In a game, if each player's change for its own strategy can be mapped into a global unique function, the function is called *potential function*, and the game is called *potential game*.

Potential function $P(x)$ satisfies the following condition:

$$U_{M_i}(x_{-M_i}, x_{M_i}) - U_{M_i}(x_{-M_i}, x'_{M_i}) > 0 \tag{16}$$

If $P(x_{-M_i}, x_{M_i}) - P(x_{-M_i}, x'_{M_i}) > 0$, for every D2D user $M_i \in M$ and for every $x_{-M_i} \in X_{-M_i}$.

The potential function in this optimization problem can be defined as

$$P(x) = \sum_{M_i \in M} U_{M_i}(X) = \sum_{M_i \in M} (R_{M_i} + \sum\nolimits_{M_i \neq M_j} \omega_{M_i,M_j} R_{M_j}) \tag{17}$$

Suppose D2D user M_i changes its spectral resource allocation from x_{M_i} to x'_{M_i}, then the change of payoff for D2D user M_i is

$$\begin{aligned} U_{M_i} &- U'_{M_i} \\ &= R_{M_i} + \sum_{M_i \neq M_j} \omega_{M_i,M_j} R_{M_j} - (R'_{M_i} + \sum_{M_i \neq M_j} \omega_{M_i,M_j} R'_{M_j}) \\ &= R_{M_i} + \sum_{k \in Z^s_{M_i} \cap Z^p_{M_i}} R_k - \left(R'_{M_i} + \sum_{k \in Z^s_{M_i} \cap Z^p_{M_i}} R'_k \right) \end{aligned} \tag{18}$$

Where $Z^s_{M_i}$ and $Z^p_{M_i}$ present the set of users who have social relations and physical relations with user M_i, respectively.

Here we suppose the strength of social relations in the same community is 1 for simplicity. The change of function $P(x)$ is

$$\begin{aligned} P(&x_{-M_i}, x_{M_i}) - P(x_{-M_i}, x'_{M_i}) \\ &= \sum_{M_i \in M} (R_{M_i} + \sum\nolimits_{M_i \neq M_j} \omega_{M_i,M_j} R_{M_j}) \\ &\quad - \sum_{M_i \in M} (R'_{M_i} + \sum\nolimits_{M_i \neq M_j} \omega_{M_i,M_j} R'_{M_j}) = U_{M_i} - U'_{M_i} \\ &\quad + \sum_{k \in M \backslash \{M_i\} \cap Z^s_{M_i} \cap Z^p_{M_i}} \left(R_k + \sum_{j \in Z^s_k \cap Z^p_k} R_j - \left(R'_k + \sum_{j \in Z^s_k \cap Z^p_k} R'_j \right) \right) \\ &= \left(\left| Z^s_{M_i} \cap Z^p_{M_i} \right| + 1 \right) \left(U_{M_i} - U'_{M_i} \right) \end{aligned} \tag{19}$$

So $U_{M_i}(x_{-M_i}, x_{M_i}) - U_{M_i}(x_{-M_i}, x'_{M_i})$ and $P(x_{-M_i}, x_{M_i}) - P(x_{-M_i}, x'_{M_i})$ have the same positive or negative values.

Finally, we conclude that

$$\begin{aligned} U_{M_i}(x_{-M_i}, x_{M_i}) - U_{M_i}(x_{-M_i}, x'_{M_i}) > 0 \quad if \\ P(x_{-M_i}, x_{M_i}) - P(x_{-M_i}, x'_{M_i}) > 0, \quad \forall M_i \in M \end{aligned}$$

So the optimization problem of resource allocation for D2D communication is potential game has been proved.

The social-community utility maximization problem of resource allocation for D2D communication is

$$\max_{x \in \in \Pi^{M_m}_{M_1} X_{M_i}} P(x) \tag{20}$$

Where every D2D user can increase $P(x)$ by changing its own resource allocation strategy.

B. NASH EQUILIBRIUM

It can be proved that potential game $G = \left\{ M, \{X_{M_i}\}_{M_i \in M}, \{U_{M_i}\}_{M_i \in M} \right\}$ has pure Nash Equilibrium. First, the definition of Nash Equilibrium is given. If any D2D user can not increase the social-community utility by changing its own resource allocation strategy, the game $G = \left\{ M, \{X_{M_i}\}_{M_i \in M}, \{U_{M_i}\}_{M_i \in M} \right\}$ has Nash Equilibrium, i.e.

$$x^*_{M_i} = \arg \max_{x_{M_i} \in \aleph_{M_i}} U_{M_i}(x_{M_i}, x_{-M_i}), \quad \forall M_i \in M \tag{21}$$

One of the characteristics of potential game is that there must be a pure Nash Equilibrium. Because each player must be monotonous for each change of its strategy, which always makes its utility higher. If the utility function's change of every player is mapped to a potential function, the potential function is also monotonous. If the potential function is monotonous, every monotonic change to it will always come to an end (until every player is satisfied and no one can change its own strategy). Then potential game comes to a pure Nash Equilibrium. It has already been proved that the problem is potential game, so pure Nash Equilibrium solution must exist in the optimization problem.

C. DISTRIBUTED RESOURCE ALLOCATION SOLUTIONS

The key to the optimization problem is that each D2D user must decide which channel of the cellular users to occupy according to the social-community utility. Based on the property of the potential game, the resource allocation strategy x^* has Nash Equilibrium, which maximizes the value of potential function. In addition, since the potential function

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Algorithm 1 Social-Aware Distributed Resource Allocation Algorithm for D2D Communication

Initialization:

Choose a channel $x_{M_i} = N_i$ randomly for each user M_i;

The base station calculates the strength of social relations with ARIMA

model between any two users;

End initialization

Set $i = 1$;

While $i < I_{\max}$ **do**
  For each user M_i **do**
    Calculate the data rate R_{M_i};
    Report the call-log data of user M_i, data rate R_{M_i} and other transmission configuration to the base station;
    The base station broadcasts the social relations and other users' data rate to user M_i;
    Compute $U_{M_i}(x_{M_i})$ for D2D user M_i;
    Choose a new channel N'_i for D2D user M_i randomly;
    if $(U_{M_i}(x'_{M_i}) > U_{M_i}(x_{M_i})\&$
      $U_{M_j}(x'_{M_j}) \geq U_{M_j}(x_{M_j}), \forall M_j \in M, M_i \neq M_j)$
      Stay in the new channel N'_i;
    else
      Get λ uniform distribution in (0,1];
    if $(\lambda < \frac{1}{1+\exp(-(U(x')-U(x))/\log(i-1))})$
      Stay in the new channel N'_i;
    else
      Go back to the original channel N_i;
    end if
    end if
  end for
  $i = i+1$;
end while
returnPotential Game Equilibrium x^*.

---

has a finite value, the potential game G has a finite improvement property. Specifically, the order in which D2D users get more efficient spectrum resources scheme can be random and D2D users can achieve Nash Equilibrium through limited steps.

Assume that the resource allocation vector $x = \{x_{M_1}, \ldots, x_{M_i}, \ldots, x_{M_j}, \ldots, x_{Mm}\}$ for a set of D2D users $M = \{M_1, M_2, \ldots M_m\}$, and the set of current resource allocation strategies is $x \in X$. For any D2D user M_i, if and only if $U_{M_i}(x'_{M_i}) > U_{M_i}(x_{M_i}) \& U_{M_j}(x'_{M_j}) \geq U_{M_j}(x_{M_j}), \forall M_j \in M, M_i \neq M_j$, the current strategy x_{M_i} can change to a new strategy x'_{M_i}. With repeating the changing operations, the potential function will monotone increasing until every player is satisfied and no one can change its own strategy. Then it will come to the Nash Equilibrium. Social-aware distributed resource allocation algorithm is presented as Algorithm 1.

In the algorithm of resource allocation for D2D communication, D2D users first send the call-log data to the base station. The social relations are calculated by ARIMA model and sent to the D2D users. Next, for any user M_i, $U_{M_i}(x_{M_i})$ is calculated based on the received social relationships and the data rate of other D2D users. Finally, D2D users choose whether to change the current channel based on the social community utility compared with the previously selected channel until that they reach the Nash equilibrium.

In order to avoid the local maximum value, when the constraint is not satisfied, we also define the acceptance probability

$$\beta_{x',x} = \frac{1}{1 + \exp(-(U(x') - U(x))/\log(i-1))} \quad (22)$$

Where i is the current times of change operations.

D. COMPLEXITY, CONVERGENCE AND STABILITY

The complexity of algorithm 1 is much lower than the centralized solution, because the change operations in algorithm 1 are used in the community, not in the whole network. After a limited number of change operations, the resource allocation algorithm converges to the final Nash stable resource allocation vector x^*.

Specifically, the upper bound of the computational complexity in the resource allocation solution is $O(n^D)$, where D is the number of D2D links, n is the number of possible strategies. However, the time complexity of our algorithm is linear because of the monotonicity of potential function. In each iteration, we define the exchange cost of social information and average utility broadcast from the base station as A and B, respectively. As for user M_i, the report overhead of its own data rate is denoted as C. The total overhead in system in each iteration can be written as: $O = A+B+C^*m$, where m is the number of users who have social relations with M_i, which is small compared to state-of-art schemes.

In each change operation in Algorithm 1, a new resource allocation vector is generated by changing to a new strategy, and the maximum number of resource allocation strategies

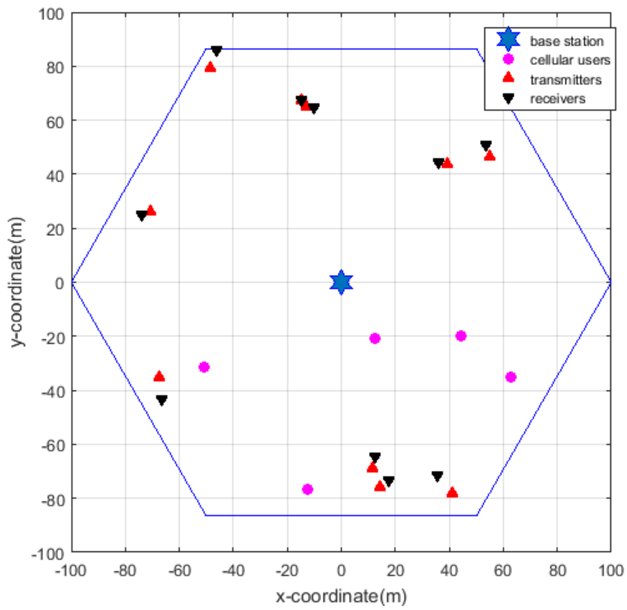


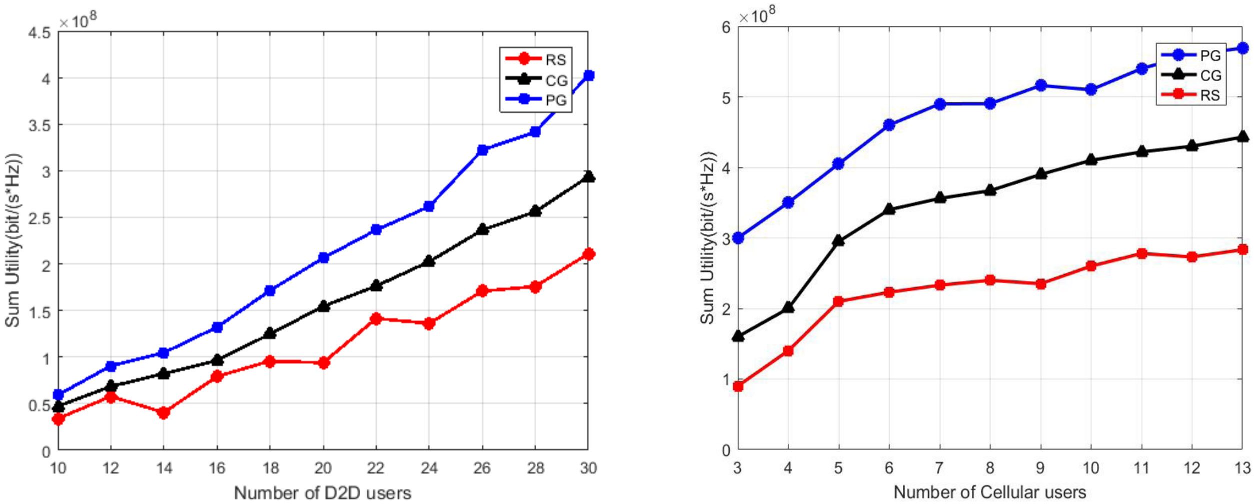
FIGURE 2. A snapshot of resource allocation with 5 cellular users and 20 D2D users Magnetization as a function of applied field.

for each D2D user is n, which is the number of cellular users. Therefore, the number of resource allocation vector for the set of D2D users M is a Bell number according to [25]. Thus, the sequence of random exchange operations will be terminated with probability 1, and the system converges to the final resource allocation vector x^* after a finite transition with a probability of 1, which proves the probability convergence of the proposed distributed algorithm [25].

As for contradiction, assume that the final resource allocation vector x^* obtained from algorithm 1 is not Nash stable. The present resource allocation vector of D2D user M_i is x_{M_i}, and there exists a new resource allocation vector $x'_{M_i} \in x^*$ which makes $U_{M_i}(x'_{M_i}) > U_{M_i}(x_{M_i}) \& U_{M_j}(x'_{M_j}) \geq U_{M_j}(x_{M_j}), \forall M_j \in M, M_i \neq M_j$ According to algorithm 1, D2D user M_i can still change from x_{M_i} to x'_{M_i}, which contradicts the fact that x^* is the final resource allocation vector. Thus, we have shown that algorithm 1 generated by the final network resource allocation vector x_{fin} must be Nash stable.

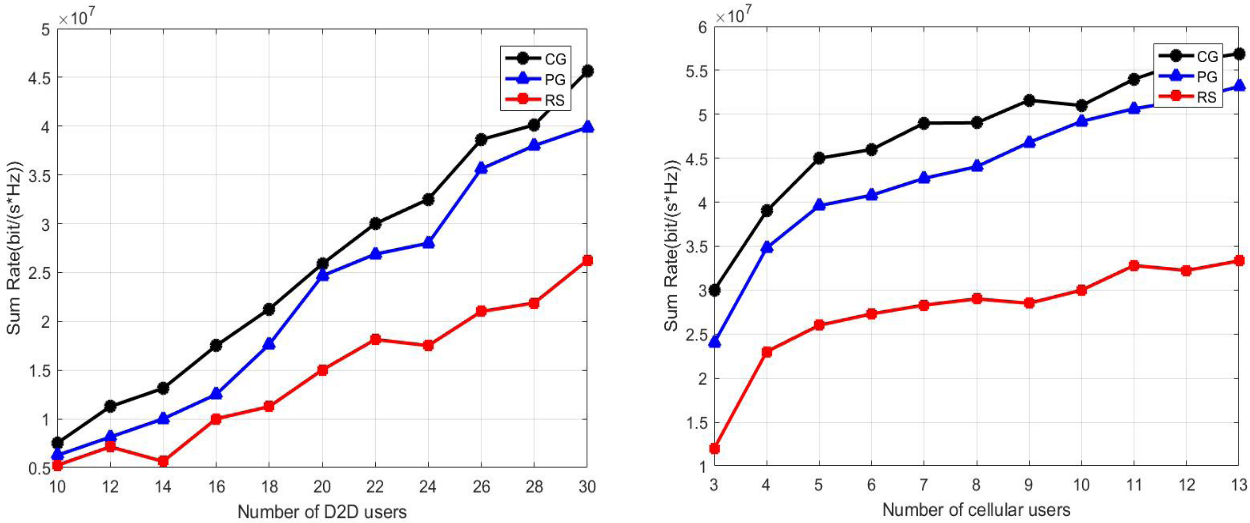
IV. PERFORMANCE EVALUATION

The performance of time-varying social-aware resource allocation for D2D is evaluated and analyzed in this section. We consider a hexagonal area of 100 meters, where the base station is in the center of the system. The cellular and D2D users are randomly deployed as shown in Fig.2. In the example, 20 D2D users occupy the spectrum resources of 5 cellular users. The transmitters of D2D links are randomly distributed within the coverage of the BS, and the receivers are randomly distributed in the circumference of the transmitter in the range of 3 meters to 10 meters. In simulations, we use the uniform distribution to generate social network. The path loss index of the free space propagation path-loss model is set to 4. Both the



(a) (b)

FIGURE 3. The social community utility of different resource allocation algorithms with (a) different number of D2D users and (b) different number of cellular users.



(a) (b)

FIGURE 4. Sum rate of different resource allocation algorithms with (a) different number of D2D users and (b) different number of cellular users.

path loss and shadow fading are taken into account for cellular and D2D links. The main parameters used in the simulation are shown in Table 1. For each simulation scenario with fixed D2D links and cellular users, we repeated the simulations for 1000 times, and each simulation will re-randomly select positions of users. Fig. 2 shows a snapshot of the wireless scene.

The performance of our scheme is compared with the following two schemes:

1) Coalition game (CG) [26], where the resources is allocated through the coalition game model. The algorithm can achieve the near-optimal solution of system sum utility.

2) Random selection (RS), where D2D links randomly choose the spectrum resource for communication.

We evaluate the following five performance indicators:

1) The sum of social community utility $P(x)$, which is determined by the D2D users' data rates and social relationships between them.

2) System sum rate R, which is the sum data rate of cellular users and D2D users. The data rate of each user is calculated by (1).

3) The influence of social strength, we will observe the sum of social community utility as social strength changes.

4) Jains fairness index [27], [28], which can determine whether the users have a fair allocation of resources.

5) The property of convergence, which can determine whether the algorithm converges.

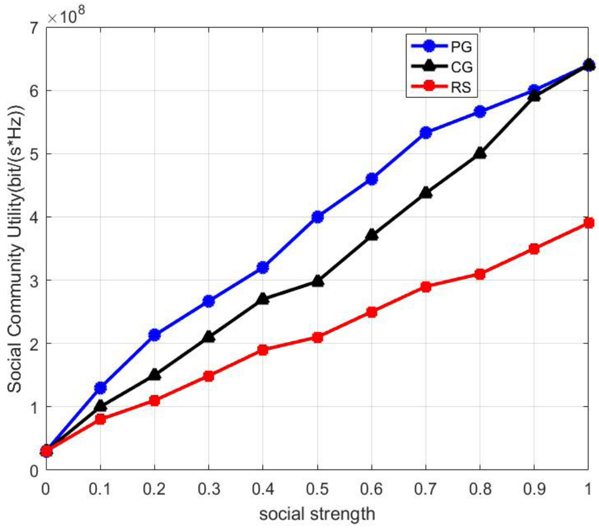


FIGURE 5. The social community utility of different resource allocation algorithms with different social strength.

A. SOCIAL COMMUNITY UTILITY

Fig. 3 shows the sum of social community utility when D2D users get spectrum resources through different schemes. In this simulation, we set the number of cellular users to be 5 and vary the number of D2D users from 10 to 30 in Fig. 3(a), and set the number of D2D users to be 30 and vary the number of cellular users from 3 to 13 in Fig. 3(b). Fig. 3(a) and (b) indicate that the sum of social community utility gets higher with the increasing number of D2D users or cellular users.

In Fig. 3(a), the sum of social community utility is higher than that of CG and RS more than 33% and 50%, respectively. In Fig. 3(b), the sum of social community utility is higher than that of CG and RS more than 36% and 60%, respectively. From the results, we can observe that that our algorithm performs better when the number of D2D or cellular users increase, which consider both physical and social relationships.

B. SYSTEM SUM RATE

Fig.4 shows the system sum rate of the three schemes. Similarly, we set the number of cellular users to be 5 and vary the number of D2D users from 10 to 30 in Fig. 4(a), which represents a resource-poor system where D2D users may need to share the same spectrum resource, and set the number of D2D users to be 30 and vary the number of cellular users from 3 to 13 in Fig. 4(b), which represents a resource-rich system where D2D users may have more spectrum selections. The results indicate the system sum rate gets higher with the increasing number of D2D users or cellular users.

In Fig. 4 (a), due to the increase of system bandwidth resources, the total system rate increases as the number of cellular user increases. In Fig.4 (b), when the number of D2D user increases, the total system rate increases because neighboring D2D users occupy the same spectrum resources of cellular users. We can see that the CG always achieves the best performance because the solution represents the ideal situation. Each D2D user has the same goal to maximize the performance of the entire network. Although the PG performance is not optimal, it represents the real situation. In fact, not all users are selfless. However, the stronger the social relationship between users, the closer the performance of PG to CG.

C. THE INFLUENCE OF SOCIAL STRENGTH

Fig. 5 shows the change of the sum of social community utility with social strength. In this simulation, we set the number of cellular users and D2D users to be 5 and 30, respectively. Fig. 5 indicates that sum of social community utility gets higher with the increasing of social strength. Obviously PG performs better under different social strength. When social

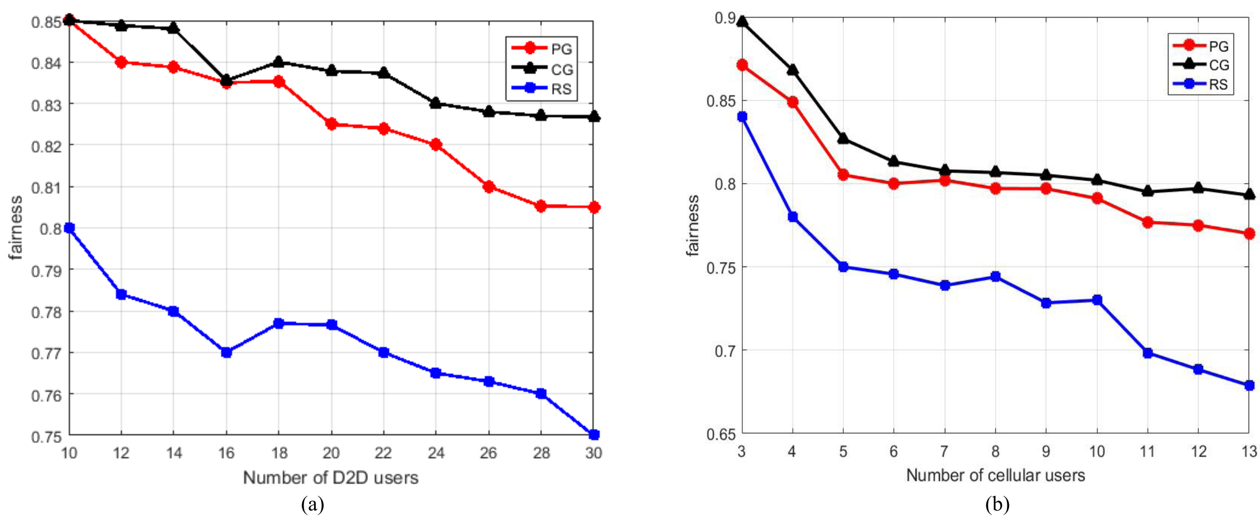


FIGURE 6. Fairness of different resource allocation algorithms with (a) different number of D2D users and (b) different number of cellular users.

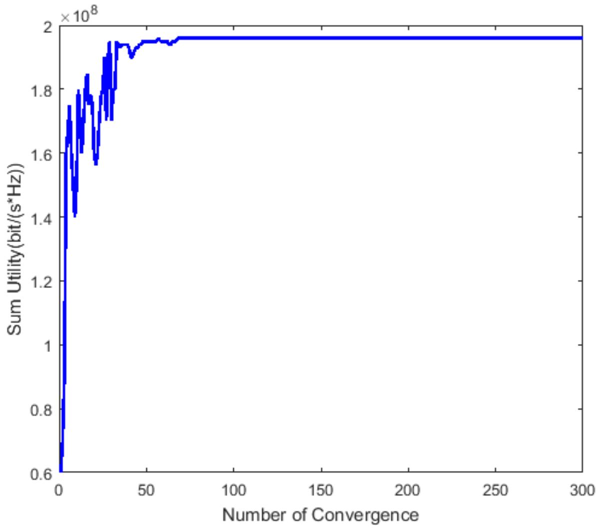


FIGURE 7. System convergence of proposed algorithm with 5 cellular users and 20 D2D users.

strength is 1, users are selfless. PG and CG have the same social community utility.

D. SYSTEM FAIRNESS

In Fig. 6, we use the Jains fairness index to get how the data is actually shared among D2D users. As shown in Figs. 6(a) and (b), when the number of D2D users and cellular users change, the system fairness of coalition game, random selection, and potential game is not affected obviously. However, coalition game has a better performance in fairness, because potential game has considered social relationships and better spectrum resources are utilized by users whose social relations are strong. Therefore, it has an impact on the fairness of the algorithm. But potential game maximizes the social community utility. Effective content distribution and content spread with the consideration of social networks among users is achieved by the social-aware resource allocation algorithm.

E. GAME CONVERGENCE

Fig. 7 shows the convergence of the proposed algorithm with 5 cellular users and 20 D2D users. Due to the poor channel conditions, even if they obtain the best spectrum resources, a small part of users can hardly achieve equilibrium. In order to avoid the influence of extreme cases, when the change operations reach a sufficient number of times, we assume that the base station will execute resource allocation procedure. By observing the social community utility of D2D users, we can find that our proposed algorithm can quickly converge to equilibrium.

V. CONCLUSIONS

In this paper, we propose a time-varying social-aware resource allocation for D2D Communication. Social relations are predicted by the Auto-Regressive Integrated Moving Average (ARIMA) model with the call records. The utility function of potential game is defined by social community. A distributed resource allocation algorithm for D2D communication is proposed and we theoretically prove that the proposed algorithm has pure Nash Equilibrium. The simulation results show that our algorithm is fair and effective. Compared with other strategies, our algorithm improves the total utility of the system by more than 30%, more than 50% higher than the random selection, effectively enhance the system capacity. On the other hand, mode selection also has influences on social-aware D2D communication. Therefore, our future works will concentrate on the joint works of resource allocation and mode selection.

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