Social-aware energy efficiency optimization for device-to-device communications in 5G networks

De-Thu Huynh[*,a,e], Xiaofei Wang[b], Trung Q. Duong[c], Nguyen-Son Vo[d], Min Chen[*,a]

[a] School of Computer Science and Technology, Huazhong University of Science and Technology, China
[b] Department of Computer Science and Technology, Tianjin University, China
[c] School of Electronics, Electrical Engineering and Computer Science, Queen's University Belfast, UK
[d] Institute of Research and Development, Duy Tan University, Vietnam
[e] Faculty of Information Technology, Ho Chi Minh City University of Transport, Vietnam

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ABSTRACT

Mobile social networks and device-to-device (D2D) communications have emerged as promising techniques to support better local advanced services in 5G networks. Nevertheless, the integration of mobile social networks and D2D communications into 5G networks poses pivotal challenges such as how to exploit the social relationships of mobile users (MUs) and manage the interference and resources (i.e., spectrum and energy) in order to improve the performance of D2D communications. To this end, we propose a social-aware energy efficiency optimization solution for D2D communications in 5G networks. In particular, we first analyze and evaluate the influence of social relationships on the performance of D2D communications, which enable us to formulate the energy efficiency optimization (EEO) problem while carefully considering both the social relationships and physical interference between all the MUs. The EEO problem is then solved for optimal channel mode selection and optimal transmission powers allocated to each MU to maximize the energy efficiency, by utilizing adaptive genetic algorithm. Numerical results show that compared with social-unaware methods, our proposed solution can achieve significant improvement in terms of energy efficiency and system throughput while preserving the quality of service (QoS) for all users by taking into account the spectrum efficiency and transmission power constraints.

1. Introduction

The fifth generation (5G) cellular networks are being developed to meet the demands for significantly increasing data traffic, generated by the ever-growing number of mobile devices and their bandwidth-hungry mobile applications [1]. The system characteristics of 5G networks consist of high capacity, extremely low latency and very high data rate to support various media-rich mobile applications with stringent quality of service (QoS) requirements [2–4]. As a promising technique for 5G networks, the emerging device-to-device (D2D) communications has the capability to improve network capacity, enhance spectrum efficiency and reduce power consumption [5–7]. In D2D communications, mobile devices in close proximity can communicate directly with each other, instead of through a base station (BS). As a result, D2D communications can support better local advanced services such as small-scale social networking, local advertising, local data sharing and Internet of Things (IoT) applications [8,9]. However,

the utilization of D2D communications in 5G networks is faced with some new technical challenges, such as interference management, resource allocation (i.e., spectrum and energy), mode selection (i.e., cellular or D2D mode), power allocation and especially how to exploit the social relationships of mobile users (MUs) [9,10].

In consideration of mobile social networks, mobile devices are held by humans who may form social networks with stable relationships [11,12]. It is obvious that the social information of MUs in social networks reflects their interactions in real life [13]. If the social relationships of MUs are exploited in an effective way, the knowledge of social networks can be leveraged in order to encourage MUs to share the data directly [14–16]. Therefore, the proliferation of social networks (e.g., Facebook, Twitter, and Sina Blog, etc.) also offers good opportunities to improve the performance of D2D communications in 5G networks. This enables better performance of numerous promising applications, such as proximity-based social networks (e.g., group gaming, location-aware advertisement, local data sharing, etc.), emergency communications in

disasters (e.g., earthquakes, fires, floods, etc.) and communications in safe traffic systems.

Moreover, the increasing QoS of mobile applications results in an increase in energy consumption of mobile devices [17]. Meanwhile, the current state-of-the-art in battery technology has not dealt with this exponential growth, leaving a huge gap between the available battery capacity and required battery capacity [18]. Therefore, the energy efficiency in D2D communications should be intensively investigated in order to save as much energy consumption as possible, contributing to the evolution of green 5G networks.

In this paper, we aim to leverage the social relationships of MUs to improve the performance of D2D communications in terms of energy efficiency, while achieving high system throughput and guaranteeing the spectrum efficiency for high QoS requirements. To do so, we propose a social-aware energy efficiency optimization solution for D2D communications in 5G networks by applying adaptive genetic algorithm. The main contributions of this work are summarized as follows:

- We analyze the challenges that appear when exploiting social relationships of MUs to improve the performance of D2D communications in 5G networks as well as the arising energy consumption in social-aware D2D communications underlaying cellular networks.
- We formulate the energy efficiency optimization (EEO) problem in D2D communications by carefully considering both the social relationships and physical interference between all MUs in the network. In our system model, multiple D2D pairs can share the same spectrum resource of one cellular user in order to enhance the spectrum efficiency.
- We then apply the adaptive genetic algorithm to solve this EEO problem for maximizing the energy efficiency while ensuring high system throughput and spectrum efficiency for high QoS requirements. Furthermore, the convergence rate of algorithm is also evaluated to show the feasibility of our proposed solution.
- Our numerical results demonstrate the significant effectiveness of our proposed solution compared with social-unaware solutions in terms of energy efficiency and system throughput for social-aware D2D communications.

The remainder of this work is organized as follows. The related works are discussed in Section 2. Section 3 provides the system model and problem formulation of social-aware D2D communications in 5G networks. Section 4 presents social-aware energy efficiency optimization problem and solution using adaptive genetic algorithm. The numerical results that demonstrate the effectiveness of our proposed method, are shown in Section 5. Finally, we conclude this work in Section 6.

2. Related works

Recently, there are some intensive studies solving the energy efficiency problem in D2D communications [19–28]. Particularly, in [19–21], the authors studied the energy-efficient resource allocation schemes for D2D communications underlaying cellular networks, to maximize the energy efficiency of D2D links. The authors in [22–24] proposed the energy-efficient power control methods for green D2D communications in order to minimize the power consumption. Another important challenge in D2D communications, which is interference management problem has been studied in [25,26] to improve the energy efficiency of D2D and cellular links. With respect to the D2D communications in unlicensed spectrum (out-band D2D communications), the authors in [27] exploited the network coding (NC) technique in bidirectional communications to propose an adaptive cooperative NC-based medium access control (ACNC-MAC) protocol for the out-band D2D communications. The simulation results demonstrated that this protocol can achieve improvements in terms of D2D throughput and energy efficiency. Moreover, in [28], the two MAC strategies based

on game theory (i.e., distributed and coordinated approach) have been proposed for energy-efficient and rapid out-band D2D content dissemination in 4G cellular networks. However, these studies [19–28] did not consider the social relationship information of MUs, which influences the performance of D2D communications. This motivates us to take into account the mobile social networks for energy efficiency optimization problem in D2D communications underlaying 5G cellular networks.

In fact, research on exploiting social networking characteristics in D2D communications has just been started [14,29–33]. Particularly, the authors in [29] utilized the contact time information, which is obtained through the social model, to maximize the resource utilization and network throughput in D2D-assisted cellular networks. However, this study only considered the contact time information for resource allocation problem, which is not sufficiently convincing. In [30], the authors proposed a solution based on the general cooperative game theory for social-aware resource allocation problem in order to maximize the social group utility in D2D communications. Similarly, the community characteristic of social networks has been exploited in [31] to propose an efficient resource allocation scheme for D2D communications underlaying cellular networks. Moreover, the cooperative D2D communications has been investigated under social networking perspectives in [32,33]. Nevertheless, these works [29–33] mainly focused on exploiting the social relationships for resource allocation problem and cooperative D2D communications, without considering the energy efficiency in D2D communications. The work in [14] proposed a social-aware cooperative D2D-MAC protocol that utilizes social relationships to increase the energy efficiency in cooperative D2D communications. However, the authors in this work focused on the integration of social networks into MAC protocol design for green D2D communications without considering the physical interference management problem.

Different from the aforementioned studies, we consider both the social relationships and physical interference between all MUs to improve the performance and increase the energy efficiency for D2D communications in 5G networks.

3. System model and problem formulation

This section will introduce the detailed system model and problem formulation, as well as the assumptions. To facilitate the readers, the important notations are shown in Table 1.

3.1. System model

In this work, the social-aware D2D communications in 5G networks are considered as a combination of the physical domain and the social domain, as shown in Fig. 1. This system model will be described in details in the sequels.

3.1.1. The physical domain

In the physical domain, the users wish to set up D2D communication links to utilize the cellular resources depending on the physical and communication constraints [30]. Therefore, we consider the D2D communications model in 5G networks in a single cell scenario where the base station is located at the center and multiple cellular users or D2D pairs (i.e., transmitter and receiver) are randomly distributed.

In this model, we take into account the communication phase with assumptions that each cellular user will be allocated an orthogonal subchannel and D2D pairs can reuse the spectrum resources of cellular user in order to enhance the spectrum efficiency. Therefore, there is no interference among cellular users but mutual interference between cellular user and D2D pairs because of non-orthogonal resource sharing. Moreover, the corresponding D2D link will be established when the distance between transmitter and receiver of D2D pair satisfies the predefined distance threshold [30] and the characteristics of channel will not change during transmission.

Table 1
Important notations.

Symbol	Explanation
N_C	Number of cellular users
N_D	Number of D2D pairs
$\mathscr{S}_\mathscr{C}$	Set of cellular users
$\mathscr{S}_\mathscr{D}$	Set of D2D pairs
C_i	i-th cellular user ($i = 1, 2, \cdots, N_C$)
D_j	j-th D2D pair ($j = 1, 2, \cdots, N_D$)
$\mathbf{U}$	Vertex set, which denotes the set of all users in social domain
$\mathbf{S}$	Edge set, which is also matrix of social relationship strength
$S_{i, j}$	Strength of social relationship between users C_i and D_j
$J_z^{i,j}$	Jaccard coefficient of z-th social factor
	($i = 1, 2, \cdots, N_C; j = 1, 2, \cdots, N_D$)
$P_{Tx}^{C_i}$	Transmission power of cellular user C_i
$P_{Tx}^{D_j}$	Transmission power of D2D pair D_j
$P_{max}^{C_i}$	Maximum transmission power of cellular user C_i
$P_{max}^{D_j}$	Maximum transmission power of D2D pair D_j
I_{C_i}	Interference power at the BS for cellular user C_i
I_{D_j}	Interference power at the D2D receiver D_{jr}
λ_{C_i, D_j}	Spectrum resources reusing indicator
R_{C_i}	Achievable link rate at the BS from the cellular user C_i
R_{D_j}	Achievable link rate at the receiver D_{jr}
$\mathfrak{R}$	System throughput
EE_{C_i}	Energy efficiency of cellular user C_i
EE_{D_j}	Energy efficiency of D2D pair D_j
EE	Overall energy efficiency of system
SE_{C_i}	Spectrum efficiency of cellular link
SE_{D_j}	Spectrum efficiency of D2D link
W_{C_i}	Channel bandwidth for cellular user
W_{D_j}	Channel bandwidth for D2D pair
δ_{C_i}	Power consumption coefficient of cellular user C_i
δ_{D_j}	Power consumption coefficient of D2D pair D_j
α	Impact coefficient of social relationship strength
γ_{C_i}	Minimum spectrum efficiency of the cellular link
γ_{D_j}	Minimum spectrum efficiency of the D2D link

Fig. 1. System model.

Fig. 2. Social relationship model of all users.

Particularly, there are N_C cellular users and N_D D2D pairs, which are randomly distributed in the considered cell. Let $\mathscr{S}_\mathscr{C}$ and denote the set of cellular users and the set of D2D pairs, respectively, that satisfy $\mathscr{S}_\mathscr{C} \cap \mathscr{S}_\mathscr{D} = \varnothing$. Then, the set of all users in the considered cell $\mathscr{S}_\mathscr{U}$ can be expressed as $\mathscr{S}_\mathscr{U} = \mathscr{S}_\mathscr{C} \cup \mathscr{S}_\mathscr{D}$. Let C_i denote the arbitrary cellular user, $C_i \in \mathscr{S}_\mathscr{C} (i = 1, 2, \cdots, N_C)$. The transmitter and receiver of the D2D pair D_j are denoted by D_{jt} and D_{jr}, respectively, here $D_j \in \mathscr{S}_\mathscr{D} (j = 1, 2, \cdots, N_D)$.

3.1.2. The social domain

We utilize the weighted graph $\mathbf{G_s(U, S)}$ to define the social relationships of all users in the system, as depicted in Fig. 2. Here, $\mathbf{U}$ is the vertex set, which denotes the set of all users in the social domain, while $\mathbf{S}$ is the relational edge set representing the social relationship strength of them. The users, which have similar hobbies or interest in the same content, may have strong social relationships. Therefore, users will rely on their social relationship information to decide to share their own contents directly, because users with stronger social relationships are more willing to help in resources sharing [34].

The matrix $\mathbf{S}$ represents the social relationship strength in the social domain, which is a matrix with $N_C \times N_D$ entries $S_{i, j}, i = 1, 2, \cdots, N_C$ and $j = 1, 2, \cdots, N_D$. Here, $S_{i, j}$ represents the strength of social relationship between users C_i and D_j, which is influenced by many social factors such as the similarity of their profiles, common interests, mutual friends, frequencies and durations of their interactions, etc. [34]. In the social domain, the strength of social relationship is normalized as $S_{i, j} \in [0,1]$ with a higher value of $S_{i, j}$ indicating a stronger social relationship.

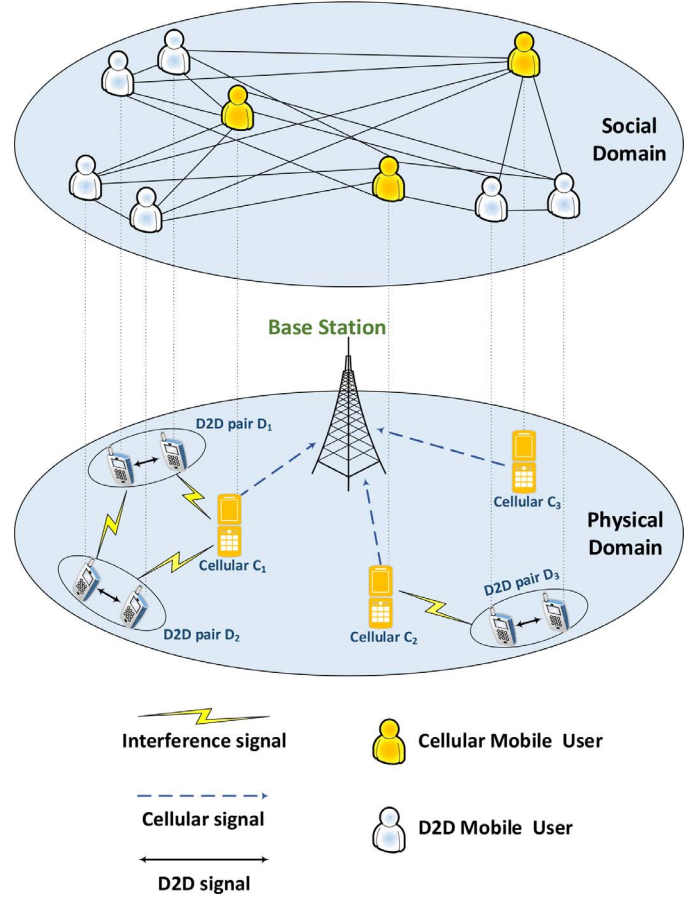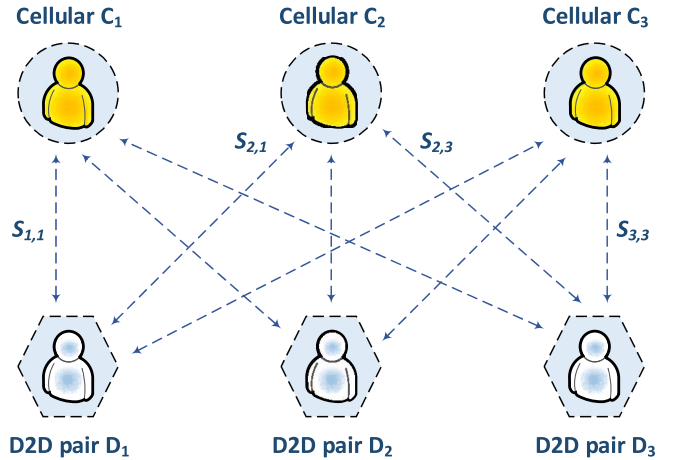In order to calculate the matrix of social relationship strength $\mathbf{S}$, we apply the Jaccard similarity method [35], which has been widely adopted in social networking analysis [34,36,37]. Mathematically, the strength of social relationship $S_{i, j}$ can be expressed as

$$S_{i,j} = \sum_{z=1}^{t} \omega_z J_z^{i,j},$$

(1)

where t denotes the total number of social factors, ω_z denotes the relative weight coefficient of z-th social factor, and $J_z^{i,j}$, which represents the Jaccard coefficient of this social factor [38], can be calculated as

$$J_z^{i,j} = \frac{F_z^i \cap F_z^j}{F_z^i \cup F_z^j}, \tag{2}$$

where F_z^i and F_z^j are z-th social factors of user C_i and user D_j, respectively. Such social factors information can be captured through the social networks.

Therefore, exploiting the social relationships of mobile users opens up a new way to improve the performance and decrease energy consumption in D2D communications.

3.2. Problem formulation

3.2.1. Energy efficiency

In order to achieve the objective of green D2D communications in 5G networks, we aim to maximize the overall energy efficiency of the system while meeting both the spectrum efficiency requirements and transmission power constraints of all users.

To compute the overall energy efficiency, we consider the Rayleigh fading channels to model all channels in the system. Hence, the received power at the BS from the cellular user C_i, which is denoted by $P_{C_i,BS}$, can be calculated as

$$P_{C_i,BS} = P_{Tx}^{C_i} G_{C_i,BS}, \tag{3}$$

where $P_{Tx}^{C_i}$ and $G_{C_i,BS}$ are transmission power of cellular user C_i and the channel gain from the cellular user C_i to the BS, respectively.

It is noted that during transmission from the cellular user C_i to the BS, the channel gain $G_{C_i,BS}$ is modeled as

$$G_{C_i,BS} = (d_{C_i,BS})^{-\eta} |h_{C_i,BS}|^2, \tag{4}$$

where $d_{C_i,BS}$ is the distance between the cellular user C_i and the BS, η is the path loss factor, and $h_{C_i,BS}$ is the Rayleigh fading channel coefficient that obeys the distribution of $\mathscr{CN}(0, 1)$.

As mentioned above, the received signals at the BS from the cellular users C_i are interfered by the D2D transmitters sharing the same spectrum resources with C_i. Therefore, the interference power at the BS for cellular user C_i, denoted by I_{C_i}, can be expressed as

$$I_{C_i} = \sum_{j=1}^{N_D} \lambda_{C_i,D_j} P_{Tx}^{D_j} G_{D_{jt},BS}, \tag{5}$$

where $P_{Tx}^{D_j}$ and $G_{D_{jt},BS}$ denote the transmission power of D2D pair D_j and the channel gain from the D2D transmitter D_{jt} to the BS, respectively. And λ_{C_i,D_j} is the reusing indicator, which describes the spectrum resources reusing and satisfies $\lambda_{C_i,D_j} \in \{0, 1\}, \forall C_i \in \mathscr{S_C}, \forall D_j \in \mathscr{S_D}$. We define $\lambda_{C_i,D_j} = 0$ to indicate that the cellular user C_i is not willing to share spectrum resources with D2D pair D_j, so the users will operate in the cellular mode. Otherwise, $\lambda_{C_i,D_j} = 1$ means that the D2D pair D_j will share spectrum resources with cellular user C_i and operate in the reusing D2D mode.

For a given subchannel, the signal-to-interference-plus-noise ratio ($SINR_{C_i}$) received at the BS for cellular user C_i is calculated as

$$SINR_{C_i} = \frac{P_{Tx}^{C_i} G_{C_i,BS}}{I_{C_i} + \sigma^2}, \tag{6}$$

where σ^2 represents the noise power of Additive White Gaussian Noise (AWGN).

Similarly, the signals at the D2D receiver D_{jr} are interfered by the cellular user and other D2D pairs that share the same spectrum resources with D_j. Hence, the interference power I_{D_j} at the D2D receiver D_{jr} of the D2D pair D_j can be calculated as

$$I_{D_j} = \sum_{i=1}^{N_C} \lambda_{C_i,D_j} \left(P_{Tx}^{C_i} G_{C_i,D_{jr}} + \sum_{k=1,k\neq j}^{N_D} \lambda_{C_i,D_k} P_{Tx}^{D_k} G_{D_{kt},D_{jr}} \right). \tag{7}$$

Consequently, the $SINR_{D_j}$ at the D2D receiver D_{jr} of the D2D pair D_j is obtained by

$$SINR_{D_j} = \frac{P_{Tx}^{D_j} G_{D_{jt},D_{jr}}}{I_{D_j} + \sigma^2}. \tag{8}$$

According to Shannon theorem [39], the corresponding achievable link rate R_{C_i} at the BS from the cellular user C_i is given as

$$R_{C_i} = W_{C_i} \log_2(1 + SINR_{C_i}), \tag{9}$$

where W_{C_i} is the bandwidth. The corresponding achievable link rate R_{D_j} at the receiver D_{jr} of the D2D pair D_j is obtained as

$$R_{D_j} = W_{D_j} \log_2(1 + SINR_{D_j}). \tag{10}$$

Therefore, we can achieve the system throughput by considering all the cellular users $\mathscr{S_C}$ and D2D pairs together, which is calculated as

$$\mathfrak{R} = \sum_{i=1}^{N_C} \left(R_{C_i} + \sum_{j=1}^{N_D} \lambda_{C_i,D_j} R_{D_j} \right). \tag{11}$$

In D2D communications, D2D users reuse the same spectrum resources of cellular users in order to enhance the spectrum efficiency. To do so, they require more cooperation information. It is noted that the exchange of cooperation information between users will cause an increase in extra energy consumption. Therefore, the energy efficiency of cellular user EE_{C_i} and D2D pair EE_{D_j} can be respectively formulated as

$$EE_{C_i} = \frac{R_{C_i}}{P_{Tx}^{C_i} + P_{Circuit}^{C_i}} - \delta_{C_i} EE_{C_i}^{Ini}, \tag{12}$$

$$EE_{D_j} = \frac{R_{D_j}}{P_{Tx}^{D_j} + P_{Circuit}^{D_j}} - \delta_{D_j} EE_{D_j}^{Ini}, \tag{13}$$

where $P_{Circuit}^{C_i}$ and $P_{Circuit}^{D_j}$ represent the circuit power consumption of cellular user C_i and D2D pair D_j, respectively. In addition, δ_{C_i} and δ_{D_j} denote the power consumption coefficients that reflect the importance of power consumption; $EE_{C_i}^{Ini}$ and $EE_{D_j}^{Ini}$ represent the initial average energy efficiency of the cellular user C_i and D2D pair D_j, respectively.

When we take social relationships in the system into account, the power consumption coefficients may vary according to the strength of social relationship, which influences the sharing enthusiasm of cellular users. We observe that this sharing enthusiasm will be greater if the social relationship between two users is stronger, leading to less power consumption coefficient. Without loss of generality, we therefore assume that the power consumption coefficient is modeled as a decaying exponential function, which can be expressed as follows [13]

$$\delta_{C_i} = \delta_{D_j} = \exp(-\alpha S_{i,j}), \tag{14}$$

where $S_{i,j}$ represents the strength of social relationship between cellular user C_i and D2D pair D_j, which can be inferred from the social domain of users and α denotes the impact coefficient of social relationship.

Finally, the overall energy efficiency of the system, which is objective function of our optimization problem, can be obtained by considering all the cellular users and D2D pairs as

$$EE = \sum_{i=1}^{N_C} \left(EE_{C_i} + \sum_{j=1}^{N_D} \lambda_{C_i,D_j} EE_{D_j} \right). \tag{15}$$

3.2.2. Spectrum efficiency

For guaranteeing the QoS for all users, we also need to consider the spectrum efficiency of cellular link SE_{C_i} and D2D link SE_{D_j}, which must satisfy the following conditions

$$SE_{C_i} \geq \gamma_{C_i}, \forall C_i \in \mathscr{S_C}, \tag{16}$$

$$SE_{D_j} \geq \gamma_{D_j}, \forall D_j \in \mathscr{S_D}, \tag{17}$$

where γ_{C_i} and γ_{D_j} denote the minimum spectrum efficiency requirements of the cellular link and the D2D link, respectively. It is noted that

$\gamma_{C_i} = R_{C_i}^{min}$ and $\gamma_{D_j} = R_{D_j}^{min}$, here $R_{C_i}^{min}$ and $R_{D_j}^{min}$ are the minimum data rate requirements of cellular user and D2D pair, respectively.

4. Social-aware energy efficiency optimization problem and solution

4.1. Social-aware energy efficiency optimization problem

Towards green communications in 5G networks, we leverage the social relationships of mobile users to propose the social-aware energy efficiency optimization problem. Our aim is to maximize the overall energy efficiency of the system in (15), by finding out the optimal spectrum resources reusing indicator λ_{C_i,D_j} (for channel mode selection) and transmission powers allocated for each user $P_{Tx}^{C_i}$, $P_{Tx}^{D_j}$. Moreover, the transmission power and spectrum efficiency must be considered in the constraints of our optimization problem. Mathematically, this social-aware energy efficiency optimization problem is formulated as follows

$$\max_{\left\{\lambda_{\mathbf{C_i,D_j}};\mathbf{P_{Tx}}\right\}} EE, \tag{18}$$

$$s.\,t. \begin{cases} C1: \sum_{i=1}^{N_C} \lambda_{C_i,D_j} \leq 1, \, \forall \, D_j \in \mathscr{S}_{\mathscr{D}}, \\ C2: SE_{C_i} \geq \gamma_{C_i}, \, \forall \, C_i \in \mathscr{S}_{\mathscr{C}}, \\ C3: SE_{D_j} \geq \gamma_{D_j}, \, \forall \, D_j \in \mathscr{S}_{\mathscr{D}}, \\ C4: 0 \leq P_{Tx}^{C_i} \leq P_{max}^{C_i}, \, \forall \, C_i \in \mathscr{S}_{\mathscr{C}}, \\ C5: 0 \leq P_{Tx}^{D_j} \leq P_{max}^{D_j}, \, \forall \, D_j \in \mathscr{S}_{\mathscr{D}}. \end{cases} \tag{19}$$

In (19), the first constraint $C1$ is applied to ensure that a D2D pair can reuse the spectrum resource of at most one cellular user in a time slot. We utilize this constraint to reduce the complication of interferences in the D2D communication environment. But the spectrum resource of one cellular should be shared with multiple D2D pairs in order to maximize the spectrum efficiency [30]. The next two constraints $C2$ and $C3$ are used to satisfy the QoS requirements (i.e., spectrum efficiency) for all users, which are previously mentioned in Section 3.2.2. The last two constraints $C4$ and $C5$ are the maximum transmission power constraints to limit the interference to D2D pairs and cellular users.

Although the Lagrange optimization approach can be used to solve this proposed social-aware energy efficiency optimization problem, its high complexity makes it less suitable for practical systems [40–43]. Hence, we will apply the adaptive genetic algorithm (Adaptive GA) [44], which is a class of adaptive heuristic searching algorithms based on the natural evolutionary principles of selection, genetic inheritance and variation, to solve our proposed optimization problem as a promising solution [40–42]. The motivation of choosing the Adaptive GA is that this algorithm is commonly used to generate high-quality solutions for complex optimization problems within a reasonable time frame [41]. Although the Adaptive GA may not achieve the polynomial time complexity, it can significantly reduce the complexity compared with the Lagrange multipliers method [40–42]. The implementation of Adaptive GA will be introduced in details in the following section.

4.2. Adaptive GA solution

We observe that the objective function (18) and constraints (19) in our proposed social-aware energy efficiency optimization problem cannot be directly applied to the Adaptive GA. Because they may cause the Adaptive GA to breed the next generations that do not guarantee the constraints. Hence, to cope with this difficulty we utilize the penalty function method to transform (18) and (19) to the optimization problem without constraints [40]. In this way, we first convert the

constraints in (19) as

$$\begin{cases} \Delta\lambda_{D_j} = 1 - \sum_{i=1}^{N_C} \lambda_{C_i,D_j} \geq 0, \, \forall \, D_j \in \mathscr{S}_{\mathscr{D}}, \\ \Delta SE_{C_i} = SE_{C_i} - \gamma_{C_i} \geq 0, \, \forall \, C_i \in \mathscr{S}_{\mathscr{C}}, \\ \Delta SE_{D_j} = SE_{D_j} - \gamma_{D_j} \geq 0, \, \forall \, D_j \in \mathscr{S}_{\mathscr{D}}, \\ \Delta P_{Tx}^{C_i} = P_{max}^{C_i} - P_{Tx}^{C_i} \geq 0, \, \forall \, C_i \in \mathscr{S}_{\mathscr{C}}, \\ \Delta P_{Tx}^{D_j} = P_{max}^{D_j} - P_{Tx}^{D_j} \geq 0, \, \forall \, D_j \in \mathscr{S}_{\mathscr{D}}. \end{cases} \tag{20}$$

Then, the penalty function can be achieved as below

$$\begin{aligned} F_{penalty} = \; & \alpha_1 \sum_{j=1}^{N_D} [\min\{0, \Delta\lambda_{D_j}\}]^2 \\ & + \alpha_2 \sum_{i=1}^{N_C} [\min\{0, \Delta SE_{C_i}\}]^2 + \alpha_3 \sum_{j=1}^{N_D} [\min\{0, \Delta SE_{D_j}\}]^2 \\ & + \alpha_4 \sum_{i=1}^{N_C} [\min\{0, \Delta P_{Tx}^{C_i}\}]^2 + \alpha_5 \sum_{j=1}^{N_D} [\min\{0, \Delta P_{Tx}^{D_j}\}]^2, \end{aligned} \tag{21}$$

where α_1, α_2, α_3, α_4 and α_5 are used to indicate the violation degree of constraints.

Finally, we will combine (18) and (21) to achieve the optimization problem without constraints as shown below

$$\max_{\left\{\lambda_{\mathbf{C_i,D_j}};\mathbf{P_{Tx}}\right\}} EE_{penalty} = EE + F_{penalty}. \tag{22}$$

So far, we apply Adaptive GA to solve (22) instead of (18) and (19) to find out the optimal spectrum resources reusing indicator λ_{C_i,D_j} (for channel mode selection) and transmission powers allocated for each user $P_{Tx}^{C_i}$, $P_{Tx}^{D_j}$.

The Algorithm 1 describes the detailed implementation of Adaptive GA for our social-aware energy efficiency optimization problem. The parameters of Adaptive GA are initialized as follows. NI is the number of individuals in a population (population size), which needs to be large enough to generate a diverse set of candidates. However, the too large population size may slow down the convergence of Adaptive GA, so NI is set to 200. For the convenient implementation of Adaptive GA, each individual will be encoded in the form of Gray binary code with $NB = 32$ bits [25,45]. Besides, NG is the maximum number of generations, which is related to the improvement of fitness function. In Adaptive GA, the fitness function usually gets major improvements in the early generations and then an asymptotically optimal value. Therefore $NG = 100$ is sufficient without increasing complexity [25]. The generation gap is represented by PG, which is the proportion of the population to be replaced in each generation. PG is set to 0.9 to have better results in the next generation [25,45,46].

In our proposed method, Algorithm 1 which will be installed into the BS, aims to solve the EEO problem. Therefore, the BS needs to have the full knowledge of the system and will be in charge of efficiently allocating resources to all MUs to maximize the energy efficiency while ensuring high system throughput and spectrum efficiency as per QoS requirements. Due to the MUs' mobility, Algorithm 1 is only executed whenever MUs newly appear within or leave the coverage of BS. It should be noted that a centralized control is deployed at the BS in our approach. This may introduce the undesired overhead, which mainly includes the costs of calculating key parameters, exchanging the co-operation information and implementing Algorithm 1. However, this overhead is acceptable because Algorithm 1 is only executed periodically and effectively thanks to powerful processing capacity of the BS. Moreover, the significant improvements in terms of energy efficiency and system throughput can be achieved through our proposed solution, which makes this overhead unimportant.

Require: Initial parameters of the Adaptive GA

$NI = 200$: Number of individuals in a population

$NB = 32$: Number of bits to denote an individual of solution set $\{S^z\} = \{\lambda_{C_i,D_j}^z, P_{Tx}^{C_i,z}, P_{Tx}^{D_j,z}\}, z = 1, 2, \ldots, NI$

$NG = 100$: Maximum number of generations

$PG = 0.9$: Generation gap

Ensure: $S^* = \lambda_{C_i,D_j}^*, P_{Tx}^{C_i,*}, P_{Tx}^{D_j,*}$

1: Generate random NI individuals of solution $\{S^z\}$

2: Calculate fitness values $EE_{penalty}(\{S^z\})$ in (22) of all individuals of $\{S^z\}$ in current generation

3: **repeat**

4:     Put $\{S^z\}$ and $EE_{penalty}(\{S^z\})$ in the mating pool

5:     Select $NI \times PG$ best individuals with better fitness values, i.e., higher values of $EE_{penalty}(\{S^z\})$, for breeding the next generation by using stochastic universal sampling operator [44]

6:     Define the diversity level of population (DL) as: $DL = \frac{best\_population\_fitness\_value}{average\_population\_fitness\_value}$

7:     Calculate $P_{cross} = \frac{1}{1+exp(1-DL)}$ (Crossover probability) and $P_{muta} = \frac{exp(1-DL)}{1+exp(1-DL)}$ (Mutation probability)

8:     Collect 2 parent individuals to breed 2 offsprings by applying single point crossover operator with crossover probability P_{cross} [44]

9:     Mutate 2 new offsprings with mutation probability P_{muta} to recover the good genes that could be lost because of the operations in previous steps

10:     Calculate the fitness values of all offsprings and add them to current population to yield the next generation

11:     $NG \leftarrow NG - 1$

12: **until** ($NG \leq 0$)

13: Find the best fitness value and the corresponding best individual S^* in the last generation

Algorithm 1. The implementation of Adaptive GA for our social-aware energy efficiency optimization problem.
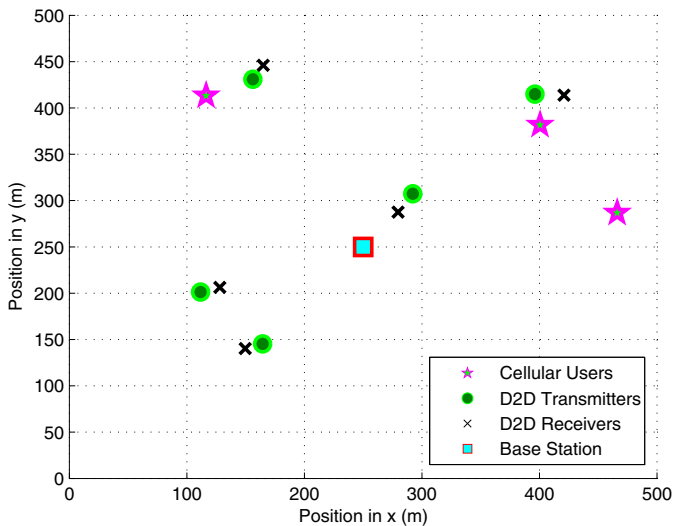
Fig. 3. Network layout.

5. Performance evaluation

In this section, we will introduce the numerical results to demonstrate the effectiveness of our proposed solution.

5.1. Parameter setting

In a single cell scenario, we deploy the system within a 500 m × 500 m network area where the BS is located at the center and multiple cellular users/D2D pairs are randomly distributed. With D2D communications, the maximum distance between D2D transmitter and D2D receiver is set to be 25 m. In order to illustrate the cellular users and D2D pairs in the simulation, we sketch the network layout with 3 cellular users and 5 D2D pairs, as shown in Fig. 3. We also set the path loss factor in Rayleigh fading channels as $\eta = 3$. The important parameters are shown in Table 2.

5.2. Convergence evaluation of adaptive GA

We implement the Adaptive GA with 100 generations to solve our social-aware energy efficiency optimization problem. From Fig. 4, we can see that the convergence of Adaptive GA holds quickly after around 20 generations when the mean fitness value of all individuals converges on the best fitness value. This result shows that the Adaptive GA are realizable to deal with our proposed social-aware energy efficiency optimization problem.

Table 2
Parameter setting.

| Parameter	Value
Network area	500 m × 500 m
Number of cellular users	N_C vary from 2 to 20
Number of D2D pairs	N_D vary from 4 to 12
Noise power of AWGN	$\sigma^2 = 10^{-13}$ W
Maximum transmission power	$P_{max}^{C_i} = P_{max}^{D_j} = 0.5$ W
Circuit power consumption	$P_{Circuit}^{C_i} = P_{Circuit}^{D_j} = 0.01$ W
D2D transmission distance	$d \leq 25$ m
Channel bandwidth for cellular user	$W_{C_i} = 180$ kHz
Channel bandwidth for D2D pair	$W_{D_j} = 15$ kHz
Impact coefficient of social relationship strength	α vary from 0.1 to 1
Initial average energy efficiency	$EE_{C_i}^{Ini} = EE_{D_j}^{Ini} = 1$ Kbps/W
Minimum spectrum efficiency of the cellular link	$\gamma_{C_i} = R_{C_i}^{min} = 50$ Kbps
Minimum spectrum efficiency of the D2D link	$\gamma_{D_j} = R_{D_j}^{min} = 5$ Kbps
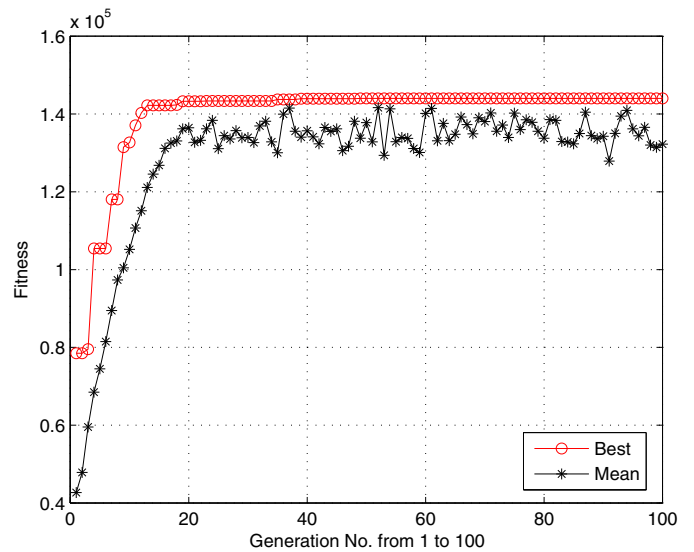
Fig. 4. Convergence rate of adaptive GA.

5.3. The performance metrics

In this work, we evaluate the performance of our proposed social-aware energy efficiency optimization solution, denoted as "EEO", by comparing the "EEO" with the other two social-unaware cases which are denoted as "ECP" and "RCP". In "ECP" scheme, both the channel mode (i.e., cellular or D2D mode) and transmission powers are equally allocated to each user, independent of social relationships. However, they must satisfy the constraints in (19). Similarly, in "RCP" scheme, both the channel mode and transmission powers are randomly allocated to each user. The performance of all schemes, i.e., the energy efficiency and system throughput will be evaluated in the sequels.

5.3.1. The impact coefficient of social relationship strength α

Figs. 5 and 6 depict the energy efficiency and system throughput in "EEO", "ECP" and "RCP" schemes versus the impact coefficient of social relationship strength α, respectively. Here, we keep $N_C = 4$, $N_D = 6$ and vary α from 0.1 to 1.

The results in Fig. 5 indicate that the energy efficiency in our proposed "EEO" scheme increases with increasing the impact coefficient of social relationship strength α. The reason is that, when the impact coefficient of social relationship strength is stronger the cooperation in
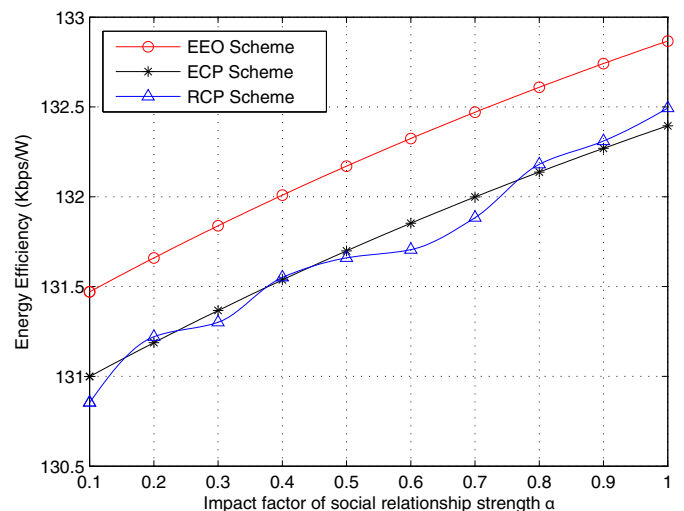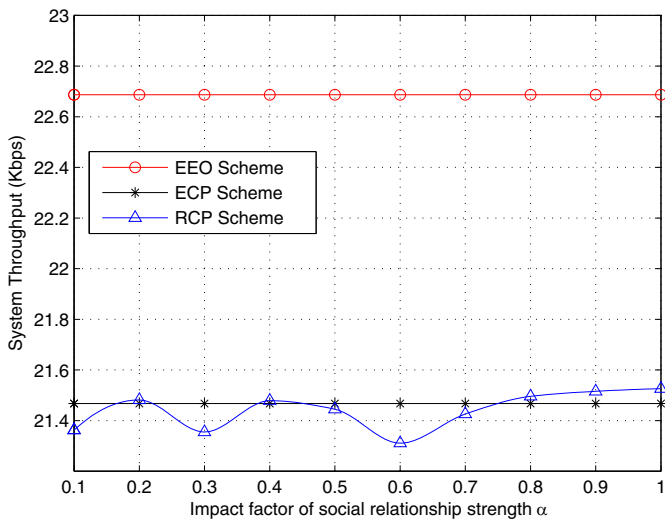

Fig. 5. Energy efficiency vs. α.

Fig. 6. System throughput vs. α.

Fig. 8. System throughput vs. N_C.

D2D communications will be more effective, leading to an increase in energy efficiency. Moreover, our proposed "EEO" always gains the best energy efficiency performance, i.e., 36% and 53% better than the "ECP" and "RCP" schemes, respectively. We also see in Fig. 6 that the system throughput in our proposed "EEO" outperforms that in the "ECP" and "RCP" schemes. These are because that our proposed "EEO" considers both the social relationships and physical interference between all MUs to improve the performance of D2D communications, while "ECP" and "RCP" cannot.

These evaluation results shown that considering the social relationships of mobile users can significantly improve the energy efficiency and system throughput in D2D communications.

5.3.2. The number of cellular users N_C

Furthermore, we also investigate the performance of "EEO", "ECP" and "RCP" schemes under influence of the number of cellular users N_C by keeping $\alpha = 1$ and $N_D = 5$ while varying N_C from 2 to 20.

As can be clearly observed in Figs. 7 and 8, increasing the number of cellular users N_C results in an enhancement in the energy efficiency and system throughput since more resource sharing opportunity in D2D communications can be obtained. In comparison, our proposed "EEO" scheme also achieves the highest energy efficiency and system throughput compared with "ECP" and "RCP" schemes because the optimization solution improves the system performance. Especially, the
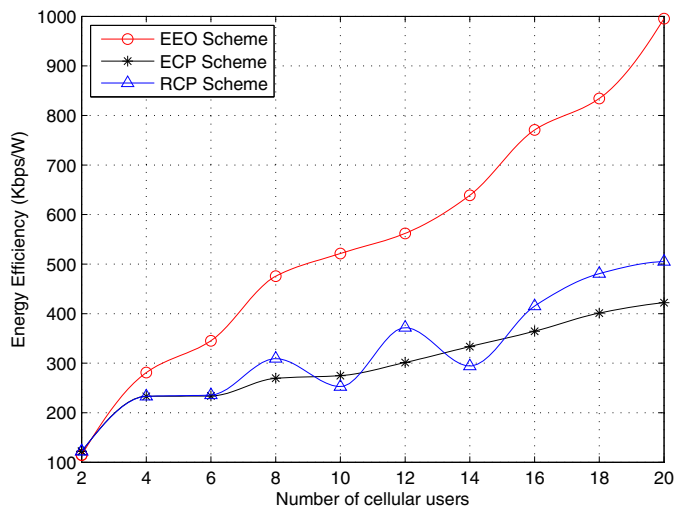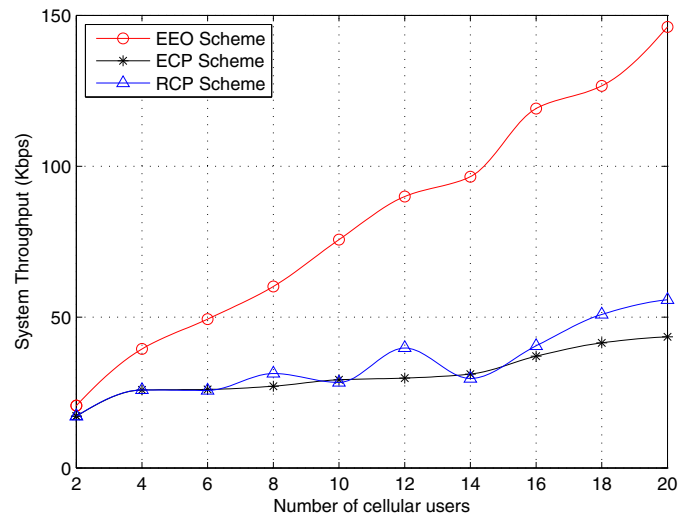
amplitude of effectiveness increases with the number of cellular users N_C. For example, the energy efficiency in our proposed "EEO" scheme is enhanced by 21% when $N_C = 4$ and 92% when $N_C = 14$ (Fig. 7). This is because when the number of cellular users N_C is larger then the effectiveness of optimization solution becomes better. In other words, the proposed social-aware energy efficiency optimization solution will achieve remarkable improvements in terms of energy efficiency and system throughput when there are more cellular users in the networks.

5.3.3. The number of D2D pairs N_D

Finally, we keep $\alpha = 1$ and $N_C = 5$ while varying N_D from 4 to 12, aiming to evaluate the performance of "EEO", "ECP" and "RCP" schemes under influence of the number of D2D pairs N_D.

As can be clearly seen from Figs. 9 and 10, when increasing the number of D2D pairs N_D, both the energy efficiency and system throughput in "ECP" and "RCP" schemes considerably drop (about 92%) while our "EEO" scheme slightly increases (about 30%). The reason is that, in "ECP" and "RCP" schemes, when the number of D2D pairs N_D increases, the mutual interference between cellular user and D2D user increases, leading to a decrease in energy efficiency and system throughput. Meanwhile our proposed "EEO" scheme considers the mutual interference problem effectively to improve the system performance. Furthermore, our proposed "EEO" scheme is always the
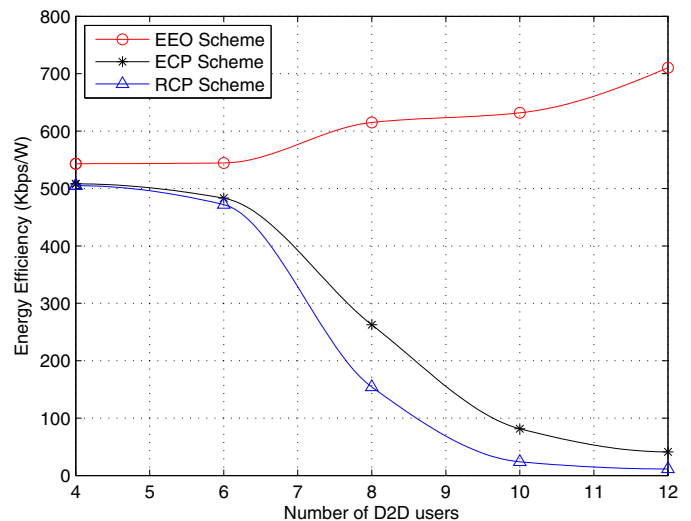

Fig. 7. Energy efficiency vs. N_C.

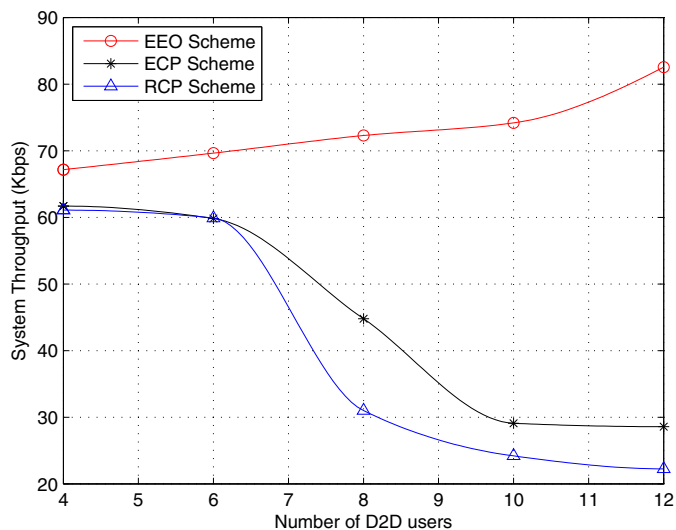
Fig. 9. Energy efficiency vs. N_D.

Fig. 10. System throughput vs. N_D.

best solution with the highest energy efficiency and system throughput compared with the other two schemes thanks to the optimal mode selection and transmission powers allocation. These observations demonstrated that our proposed social-aware energy efficiency optimization solution also significantly improves the performance of D2D communications under different number of D2D pairs in the networks.

6. Conclusions

In this work, we have proposed a social-aware energy efficiency optimization solution for D2D communications in 5G networks by applying adaptive genetic algorithm when carefully considering both the social relationships and physical interference between all mobile users. In particular, we have considered the mutual interference in D2D communications environment, the constraints of transmission power and spectrum efficiency requirements, especially the impact of social relationships, to find out the optimal channel mode selection and transmission powers allocated for all users in the network. The numerical results demonstrated that our proposed social-aware energy efficiency optimization solution can greatly enhance the energy efficiency and system throughput for social-aware D2D communications while ensuring the spectrum efficiency and transmission power constraints for high QoS requirements.

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De-Thu Huynh received the B.Sc. degree in Electronics and Telecommunications from Ho Chi Minh City University of Transport, Vietnam and M.Sc. degree in Computer Science from Huazhong University of Science and Technology, Wuhan, China in 2007 and 2011, respectively. From 2007 to 2015, he worked as a lecturer and researcher in Faculty of Information Technology at Ho Chi Minh City University of Transport, Vietnam. He is currently pursuing his Ph.D. in Computer Science from Huazhong University of Science and Technology, China. His current research interests were in the areas of Wireless Sensor Networks, Wireless Body Area Networks, Device-to-Device Communications, Internet of Things and Network Security. He has served as a reviewer for several IEEE conferences and journals.

Xiaofei Wang received the B.S. degree from the Department of Computer Science and Technology, Huazhong University of Science and Technology, in 2005, and the M.S. and Ph.D. degrees from the School of Computer Science and Engineering, Seoul National University, in 2008 and 2013, respectively. He was a Post-Doctoral Research Fellow with the Department of Electrical and Computer Engineering, The University of British Columbia. He is currently a Professor with the Tianjin Key Laboratory of Advanced Networking, School of Computer Science and Technology, Tianjin University. His current research interests are social-aware multimedia service in cloud computing, cooperative base station caching, and traffic offloading in mobile content-centric networks.

Trung Q. Duong (S'05, M'12, SM'13) received his Ph.D. degree in Telecommunications Systems from Blekinge Institute of Technology (BTH), Sweden in 2012. Since 2013, he has joined Queen's University Belfast, UK as a Lecturer (Assistant Professor). His current research interests include physical layer security, energy-harvesting communications, and cognitive relay networks. He is the author or co-author of 280 technical papers published in scientific journals and presented at international conferences. Dr. Duong currently serves as an Editor for the IEEE Transactions on Communications, IEEE Trans on Wireless Communications. He was an Editor for the IEEE Communications Letters, IET Communications, Wiley Transactions on Emerging Telecommunications Technologies, and Electronics Letters. He has also served as the Guest Editor of the special issue on some major journals including IEEE Journal in Selected Areas on Communications, IET Communications, IEEE Wireless Communications Magazine, IEEE Communications Magazine, EURASIP Journal on Wireless Communications and Networking, EURASIP Journal on Advances Signal Processing. He was awarded the Best Paper Award at the IEEE Vehicular Technology Conference (VTC-Spring) in 2013, IEEE International Conference on Communications (ICC) 2014. He is the recipient of prestigious Royal Academy of Engineering Research Fellowship (2016–2020) and the prestigious Newton Prize 2017.

Nguyen-Son Vo received the B.Sc. degree in electrical and electronics engineering and the M.Sc. degree in radio engineering and electronics from Ho Chi Minh City University of Technology, Ho Chi Minh City, Vietnam, in 2002 and 2005, respectively, and the Ph.D. degree in communication and information systems from Huazhong University of Science and Technology, Wuhan, China, in 2012. He is currently with Duy Tan University, Da Nang, Vietnam. His current research interests include multimedia streaming over wireless networks, physical layer security, energy harvesting, and optimization design. He was awarded the Best Paper Award at the IEEE Global Communications Conference (GLOBECOM) 2016. Dr. Vo has served as Guest Editor of ACM/Springer Mobile Networks & Applications (MONET), Special Issue on "Wireless Communications and Networks for Smart Cities", 2017 and also as Guest Editor of IET Communications, Special Issue on "Recent Advances on 5G Communications", 2018.

Min Chen is a full professor in School of Computer Science and Technology at Huazhong University of Science and Technology (HUST) since Feb. 2012. He is the director of Embedded and Pervasive Computing (EPIC) Lab at HUST. He is Chair of IEEE Computer Society (CS) Special Technical Communities (STC) on Big Data. He was an assistant professor in School of Computer Science and Engineering at Seoul National University (SNU). He worked as a Post-Doctoral Fellow in Department of Electrical and Computer Engineering at University of British Columbia (UBC) for three years. Before joining UBC, he was a Post-Doctoral Fellow at SNU for one and half years. He received Best Paper Award from QShine 2008, IEEE ICC 2012, ICST IndustrialIoT 2016, and IEEE IWCMC 2016. He serves as editor or associate editor for Information Sciences, Information Fusion, and IEEE Access, etc. He is a Guest Editor for IEEE Network, IEEE Wireless Communications, and IEEE Trans. Service Computing, etc. He is Co-Chair of IEEE ICC 2012-Communications Theory Symposium, and Co-Chair of IEEE ICC 2013-Wireless Networks Symposium. He is General Co-Chair for IEEE CIT-2012, Tridentcom 2014, Mobimedia 2015, and Tridentcom 2017. He is Keynote Speaker for CyberC 2012, Mobiquitous 2012, Cloudcomp 2015, IndustrialIoT 2016, and The 7th Brainstorming Workshop on 5G Wireless. He has more than 300 paper publications, including 200+ SCI papers, 80+ IEEE Trans./Journal papers, 13 ISI highly cited papers and 8 hot papers. He has published four books: OPNET IoT Simulation (2015), Big Data Inspiration (2015), 5G Software Defined Networks (2016) and Introduction to Cognitive Computing (2017) with HUST Press, a book on big data: Big Data Related Technologies (2014) and a book on 5G: Cloud Based 5G Wireless Networks (2016) with Springer Series in Computer Science. His latest book (co-authored with Prof. Kai Hwang), entitled Big Data Analytics for Cloud/IoT and Cognitive Computing (Wiley, U.K.) appears in May 2017. His Google Scholars Citations reached 10,700+ with an h-index of 51. His top paper was cited 1100+ times. He is an IEEE Senior Member since 2009. He got IEEE Communications Society Fred W. Ellersick Prize in 2017. His research focuses on Cyber Physical Systems, IoT Sensing, 5G Networks, Mobile Cloud Computing, SDN, Healthcare Big Data, Medical Cloud Privacy and Security, Body Area Networks, Emotion Communications and Robotics, etc.