Delay Aware Resource Allocation for Device-to-Device Communication Underlaying Cellular Networks

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Abstract. Device-to-device (D2D) communications can bring significant performance improvement by allowing direct communications between users. Most of previous work usually focuses on the optimization of throughput, energy efficiency, offloading and so on. However, the delay performance of D2D users is less considered. In this paper, we formulate a resource allocation problem to maximize the system throughput while guarantying the delay performance for each user. The resource allocation is dynamic due to the consideration of both channel state and the queue length information. The optimization problem is a mixed integer non-linear programming problem and the solution space is large. Then in order to solve the problem with low complexity, we introduce particle swarm optimization algorithm to the resource allocation scheme. Various simulation results show that the throughput of the scheme is close to the global optimum and the delay performance for each user is guaranteed.

Keywords: Device-to-device communication · Resource allocation
Particle swarm optimization · Delay

1 Introduction

To accommodate the increasing traffic in future cellular systems, device-to-device (D2D) communications is a potential technology to achieve higher data rate and consume lower transmit power. Recently, D2D communications underlaying a cellular network infrastructure has been proposed and attracted much attention [1–3]. This hybrid infrastructure can bring several advantages such as higher system throughput, less network congestion and lower power consumption. However, in underlay mode D2D users share the same spectrum resources with regular cellular users. Sophisticated resource allocation for cellular and D2D users needs to be performed to protect cellular users and to achieve improved overall performance.

Much work has been done on resource allocation for D2D communications. Zhang et al. [4] propose a graph-based resource allocation method for cellular networks with underlay D2D communications which accounts for interference and capacity of the network. The simulation results show that the graph-based approach performs close to

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the throughput-optimal resource allocation. The author of [5] considers the fair resource allocation problem for device-to-device communications in Orthogonal Frequency Division Multiple Access (OFDMA)-based wireless cellular networks. He proposes a two-phase solution approach where resource allocation for cellular downlink and uplink flows with max-min fairness is performed in the first phase and resource allocation for D2D flows with rate protection for cellular flows is conducted in the second phase. In [6–8], the authors propose simple interference avoidance mechanisms in OFDMA network, which commonly enables D2D users to reuse appropriate resource using resource allocation information of legacy users in control signaling. Marco et al. [9] propose a flexible resource reuse scheme incorporating mode selection and power allocation. It minimizes the overall power consumption, but not maximizes the system throughput. Yu et al. [10] propose to use Han-Kobayashi rate splitting techniques to improve the throughput of D2D communications. Xu et al. in [11] consider the sum-rate optimization in a single cell scenario with underlayed D2D communications. They adopt the iterative combinatorial auction game in their proposed spectrum resource allocation mechanism.

Although much work has been done on resource allocation, the delay factor is ignored. Since many services are real-time and delay-sensitive, for example, voice conversation, video streaming, and interactive gaming, it is important to take delay into account when designing the protocols and algorithms for D2D communications. Wang et al. [12] propose a low complexity practical solution to solve the delay-aware resource allocation problems for D2D communications by exploiting the interference filtering property of CSMA-like MAC protocols. Lei et al. [13] propose an optimization framework on delay-aware resource control with bursty traffic and formulate a general queuing model for performance evaluation and optimization. However, they still fail to pay attention to subchannel allocation with the consideration of delay performance.

In this paper, we study a delay based resource allocation problem for the OFDMA cellular network underplayed with D2D user pairs. The system throughput is maximized while the parameter of transmission delay is set as the constraint in the problem formulation. Considering the proposed problem is a mixed integer non-linear programming problem with high complexity, we present a resource allocation scheme based on particle swarm optimization (PSO). It can provides joint subchannel scheduling and simple power allocation for both cellular users and D2D users.

The remaining of this paper is organized as follows. Section 2 provides the system model considered in this paper and formulations of the optimization problem. In Sect. 3, we briefly introduce the standard particle swarm optimization and describe the PSO-based resource allocation scheme. We provide numerical results in Sect. 4 and draw conclusions in Sect. 5.

2 System Model

As is illustrated in Fig. 1, we consider the downlink transmission in an OFDMA single cell network where K_1 cellular users and K_2 D2D pairs share N subchannels in underlay mode. The set of cellular users and D2D pairs are denoted as $C = \{c_1, c_2, \cdots, c_{K_1}\}$ and $D = \{d_1, d_2, \cdots, d_{K_2}\}$, respectively. Furthermore, we uniformly label cellular users and D2D pairs with $k = 1, 2, \cdots, K$, where K equals $K_1 + K_2$. Here D2D communications reuse the downlink resources of cellular network. We assume that the BS can get to know all downlink channel states information and thus it can allocate resources between users flexibly.

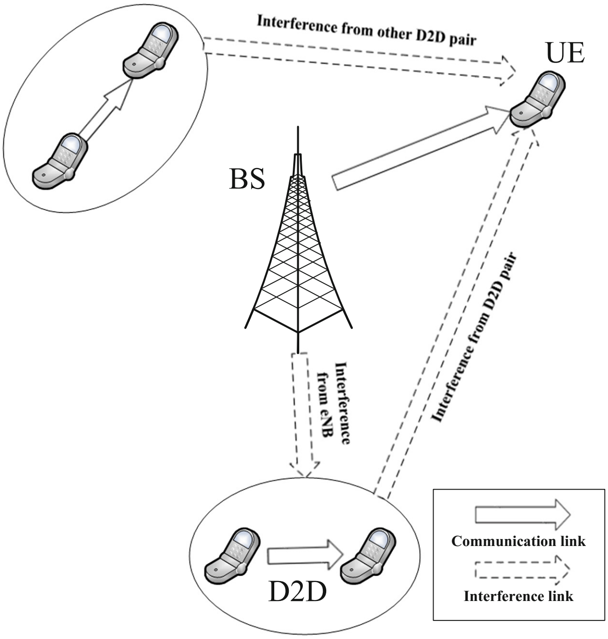

Fig. 1. System model

Let x_k^n be a binary variable where $x_k^n = 1$ if subchannel n is allocated for user k and $x_k^n = 0$ otherwise. We assume that the BS has the maximum power budget of $P_{BS}^{\max}$, and meanwhile, the transmit power constraint of D2D users is $P_d^{\max}$. Denoting the transmit power of D2D pair k on subchannel n by P_k^n and the transmission power allocated to cellular user k on subchannel n at the BS by P_{BS}^n. g_{kk}^n and g_{BSk}^n respectively represent the channel gain from the transmitter to the receiver of D2D pair k on subchannel n and the channel gain from the BS to cellular user k on subchannel n. Then the SINR at cellular user k or the receiver of D2D pair k on subchannel n can be written as:

$$S_k^n = \begin{cases} \dfrac{P_{BS}^n g_{BSk}^n}{I_k^n + \sigma_k^n} & k \in \mathrm{C} \\ \dfrac{P_k^n g_{kk}^n}{I_k^n + \sigma_k^n} & k \in D \end{cases} \tag{1}$$

where σ_k^n denotes the noise power and I_k^n represents the interference power from other users on subchannel n. If a D2D pair occupies a subchannel which is assigned to a cellular user, it will suffer interference from the BS. Cellular users will be interfered by D2D pairs which sharing the same subchannels with them. In general, channel capacity can be calculated by Shannon formula but can not be achieved in reality. So we use a factor $\Gamma(\Gamma \leq 1)$ represents the gap to the Shannon capacity. The transmission rate of cellular user k or D2D pair k on subchannel n can be expressed as

$$r_k^n = B\log_2(1 + \Gamma S_k^n) \tag{2}$$

where B is the bandwidth of subchannel n. For the sake of simplicity, we assume one subchannel only can be assigned to one D2D pair so that there will be no interference among D2D pairs. Let l_k denote the queue length of cellular user k or the transmitter of D2D pair k and the arrival rate of packets is subject to Poisson distribution. Then we can formulate the resource allocation problem as follows:

$$\max \sum_k \sum_n x_k^n r_k^n \tag{3}$$

$$\text{s.t} \sum_{k \in C} x_k^n \leq 1, \, \forall n \tag{3.a}$$

$$\sum_{k \in D} x_k^n \leq 1, \, \forall n \tag{3.b}$$

$$x_k^n = \{0, 1\}, \, \forall n, k \tag{3.c}$$

$$\sum_n \sum_{k \in C} x_k^n P_{BS}^n \leq P_{BS}^{\max} \tag{3.d}$$

$$\sum_n x_k^n P_k^n \leq P_d^{\max}, \, \forall k \in D \tag{3.e}$$

$$\frac{l_k}{\sum_n x_k^n r_k^n} \leq D_k^{threshold}, \, \forall k \tag{3.f}$$

Our objective is to maximize the system throughput. Constraints (3.a) and (3.b) ensure that each subchannel can be allocated to at most one cellular user or one D2D pair. Function (3.c) indicates whether subchannel n is allocated to cellular user or D2D pair k. Constraints (3.d) and (3.e) restrict the maximum transmission power of BS and the transmitter of D2D pair. Constraints (3.f) describes the delay threshold denoted by $D_k^{threshold}$ for every user. The optimization problem above is a mixed integer non-linear programming problem with a large solution space.

3 PSO-Based Resource Allocation Scheme

Particle Swarm Optimization is a stochastic population based optimization algorithm with inherent simplicity and high efficiency, so it has been a popular candidate for solving various complex optimization problems [14]. In basic PSO, the position of each particle represents a potential solution to the optimization problem, and an objective function is defined to evaluate the quality of the solutions. A swarm of S particles move around in a M-dimensional problem search space to look for the global optimum position that produces the best fitness of the objective function. In every iteration, every particle adjusts its velocity to follow the historical personal best position (denoted by $pbest_i$) and global best position (denoted by $gbest$) found so far in order to lead them to the best solution.

The velocity and position of particle i are updated with the following equations:

$$\begin{aligned} v_i^m(t+1) = w \times v_i^m(t) + c_1 \times r_1 \times (pbest_i(t) - x_i^m(t)) \\ + \; c_2 \times r_2 \times (gbest(t) - x_i^m(t)) \end{aligned} \tag{4}$$

$$x_i^m(t+1) = x_i^m(t) + v_i^m(t+1) \tag{5}$$

The parameters, x_i^m and v_i^m represent the position and velocity of particle i where $i = 1, 2, \cdots, S$ and $m = 1, 2, \cdots, M$. c_1 and c_2 are two positive constant named as learning factors, usually set as $\mathrm{c}_1 = c_2 = 2$. r_1 and r_2 are random variables between $[0, 1]$. w is an inertia weight factor that control the velocity of the particle.

The standard PSO is used to solve an optimization problem in a continuous solution space which is not appropriate for the delay based resource allocation in this paper. Under this context, we propose a PSO-based resource allocation scheme. The main issues are the way to represent particles that can map integer solutions onto continuous space and how to define the fitness function to evaluate the quality of particles with all that constraints.

The problem in Sect. 2 contains two parts including power allocation and subchannel allocation, respectively. To decouple the power allocation and subchannel allocation, we assume that the transmitters of D2D pairs and the BS allocate equal power to the subchannels, which is a simple and practical power allocation policy. Then we can merely consider the subchannel allocation without violate the constraints (3.d) and (3.e). As such, the representation of particles will just deal with indicator x_k^n, which has a discrete value. Of course we can use discrete PSO to solve the problem, but it is difficult to design a discrete PSO for such a problem. So we convert the problem into a continuous one.

We use a vector consisting of $2N$ real elements to denote the position of each particle, each element is between 0 and 1. The position of particle represents subchannel allocation for cellular users and D2D pairs. In this paper, we jointly allocate subchannels for cellular users and D2D pairs so that we can jointly optimize them to achieve better system performance than just dynamically allocate subchannels for D2D pairs when cellular users' subchannel allocation is fixed.

Thus there are two elements in the vector correspond to each subchannel. For N subchannels and S particles, the position of particle i can be expressed as $\mathrm{X}_i = (x_i^1, x_i^2, \cdots, x_i^n, \cdots, x_i^N, x_i^{N+1}, x_i^{N+2}, \cdots, x_i^{N+n}, \cdots, x_i^{2N})$, $i = 1, 2, \cdots, S$. The two elements correspond to subchannel n are x_i^n and x_i^{N+n}. The index of cellular user and D2D pair who gets subchannel n can be decoded by x_i^n and x_i^{N+n} respectively. To decode the vector, we divide X_i into two parts evenly, which are $(x_i^1, x_i^2, \cdots, x_i^n, \cdots, x_i^N)$ and $(x_i^{N+1}, x_i^{N+2}, \cdots, x_i^{N+n}, \cdots, x_i^{2N})$. Then the element of each part can be decoded into integers as follows:

$$D(x_i^n) = floor(x_i^n \times (K_1 + 1)),\ x_i^n \in (0, 1) \tag{6}$$

$$D(x_i^{N+n}) = floor(x_i^{N+n} \times (K_2 + 1)) + K_1 + 1,\ x_i^{N+n} \in (0, 1) \tag{7}$$

It is obvious that the values of $D(x_i^n)$ range from 0 to K_1 and the values of $D(x_i^{N+n})$ range from $K_1 + 1$ to $K_1 + K_2 + 1$. The values of $D(x_i^n)$ and $D(x_i^{N+n})$ means the index of cellular users and D2D pairs who is allocated subchannel n while 0 and $K_1 + K_2 + 1$ indicate subchannel n isn't allocated to cellular users and D2D pairs respectively.

After finding the way to represent particles and decode it into the result of subchannel allocation, the power allocation problem is solved by the BS and the transmitters of D2D pairs allocate their total power equally among the subchannels assigned to them. All the constraints except (3.f) are satisfied. So the resource allocation problem becomes maximizing the system throughput under constraint (3.f).

To transform a constrained problem into an unconstrained one, we import a penalty function. It is a technique to handle constrained problem by adding a penalty function to the objective function to cancel the constraint. The penalty function we defined can be expressed as:

$$Penalty = \sum_k \left[\min\left(0, D_k^{threshold} - \frac{l_k}{\sum_n x_k^n r_k^n}\right) \right]^2 \tag{8}$$

Then the fitness function would be:

$$Fitness = \sum_k \sum_n x_k^n r_k^n - P \sum_k \left[\min\left(0, D_k^{threshold} - \frac{l_k}{\sum_n x_k^n r_k^n}\right) \right]^2 \tag{9}$$

where $P \in R^+$ is a penalty factor. The penalty function is an important aspect to guide the particle to get out of the non-feasible region as soon as possible. As a feasible solution, the penalty function should equal 0 and the answer of fitness function is the solution to the resource allocation problem we proposed.

The PSO-based resource allocation scheme can be describe as follows:

PSO-based resource allocation scheme

Initialization Set the particles positions x_i^m and velocities v_i^m with random number between 0 and 1, and $pbest_i$ and $gbest$ with 0, $i = 1, 2, \cdots, S$ and $m = 1, 2, \cdots, 2N$.
for each iteration **do**
  for each particle **do**
    Update the velocity v_i^m and the position x_i^m according to (4) and (5).
    Decode the position x_i^m of particle into $\mathrm{D}(x_i^m)$ according to (6) and (7).
    Calculate the power on each subchannel P_k^n and P_{BS}^n.
    Calculate the fitness function according to (8) and (9).
    Update the personal best position pbest_i according to the value of fitness function.
  end for
  Update the global best position gbest according to the value of fitness function.
end for

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4 Numerical Result

In this section, simulation results are provided to evaluate the performance of the proposed PSO-based resource allocation scheme. We consider a single cell OFDMA cellular network with a radius of R = 500 m. Cellular users and D2D pairs are distributed uniformly over the cell area, while the number of cellular users is 3 and the number of D2D pairs varies from 2 to 7. The distance-dependent path loss is modeled as $L(d) = 128.1 + 37.6\log_{10} d$ for the links between BS to users and $L(d) = 148 + 40\log_{10} d$ for the D2D links, where d is distance in kilometers. The system bandwidth is 3 MHz and it is divided into 15 subchannels with equal bandwidth. The delay threshold of all users is set as $D_k^{threshold}$=100 ms. The transmit power of BS and UE is 36 dBm and 17 dBm respectively. Meanwhile, the noise power spectral density is set to be −174 dBm/Hz. Moreover, the parameters of the PSO algorithm are set as follows. The number of iterations $T = 1000$, the number of particles $S = 20$, two learning factors are set as $c_1 = c_2 = 2$, the inertia weight factor w decreasing linearly from 0.95 to 0.4.

The PSO-based scheme is compared with traverse resource allocation scheme and random resource allocation scheme. The traverse scheme go through every kind of resource allocation and select the one that can maximize the system throughput while each user's delay threshold is satisfied. The random scheme assign one subchannel to one user randomly until all subchannels are allocated, and it doesn't consider any constraint at all.

In Figs. 2 and 3, we respectively provide the system throughput and the average user delay of three schemes, while the number of D2D pairs increases from 2 to 7 and the distance between D2D transmitter and D2D receiver is set to 50 m. The system throughput of PSO-based scheme is a little lower than the traverse scheme, because the solution of traverse scheme is global optimum for considering every condition and the solution of PSO-based scheme is local optimum when the iteration number is limited. However, the complexity of traverse scheme is much higher than PSO-based scheme. So we sacrifice a little performance on system throughput to dramatically decrease the complexity of the scheme. Our target is to maximize the system throughput, so we already make full use of the system resources no matter what the number of D2D pairs is. Hence as the number of D2D pairs grows, the system throughput just grows a little bit. It is obvious that the system throughput and the average user delay of random scheme vary randomly and its performance is worse than other schemes because it has no mechanism to ensure the system performance.

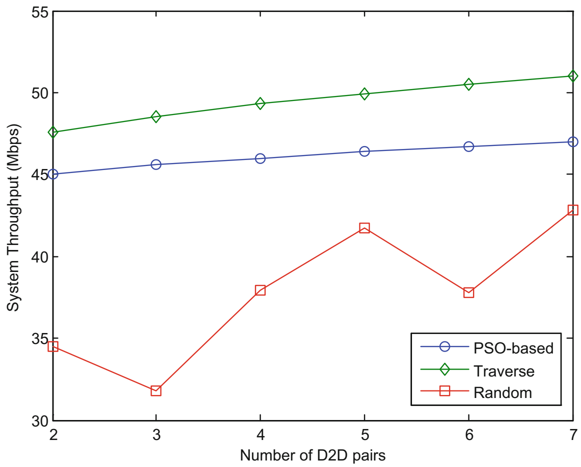

Fig. 2. System throughput versus number of D2D pairs

The average user delay of the PSO-based scheme and the traverse scheme are pretty close according to Fig. 3. Moreover, the average user delay increases with the number of D2D pairs because the resource for each user is less than before. There is one thing needs to be clarify. It is possible that not all users are allocated with subchannels while using the random scheme, especially when the number of D2D pairs grows. When a user isn't allocated with subchannels, the throughput would be zero and the delay would be infinite for this user. Then we wouldn't take the user into account when we calculate the system performance.

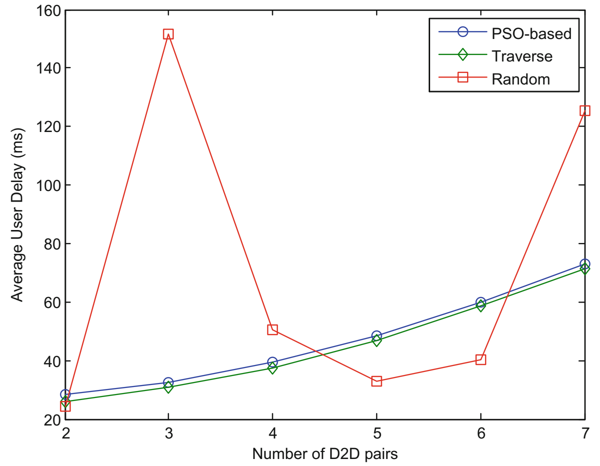

Fig. 3. Average user delay versus number of D2D pairs

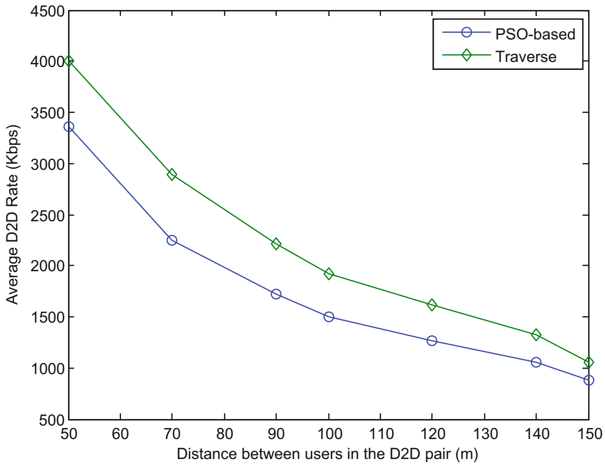

Fig. 4. Average D2D rate versus distance

Figures 4 and 5 illustrate the average rate and the average delay of D2D pairs versus the distance between users in the D2D pair, and the number of D2D pairs is set to 3. We don't consider the random scheme here because it has no certain pattern of changing. As the distance between users in the D2D pair grows, the average D2D rate decreases rapidly at first, then it becomes to decrease gently. When the distance is small, the channel condition between D2D users will be the best. In this case, our scheme schedules subchannels to the D2D pairs mostly to maximize the system throughput. However, as the distance between users in the D2D pair is getting larger, the average D2D rate is decreasing since the channel condition is getting worse. On the

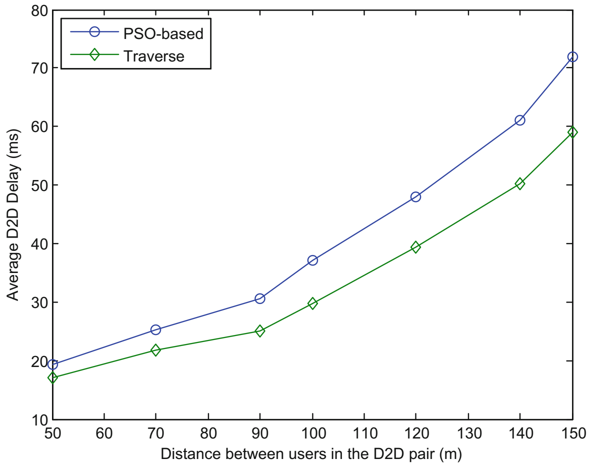

Fig. 5. Average D2D delay versus distance

other hand, every user has to satisfy the delay constraint, so the average D2D rate then becomes to decrease gently.

It is obvious that the average delay of D2D pairs increases with the distance. The difference of average delay between the PSO-based scheme and the traverse scheme is getting bigger when the distance grows, because the rate of D2D users is getting smaller.

5 Conclusion

In this paper, we develop the PSO-based scheme to maximize the system throughput for D2D communication underlay of cellular networks, which can jointly schedule the subchannels of cellular users and D2D pairs with the constraint of users' delay threshold. This scheme maps resource allocation solutions onto the representation of particles and construct a fitness function while handling constraints with penalty function. Through the simulation results, we have shown that the local optimum we get through the PSO-based scheme with low complexity is close to the global optimum on system performance. The result also show that the performance of D2D communications is highly affected by distance between users in D2D pairs.

References

1. Lei, L., et al.: Operator controlled device-to-device communications in LTE-advanced networks. IEEE Wirel. Commun. **19**(3), 96–104 (2012)
2. Fodor, G., et al.: Design aspects of network assisted device-to-device communications. IEEE Commun. Mag. **50**(3), 170–177 (2012)

3. Wei, L., et al.: Enable device-to-device communications underlaying cellular networks: challenges and research aspects. IEEE Commun. Mag. **50**(3), 170–177 (2014)
4. Zhang, R., et al.: Interference-aware graph based resource sharing for device-to-device communications underlaying cellular networks. In: 2013 IEEE Wireless Communications and Networking Conference (WCNC), pp. 140–145. IEEE (2013)
5. Le, L.B.: Fair resource allocation for device-to-device communications in wireless cellular networks. In: 2012 IEEE Global Communications Conference (GLOBECOM). IEEE (2012)
6. Kim, H.-S., Na, J.-H., Cho, E.: Resource allocation policy to avoid interference between cellular and D2D Links/and D2D links in mobile networks. In: 2014 International Conference on Information Networking (ICOIN). IEEE (2014)
7. Guo, B., Sun, S., Gao, Q.: Downlink interference management for D2D communication underlying cellular networks. In: 2013 IEEE/CIC International Conference on Communications in China-Workshops (CIC/ICCC). IEEE (2013)
8. Xu, S., Wang, H., Chen, T.: Effective interference cancellation mechanisms for D2D communication in multi-cell cellular networks. In: 2012 IEEE 75th Vehicular Technology Conference (VTC Spring). IEEE (2012)
9. Belleschi, M., Fodor, G., Abrardo, A.: Performance analysis of a distributed resource allocation scheme for D2D communications. In: 2011 IEEE GLOBECOM Workshops (GC Wkshps). IEEE (2011)
10. Yu, C.-H., Tirkkonen, O.: Device-to-device underlay cellular network based on rate splitting. In: 2012 IEEE Wireless Communications and Networking Conference (WCNC). IEEE (2012)
11. Xu, C., et al.: Resource allocation using a reverse iterative combinatorial auction for device-to-device underlay cellular networks. In: 2012 IEEE Global Communications Conference (GLOBECOM). IEEE (2012)
12. Wang, W., Lau, V.K.N.: Delay-aware cross-layer design for device-to-device communications in future cellular systems. IEEE Commun. Mag. **52**(6), 133–139 (2014)
13. Lei, L., et al.: Resource control in network assisted device-to-device communications: solutions and challenges. IEEE Commun. Mag. **52**(6), 108–117 (2014)
14. Tsujimoto, T., et al.: A relationship between network topology and search performance of PSO. In: 2012 IEEE Congress on Evolutionary Computation (CEC). IEEE (2012)