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Article

Performance of Resource Allocation in Device-to-Device Communication Systems Based on Evolutionally Optimization Algorithms

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Abstract: In this study, the resource blocks (RB) are allocated to user equipment (UE) according to the evolutional algorithms for long term evolution (LTE) systems. Particle Swarm Optimization (PSO) algorithm is one of the evolutionary algorithms, based on the imitation of a flock of birds foraging behavior through learning and grouping the best experience. In previous work, the Simple Particle Swarm Optimization (SPSO) algorithm was proposed for RB allocation to enhance the throughput of Device-to-Device (D2D) communications and improve the system capacity performance. In simulation results, with less population size of M=10, the SPSO can perform quickly convergence to sub-optimal solution in the 100th generation and obtained sub-optimum performance with more 2 UEs than the Rand method. Genetic algorithm (GA) is one of the evolutionary algorithms, based on Darwinian models of natural selection and evolution. Therefore, we further proposed a Refined PSO (RPSO) and a novel GA to enhance the throughput of UEs and to improve the system capacity performance. Simulation results show that the proposed GA with 100 populations, in 200 generations can converge to suboptimal solutions. Therefore, with comparing with the SPSO algorithm the proposed GA and RPSO can improve system capacity performance with 1.8 and 0.4 UEs, respectively.

Keywords: device-to-device; LTE systems; resource allocation; particle swarm optimization algorithm; genetic algorithm; system capacity

1. Introduction

Orthogonal frequency division multiple access (OFDMA) combines the orthogonal frequency division multiplexing (OFDM) and frequency division multiple access (FDMA) technology, for multiple access of multiple users with high data rate. The OFDMA scheme in the fourth generation mobile communication system (4G) long term evolution (LTE) technology not only upgrades spectrum efficiency but also provides high resistance for frequency-selective fading channels [1]. The Device-to-Device (D2D) is a developing key technique for next generation (5G) mobile communication systems [2]. The D2D technique allows unauthorized users equipments (UEs) to access unused authorized cellular UE band, thereby improving the utilization efficiency of bandwidth resource.

The D2D can maximize communications services in adjacent areas due to transfer data without going through the base station. For example, the regional transmission and Wi-Fi combined [3,4] can provide more neighboring users multimedia services, or find a nearby friend, real-time communications conversations, and product advertising. It also has the potential to be applied in settings of emergency medicine [5] and disaster scene [6] where patients far outnumber healthcare providers and the outreaching communication bandwidth is limited.

In this study, the resource blocks (RBs) are allocated to UEs according to the evolutional algorithms for LTE systems. The advantages of D2D techniques are such as improving energy efficiency of transmission, energy saving [7] and coverage rate improvement [6]. In the serious interfering environments of communication systems, most of directly transmission UEs cannot reach transmission rate requirement when the UEs is far from the base station. However, with relay station for transmission, most UEs can reach the minimum requirements of transmission rate [10]. Therefore, the application of relay station for transmission in the serious interference environment, the performance of system outperforms the directly transmission systems.

Particle Swarm Optimization (PSO) algorithm [8] is one of the evolutionary algorithms, based on the imitation of a flock of birds foraging behavior through learning and grouping the best experience. In previous works [8], a Simple Particle Swarm Optimization (SPSO) algorithm was developed for resources allocation to achieve quality of service (QoS) and to maximize system capacity. Therefore, in this paper, we further proposed a Refined PSO (RPSO) to enhance the throughput of UEs and to improve the system capacity performance

The GA is a stochastic search algorithm whose procedures are based on the Darwinian models of natural selection and evolution [9]. Given some arbitrary initial solutions, the GA will generate the better solution through a series of genetic operations including selection, crossover, and mutation. Furthermore, The GA searches the solution space in parallel, that is, a set of possible solutions are manipulated in the same generation, so multiple local optimum can be reached simultaneously and thereby the likelihood of finding the global optimum is increased. In previous works [10], we proposed a novel redundancy-saving genetic algorithm (RSGA) based on the cost value of the fitness function to improve the complexity in term the BER requirement for DS-CDMA systems. However, it is not suitable for OFDMA systems. Therefore, in this study, we further proposed a novel GA for the RB allocation for D2D systems.

2. System Models

In this paper the LTE communication systems based resources allocation issues are investigated. The systems architecture is shown in Fig. 1. In this hybrid system, D2D UEs and traditional Cellular users' equipments (CeUEs) share all resources. In Figure 1, totally three relay stations are deployed in the cellular system, where UEs are uniformly random distributed in relay stations. In this study, base station is located in the center, and three relay stations form a triangle around the base station. Each relay station signal coverage with radius of 200 m. The CeUEs are uniformly random distributed in each relay stations within range. Each D2D pair includes a receiver UE and a transmitter UE distributed with 80 m distance from relay station. Channel models include Raleigh Fading, Shadowing Fading and path loss [11].

In Figure 1, each uplink data transfer includes two hops. In the first hop, the u_i-th UE transmits signal to the lth relay station by channel gain $h_{u_i,l}^{(n)}$. The lth relay station relays the transmission to base station using the nth resource block (RB). However, when the u_j-th D2D UE transmits signal to the lth relay station, it will occurs the interference link gain $g_{u_j,l}^{(n)}$ to the lth relay station.

In this study, the channel models include path loss and shadowing fading. Thus, the fading channel model from UE to relay station (UE-relay) can be expressed by

$$PL_{u_i,l}(\ell)_{[\mathrm{dB}]}=103.8+20.9\log(\ell)+L_{su}+10\log(\zeta) \quad (1)$$

where 103.8 is antenna gain; L_{su} is shadowing fading with log-normal distributed random variable where the standard deviation $\sigma = 10$; $10\log(\zeta)$ is Rayleigh fading effect, ℓ is the distance between UE to relay station. Similarly, the fading channel model from relay station to BS (relay-BS) can be expressed by [11]

$$PL_{l,eNB}(\ell)_{[dB]}=100.7+23.5\log(\ell)+L_{su}+10\log(\zeta) \quad (2)$$

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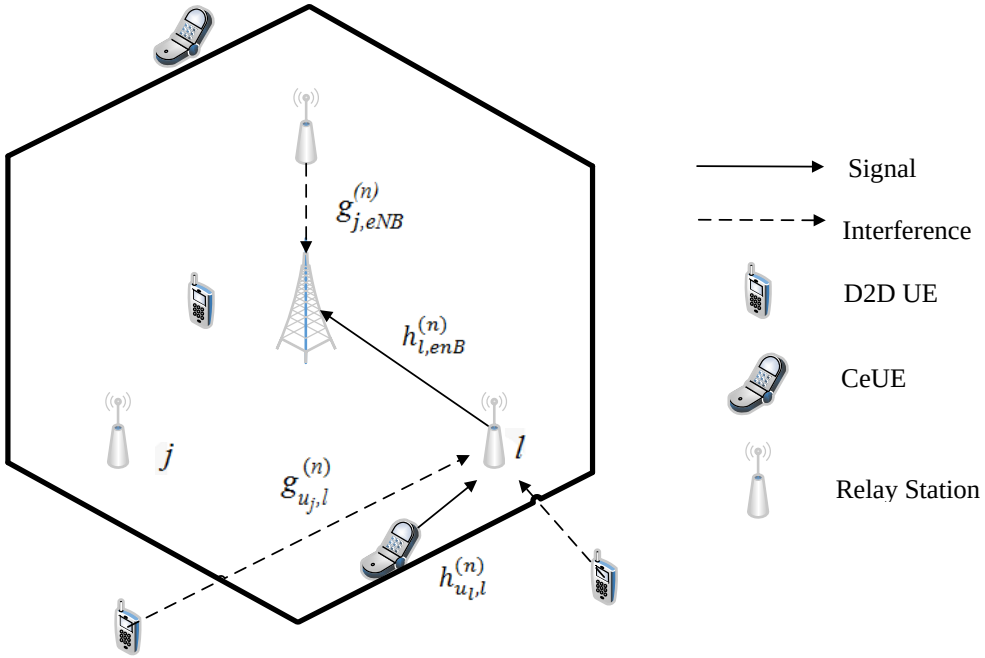

Figure 1. Systems architechure with deployment of three relay station.

It is assumed that Base Station (BS) has know well the Channel State Information (CSI) of all channels. Then, the unit Power Signal-to-Interference-Plus-Noise Ratio (Unit Power SINR) of the first hop can be expressed by

$$\gamma_{u_l,l,1}^{(n)} = \frac{P_{u_l,l}^{(n)} h_{u_l,l}^{(n)}}{\sum_{\forall u_j \in U_j, j \neq l, j \in L} x_{u_j} P_{u_j,l}^{(n)} g_{u_j,l}^{(n)} + \sigma^2} \quad (3)$$

where $h_{u_l,l}^{(n)}$ is the channel gain from the u_l-th UE to the lth relay with the nth RB. x_{u_l}=1 or 0. Each UE can only use one RB, x_{u_l}= 1 indicates with one RB, however, x_{u_l}= 0 indicates without any RB. U_j is the set of D2D UEs in the jth relay area. $P_{u_l,l}^{(n)}$ and $P_{u_j,j}^{(n)}$ are transmission power of the u_l-th UE and the u_j-th CeUE, respectively. $g_{u_j,l}^{(n)}$ is the interference link gain from the u_j-th CeUE to the lth relay. $\sigma^2 = N_0 B_{RB}$. N_0 is power spectral density of the added white Gaussian noise (AWGN). B_{RB} is bandwidth of an RB. Similarly, the unit power SINR of the second hop can be expressed by

$$\gamma_{l,eNB,2}^{(n)} = \frac{P_{l,eNB}^{(n)} h_{l,eNB}^{(n)}}{\sum_{\forall u_j \in U_j, j \neq l, j \in L} x_{u_j} P_{j,eNB}^{(n)} g_{j,eNB}^{(n)} + \sigma^2} \quad (4)$$

where $h_{l,eNB}^{(n)}$ is the channel gain from the lth relay to the Base Station (eNB) with the nth RB. $P_{l,eNB}^{(n)}$ and $P_{j,eNB}^{(n)}$ are transmission power of the l-th relay and the j-th relay, respectively. $g_{j,eNB}^{(n)}$ is the interference link gain from the jth relay to the eNB with the nth RB.

In this study, there are two links in the second hop. Eq. (4) expresses the SINR of the lth relay station to BS. Similarly, the SINR of the lth relay station to the receiver of D2D pair can be expressed by

$$\gamma_{l,u_l,2}^{(n)} = \frac{P_{l,u_l}^{(n)} h_{l,u_l}^{(n)}}{\sum_{\forall u_j \in U_j, j \neq l, j \in L} x_{u_j} P_{j,u_l}^{(n)} g_{j,u_l}^{(n)} + \sigma^2} \quad (5)$$

In Eqs. (3)-(5), the SINR for all the links will be obtained. Then the throughput (Kbps) of the first hop can be derived by

$$r_{u_l,1}^{(n)} = B_{\mathrm{RB}} \log_2(1+\gamma_{u_l,l,1}^{(n)}) \quad (6)$$

Similarly, the throughput of the second hop can be obtained by

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$$r_{u_l,2}^{(n)} = B_{\mathrm{RB}} \log_2(1+\gamma_{l,u_l,2}^{(n)}) \tag{7}$$

Thus, the throughput for the nth RB by the user u_l can be obtained by

$$R_{u_l}^{(n)} = \frac{1}{2} \min\{ r_{u_l,1}^{(n)}, r_{u_l,2}^{(n)} \} \tag{8}$$

With Eq. (8), the total throughput of N RBs is $\sum_{l\in L}\sum_{u_l\in U_l}\sum_{n=1}^{N} x_{u_l}^{(n)} R_{u_l}^{(n)}$. All UEs are desired to obtain the RBs to reach the maximal throughput. Therefore, to avoid deteriorating the communication quality a threshold Q_{u_l} is set to meet the required throughput for most UEs. Some constraints are set to perform the optimization problem as

$$\text{s.t} \begin{cases} \sum_{u_l\in U_l} x_{u_l}^{(n)} \le 1, \ \forall n \in N & \text{(9a)} \\ \sum_{n=1}^{N} x_{u_l}^{(n)} P_{u_l,l}^{(n)} \le P_{u_l}^{max}, \ \forall u_l \in U_l & \text{(9b)} \\ \sum_{n=1}^{N} x_{l}^{(n)} P_{l,u_l}^{(n)} \le P_{l}^{\max}, \ \forall u_l \in U_l & \text{(9c)} \\ \mathrm{R}_{u_l} \ge \mathrm{Q}_{u_l}, \ \forall u_l \in U_l & \text{(9d)} \end{cases}$$

where Eq. (9a) set the constraints for that each UE use only one RB. Eq. (9b) and (9c) are the constraints on the minimum power for UEs and relay stations, respectively. Eq. (9d) is the minimum throughput requirements of QoS for UEs.

Moreover, the interference of the first hop and the second hop for system is expressed by

$$I_{u_l,l,1}^{(n)} = \sum_{\substack{\forall u_j\in U_j, \\ j\neq l, j\in L}} x_{u_j} P_{u_j,l}^{(n)} g_{u_j,l}^{(n)} \tag{10}$$

and

$$I_{u_l,l,2}^{(n)} = \begin{cases} \sum_{\substack{\forall u_j\in U_j, \\ j\neq l, j\in L}} x_{u_j} P_{j,eNB}^{(n)} g_{j,eNB}^{(n)}, u_l \in \{C\cap U_l\} \\ \sum_{\substack{\forall u_j\in U_j, \\ j\neq l, j\in L}} x_{u_j}^{(n)} P_{j,u_j}^{(n)} g_{j,u_l}^{(n)}, u_l \in \{D\cap U_l\} \end{cases} \tag{11}$$

, respectively.

In the system model, it is assumed that the base station coverage area is a circle with the radius 175 m. In this area, there are three relay station uniformly deployed with a traiangle as shown in Figure 1. The coverage area of each relay station is a circle with radius 100 m. The celllular UEs are uniformly random distributed around the relay station. D2D pairs are deployed on a circle with radius 80 m around each relay station as shown in Figure 2. The numbers of UEs in the relay station are the same. It is assumed that the CSI of the links are known to base station. The simulation parameters are listed in Table 1.

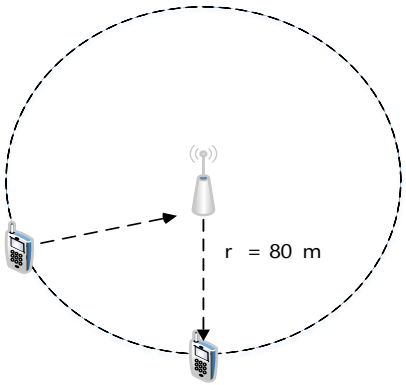

Figure 2. D2D pairs deployed on the circle around the relay station.

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Table 1. System simulation parameters.

System bandwidth (MHz)	2.5
Bandwidth of subcarrier (Hz)	1500
Number of RBs	13
Radius of the coverage area of relay station (meter)	200
Distance between base station and relay station (meter)	125
Number of CeUE	9, 12, 15
Number of D2D pairs	3, 6, 9
Minimum distance between base station and UEs (meter)	10
Power of relay station (P_l, dBm)	30
Power of UEs (P_{ul}, dBm)	23
Minimum throughput requirements of CeUEs (R_{th_C}, Kbps)	128
Minimum throughput requirements of D2D pairs (R_{th_D}, Kbps)	256
Standard deviation of Shadowing fading between relay and BS (dB)	6
Standard deviation of Shadowing fading between UEs and relay station (dB)	10
Power Spectral density of AWGN (dBm/Hz)	-174

3. PSO based Resource Allocation

PSO algorithms are used to simulate the bird swarm foraging situation, which is in the search for food space with particles. Each particle simulates a bird, in addition to its own normal movement, also refer to its own best moving experience. The personal best experience is denoted by $\mathbf{s}^{\text{pbest}}$. Then the global experience is referred from the group's best moving experience with global best, denoted by $\mathbf{s}^{\text{gbest}}$. According to the above kinds of data with an iterative evolution, the final convergence obtains the optimal solution.

In this study, the number of particles is *M*, and the value of the particle's target function is the pointer to the efficiency of the iteration. The particle with the highest target function value is the best solution. A simplified formula for particle swarm optimization, called SPSO, is proposed to improve the performance of the resource allocation for D2D communication systems. The SPSO algorithm performs the optimization of resource block allocation, and all the relay stations cover the UEs of the allocated RB as the particle $\mathbf{s}_i$. The particle is uniformly distributed in the solution space. Total 13 RBs and 3 relay stations are available. The moving velocity of the first particle in the (g+1)-generation is expressed by

$$\mathbf{v}_i^{g+1} = c_1 \times rand() \times \left(\mathbf{s}^{pbest} - \mathbf{s}_i^g\right) + c_2 \times rand() \times \left(\mathbf{s}^{gbest} - \mathbf{s}_i^g\right) \quad (12)$$

where $\mathbf{s}_i^g$ is the position vector of the ith particle in g-generation, $\mathbf{s}_i^g = [\mathbf{s}_{i_1}^g, \ldots, \mathbf{s}_{i_l}^g, \ldots, \mathbf{s}_{i_3}^g]$, and $\mathbf{s}_{i_l}^g$ is the position of the ith particle of the lth relay station. The local optimal positions of all particles are denoted by $\mathbf{s}^{pbest} = [\mathbf{s}^{pbest_1}, \ldots, \mathbf{s}^{pbest_l}, \ldots, \mathbf{s}^{pbest_3}]$, where $\mathbf{s}^{pbest_l}$ is the local optimal position of the lth relay station. $\mathbf{s}^{gbest}$ is the global optimal positions of all particles in the nearest generation. both c_1 and c_2 are the acceleration coefficients, called by individual factor and social factor, respectively. Generally, the factors are set by c_1=2 and c_2=2. The $rand()$ is the random function with uniformly distributed in [0,1].

Moreover, the position updating at (g+1)-generation can be expressed by

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$$\mathbf{s}_i^{g+1}=\mathbf{s}_i^g+\mathbf{v}_i^{g+1} \tag{13}$$

In SPSO, all the K UEs distributed in the coverage area of relay station are allocated RBs and composited as a particle $\mathbf{s}_i$ with an array of 1×K. The M particles are uniformly distributed in the solution space, and a total of 13 RBs are available to be allocated to the UEs in three relay stations.

In SPSO the object function is defined by

$$f_C=\sum_{u_l=1}^{K} y_{u_l} \tag{14}$$

where $\Sigma_{u_l=1}^{K} y_{u_l}$ is the system capacity and y_{u_l} is defined by

$$y_{u_l}=\begin{cases}1, & \sum_{n=1}^{N} x_{u_l}^{(n)} R_{u_l}^{(n)} \geq R_{th} \\ 0, & \text{otherwise}\end{cases} \tag{15}$$

The procedure of SPSO algorithms applied in this study can be described by the following example with K=18 and M=3:

1) Initialization (g=1): Generate the positions of M particles, $\mathbf{s}_i^1\,\mathbf{s}_i^1$, i =1, ..., M and velocity, $\mathbf{v}_i^1$, i=1, ..., M. One example of the position of a particle $\mathbf{s}_i^1\mathbf{s}_i^1$ can expressed by $\mathbf{s}_1^1$ = [1 1 3 4 5 6 | 2 8 3 11 11 13 | 1 6 7 8 4 9].
2) Calculate the objective function value of all particles according to Eq. (8) and find the $\mathbf{s}^{spb}$ and $\mathbf{s}^{gbest}$ for this generation. One example of $\mathbf{s}^{spb}$ and $\mathbf{s}^{gbest}$ can be $\mathbf{s}^{spb_1}$ = [1 1 3 4 5 6]; $\mathbf{s}^{spb_2}$ = [7 8 9 10 11 12]; $\mathbf{s}^{spb_3}$ = [1 3 4 5 7 6] and $\mathbf{s}^{gbest}$ = [3 4 5 6 7 5 | 7 8 9 10 11 12 | 1 3 4 5 7 6], respectively.
3) Let g=g+1. According to step (2), we calculate the speed and position of the next generation (g+1) particle, after one generation calculation. Then one example of the position can be $\mathbf{s}_1^1$ = [2 3 1 4 5 6 | 9 7 6 11 13 10 | 1 6 7 8 4 9].
   If the number of generations g < G, return to step (2) to update the individual optimal solution and the population optimal solution. One example can be as: the previous $\mathbf{s}^{spb_1}$ is unchanged by $\mathbf{s}^{spb_1}$ = [1 1 3 4 5 6]. But the other two individual optimal solutions is updated by $\mathbf{s}^{spb_2}$ = [9 7 6 11 13 10] and $\mathbf{s}^{spb_3}$ = [2 7 8 9 3 5], respectively. Moreover, the new $\mathbf{s}^{gbest}$ is updated according the object function by $\mathbf{s}^{gbest}$= [2 3 1 4 5 6 | 9 7 6 11 13 10 | 1 6 7 8 4 9].
4) If the number of generation is g = G, the calculation is ended.

Then after N($N \leq G$) generations, one of the positions $\mathbf{s}_i^1$ is selected by $\mathbf{s}_1^1$ = [8 4 5 7 3 2 | 7 8 9 10 11 12 | 1 5 4 9 6 7]. The global optimal solution $\mathbf{s}^{gbest}$ is obtained by $\mathbf{s}^{gbest}$= [2 3 1 4 5 6 | 9 7 6 11 13 10 | 1 6 7 8 4 9]. Hence, in this PSO calculation, the solution is $\mathbf{s}^{gbest}$= [2 3 1 4 5 6 | 9 7 6 11 13 10 | 1 6 7 8 4 9].

To upgrade effectiveness of SPSO, this research according to system schema of relay station partition characteristics on SPSO for optimization, in (12), the learning factor with weight parameter cw1 and cw2, to speedup optimization searching. This PSO is called Refined PSO (RPSO). Then, its next generation of evolution speed of particle $\mathbf{s}_i^{g+1}$ can be obtained by

$$\mathbf{v}_i^{g+1}=c_1\cdot\mathbf{cw}_1\cdot rand()\times(\mathbf{s}^{pbest}-\mathbf{s}_i^g)+c_2\cdot\mathbf{cw}_2\cdot rand()\times(\mathbf{s}^{gbest}-\mathbf{s}_i^g) \tag{16}$$

where $\mathbf{cw}_1$ and $\mathbf{cw}_2$ are 1×K vector, where K is the number of UE, both on behalf of weights for adjusting the searching efficiency of particles.

The modifying rule of $\boldsymbol{cw}_1$ is the followings:

1) $\boldsymbol{cw}_1(u_l)$ = 1 for that the RB of the u_l-th UE in $\mathbf{s}^{pbest_l}$ does not conflict with the RBs of other relay stations.

2) $cw_1(u_l) = 0$ for that the RB of the u_l-th UE in s^{pbest_l} conflicts with the RBs of other relay stations once.
3) $cw_1(u_l) = 3$ for that the RB of the u_l-th UE in s^{pbest_l} conflicts with the RBs of other relay stations once more.

The modifying rule of cw_2 is the followings:

1) $cw_2(u_l) = 1$ for that the RB of the u_l-th UE in s^{gbest} does not conflict with the RBs of UEs of other relay stations. $cw_2(u_l) = 1$ for g>10.
2) $cw_2(u_l) = 3$ for that the RB of the u_l-th UE in s^{gbest} conflicts with the RBs of other relay stations once or more in g≤10.

4. RB Allocation with GA Discussion

In genetic algorithms (GAs) [12,13], the main idea is to follow the fittest evolutionary laws of nature, by the procedures of selection, crossover and mutation to improve the fitness value of chromosomes. With GA, there are random search, and other ways to search for the optimal solution. Therefore, the GA is often used to apply on optimization issues. In this study, the GA is applied for resources allocation optimization, with the objective functions on maximal system capacity and throughput.

The procedures in GA are the followings: (1) data coding, (2) producing initial population, (3) calculation fitness values, (4) selection, (5) crossover, and (6) mutation. The procedures are proceeded iterated from (3) to (6), until meeting the terminated conditions. Then the solution are obtained as the optimal results.

In the parent group, it is in accordance with the fitness value of chromosomes, to determine whether it will be retained or eliminated. In the select operation in this study, the ranking method, ranks the fitness value of each chromosome. This method can avoid inbreeding [10].

The crossover of GA is by selecting two chromosomes from the mating pool, and swapping the genes into two new chromosomes. It is expected that crossover procedures can generate better offspring chromosomes. Higher crossover rate in GA will bring the higher evolutional rate for the chromosomes.

The mutation can increase the ethnic diversity of GA operations. The aforementioned selection, crossover and other procedures in both groups search for better children, but its genetic characteristics must be associated with the parent. Because there are no new chromosomes joining the group in each generation, it makes that the searching area cannot be expanded. It will lead the evolution to converge earlier. However, through mutation, some new chromosomes will join the search space to avoid GA early convergence problems.

In GA the object function is defined by

$$f_C = \sum_{u_l=1}^{K} y_{u_l} \tag{17}$$

where $\Sigma_{u_l=1}^{K} y_{u_l}$ is the system capacity and y_{u_l} is defined by

$$y_{u_l} = \begin{cases} 1, & \sum_{n=1}^{N} x_{u_l}^{(n)} R_{u_l}^{(n)} \geq R_{th} \\ 0, & \text{otherwise} \end{cases} \tag{18}$$

5. Simulation Results

5.1. PSO

The simulation parameters based on SPSO and RPSO are shown in Table 2. In Figure 3, simulation results show that when the total number of UEs are K = 12, system capacity reaches 12 UEs. However, when K = 18, the system capacity reaches 16.5 UEs. Moreover, when K = 24, system capacity is 18.3 UEs.

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Figure 4 shows the comparisons between the proposed SPSO with c_1=c_2=2, $M = 10$ and random allocation methods. The random method (Rand) is performed by random allocated the RBs to the UEs in each generation. But the system retains the best results to the next generation based on the same object function as SPSO. From Figure 4, it is easy to observe that the proposed SPSO outperform the Rand at the 20th iterations and highly improve the system capacity to 16 UEs at the 100th iterations, which is 2 UEs more than that of Rand.

Table 2. Simulation parameters of PSO.

Maximal generations (*G*)	200
Number of particles (*M*)	10
Learning factors $(c_1=c_2)$	2
Number of user equipment (*K*) (Including CeUE and D2D UEs)	12, 18, 24
Number of relay station	3
ID of RBs	1 – 13

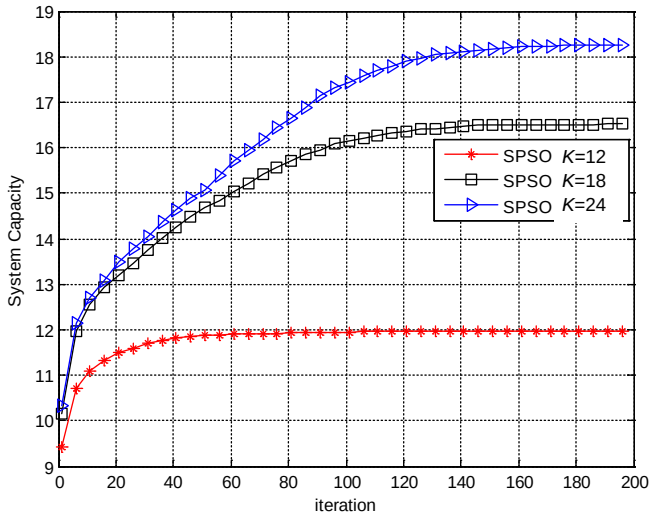

Figure 3. Simulation results of SPSO method with *M*=10.

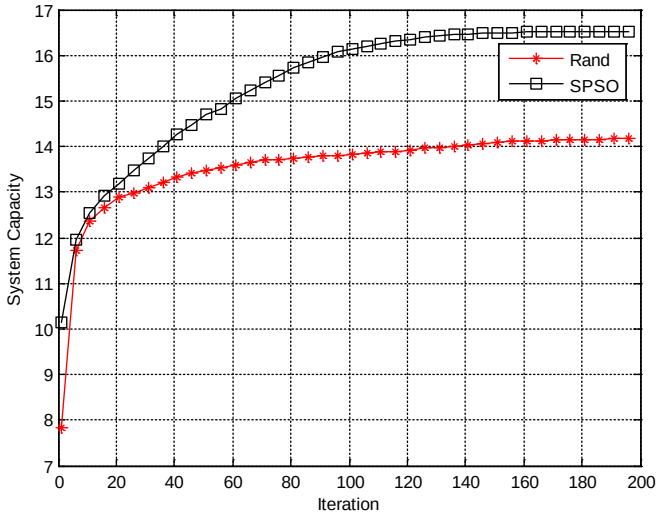

Figure 4. Simulation results comparisons between SPSO and random allocation method with *M*=10, *K*=18.

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Figure 5 displayed the comparisons between RPSO and SPSO. In Figure 5, it is shown that RPSO speed up more than SPSO algorithm to converge the optimal for K = 12. Moreover, for K = 18 and K = 24, system capacity of RPSO outperforms SPSO.

Table 3 shows the performance comparisons of SPSO, RPSO and random allocation (Rand) for K=12, 18, 24, with M=10, and c_1=c_2 = 2. Compared with the Rand, SPSO algorithm can improve the efficiency of about 17-20%, for K =18, 24. Moreover, the proposed RPSO algorithm can improve the efficiency of 18-24% than Rand.

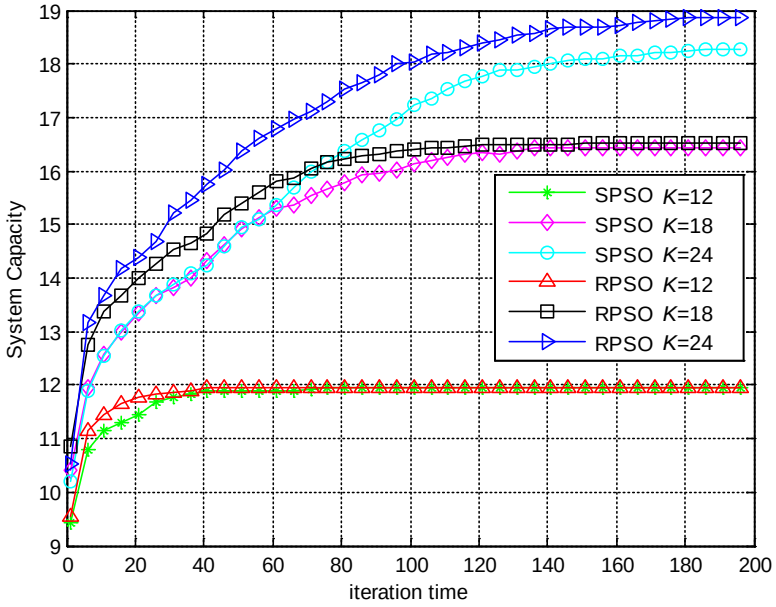

Figure 5. The comparisons of convergence between RPSO and SPSO.

Table 3. The comparisons between RPSO, SPSO and Rand.

Number of UE (K)	12	18	24
a. RPSO	12	16.66	18.89
b. SPSO	12	16.52	18.3
c. Rand	11.8	14.1	15.2
$Gain_1$ *(a-c) / c*	1.69%	18.16%	24.28%
$Gain_2$ *(b-c) / c*	1.69%	17.16%	20.39%

5.2. GA

The simulation parameters based on GA are shown in Table 4. Figure 6 shows that the system capacity for different population size in GA with K = 18. The objective function is $f_{obj\_C}()$ in Eq. (12). When M = 10, the system capacity performance can reach 15 UEs. However, when $M \geq 100$, the system capacity reaches saturated with near optimal solution with 18 UEs. From Figure 6, it is observed that the large population size can reach the optimal solution.

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Table 5 shows the performance comparisons of RPSO, GA and Rand methods with M=100 and G=200. From the results in Table 5, it is observed that the when M=100, the proposed GA outperform RPSO with 1.4 UEs of system capacity for K=24.

Table 4. Simulation parameters in GA.

Maximal generations (G)	200
Number of chromosomes (M)	10-500
Crossover rate (R_c)	0.9
Mutation rate (R_m)	0.07

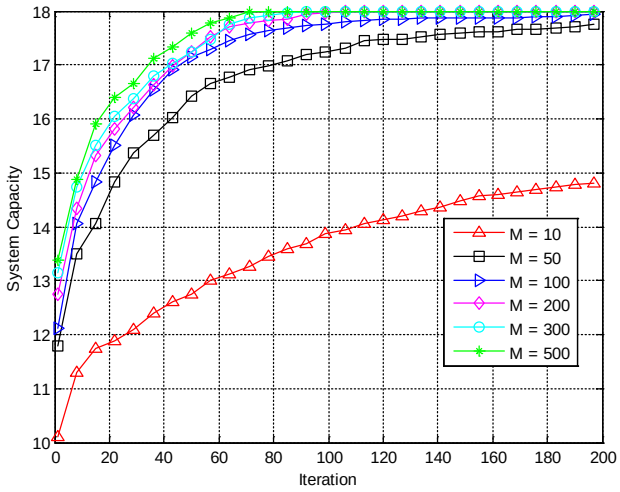

Figure 6. System capacity for various population size with K = 18.

Table 5. System capacity comparisons of RPSO, GA and Rand methods with M=100 and G=200.

K	12	18	24
GA	12	17.96	21.8
RPSO	12	17.86	20.41
Rand	12	15.08	16.27

5.3. QoS Based Capacity Maximization

In this section, the Quality of Service (QoS) based system capacity maximization are investigated. The QoS based multi-object function can be written as

$$f_\alpha = \alpha \cdot f_C + (1-\alpha) f_R \tag{19}$$

where α is the weighting factor for balance between capacity and throughput and the object function for system throughput is defined by

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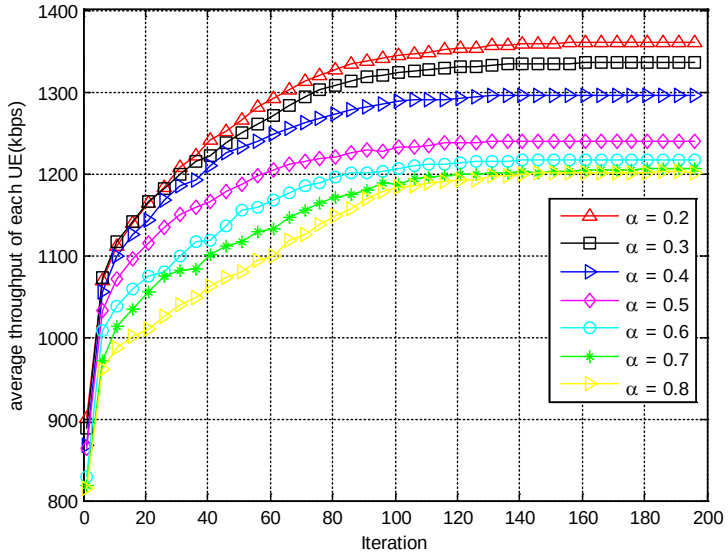
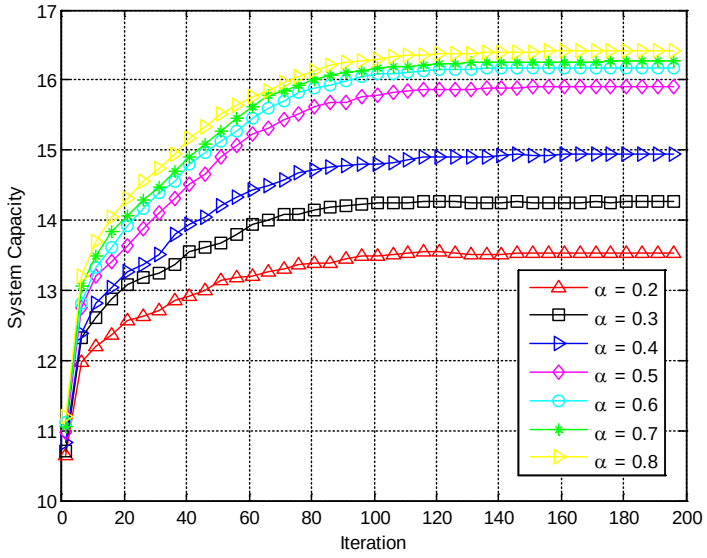
$$f_R = \sum_{n=1}^{N} x_{u_l}^{(n)} R_{u_l}^{(n)} \tag{20}$$

where x_{u_l}=1 or 0. Each UE can only use one RB, x_{u_l}= 1 indicates with one RB. And $R_{u_l}^{(n)}$ is the throughput for the nth RB used by the user u_l.

Figure 7 shows the simulated results with different weight values for *UE*=18, which respectively represent the transmission capacity and system capacity of each UE. In Figure 7(a), during the period of about the first 10 generations of this period, regardless of the numerical value, the rate of increase of the average throughput is similar, indicating that the weight value has little effect. But after the number of generations exceeds 10 generations, the weighting starts to take effect. The smaller the weight value, the larger the amount of transmission. Figure 7(b) shows that after more than 10 generations, the larger the weight, the larger the system capacity. This result indicates that there is a conflict between maximizing the system capacity and the individual throughput of UEs.



(a)



(b)

Figure 7. System performance comparisons in 200 generations for (a) throughput (b) system capacity with K = 18.

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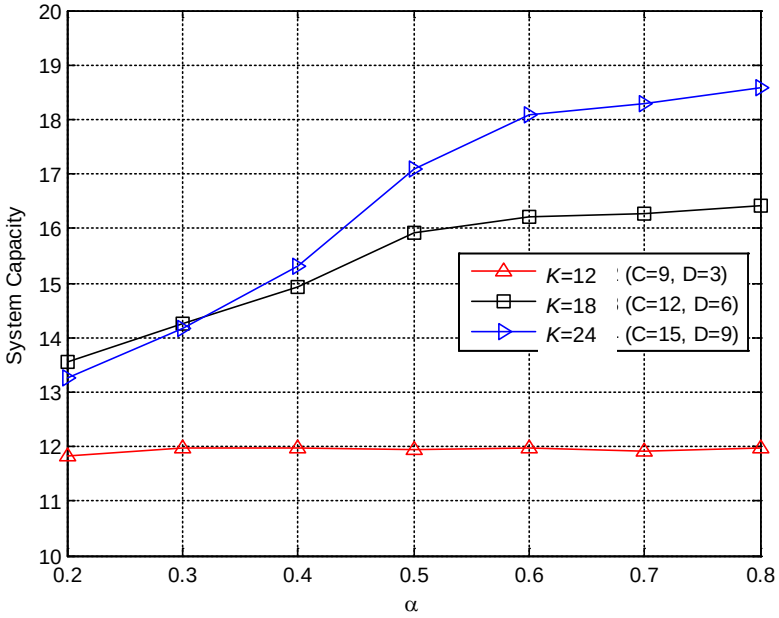
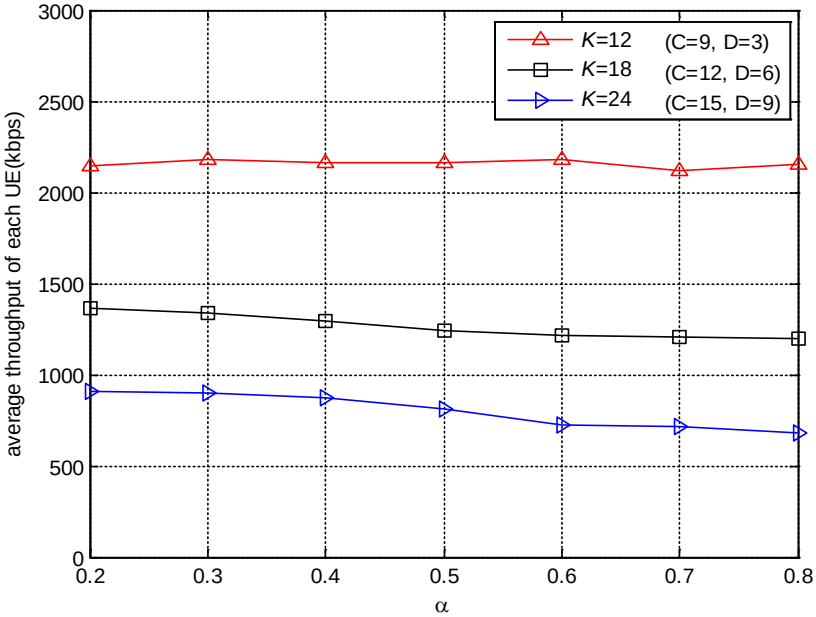
Figure 8 shows the comparison between the system capacity and the throughput obtained for K = 12, 18, 24. In Figure 8(a), the more UEs are found, the greater the difference in performance, indicating that the transmission capacity and system capacity are increasing. After the complex situation is raised to a certain value, the mutual influence is greater, and the difference is the largest at 0.5-0.6.

In this study, the system capacity is taken as the higher priority requirement, and then the weighting is set to 0.6 according to Fig. 8. Under this weighting parameter, the system capacity when K = 18 can reach close to 16 UEs. Moreover, Figure 8(b) shows the comparison of the throughput of each UE under the condition of α=0.2-0.8. When α=0.6 and K = 18, the throughput can still reach 1300 Kbps, and the system capacity can reach 16 UEs. Therefore, with the proposed multi-objective function, not only the throughput can be approved transmission, but also system capacity can be guaranteed.



(a)



(b)

Figure 8. The comparisons of (a)system capacity and (b) throughput for different weighting α.

6. Conclusions

In this paper, the PSO algorithm is proposed to optimize resource allocation in D2D system. Simulation results show that resource allocation optimization is performed using proposed RPSO can significantly improve the system capacity performance. In this paper, the GA is proposed to optimize resource allocation in D2D systems. Simulation results show that the proposed GA can improve the system capacity performance. With population size M=100 and generations g=200, the proposed GA can outperform the proposed SPSO 1.8 users for system capacity.

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Conflicts of Interest: The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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