A Resource Allocation Scheme Based on Genetic Algorithm for D2D Communications Underlaying Multi-channel Cellular Networks

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Abstract. In this paper, a resource allocation scheme based on genetic algorithm for device-to-device (D2D) communication underlaying Muti-channel cellular networks is proposed. In our scenarios, N cellular user equipments (CUEs) and M D2D user equipments (DUEs) coexist and share total channel resources. One DUE pair includes a D2D transmitting user equipment (DTUE) and a D2D receiving user equipment (DRUE). The introduction of additional between CUEs and DUEs leads to increases in complexity of resource allocation. First of all, the system model of D2D communications is presented. Then the resource allocation problem based on genetic algorithm is formulated. Next a resource allocation scheme based on genetic algorithm is proposed. Finally, the analysis and simulation results show the performance of proposed scheme outperform that of random algorithm and is very close to that of exhaustive algorithm. This result can provide an effective solution for resource allocation and optimization of D2D communications.

Keywords: D2D communications · Resource allocation · Genetic algorithm

1 Introduction

With the development of society, demands of users for data service increase rapidly. The rare of frequency resource makes the problem more troublesome. Device-to-device (D2D) communications is proposed as an efficient method to resolve this problem [1–3]. As the key technology of 5G, D2D communications can effectively improve resource utilization for cellular networks [4–6].

Resource allocation is a crucial issue in D2D communications [7–12]. In recent years, many researchers adopt various traditional optimization methods to solve resource allocation problem in various application scenarios [13–20]. Meanwhile, there are some papers about the resource allocation based on genetic algorithm. In [21], a genetic algorithm based joint resource allocation and user matching scheme is proposed to minimize the intra-cell interference. This algorithm is used to globally search optimal user matching solution to maximize system throughput. In [22], a genetic algorithm

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based user machine scheme with optimal power allocation to achieve the multi-dimension optimization is proposed and discussed. The genetic algorithm is applied to obtain the near-optimal user matching in the whole network. In [23], based on the optimization target focusing on device energy efficiency under certain system throughput insurance rather than the traditional system throughput, a modified genetic algorithm-based scheme is applied to address the facing non-deterministic polynomial-time hard problem with higher convergence and lower complexity. In [24], the authors consider the design of link assignment, channel allocation and power control in D2D-aided content delivery scenario for both user fairness and system throughput under QoS requirement. The genetic algorithm is adopted optimize link assignment. And when deriving the fitness of each chromosome, power control optimization will be involved. In [25], a heuristic genetic algorithm to evaluate the secrecy rate is represented. In addition, the authors also propose approximated optimization solutions by considering power allocation of upper and lower bounds to simplify the problem, by leveraging the fractional programming oriented Dinkelbach-type algorithm. In [26], the authors investigate the optimization of the connectivity of different UEs with the target to minimize the total transmission power. An optimization framework and a distributed strategy based on Q-learning and softmax decision making is presented.

However, these papers mainly focus the situation that one CUE and one DUE pairs share the channel resource. To full use of the superiority introduced by D2D technology, we analyse the resource allocation problem under the condition that the number of DUE pairs is far than that of CUEs. In this paper, a resource allocation scheme based genetic algorithm for D2D communications underlaying Muti-channel cellular networks is proposed. In our scenarios, the number of DUE pairs is far more than that of CUEs. The main contributions of our work are as follows:

(1) We propose a resource allocation scheme based genetic algorithm for D2D communications underlaying Muti-channel cellular networks.
(2) We evaluate the capacity of D2D communications and the average transmission power of CUEs.

The rest of this paper is organized as follows. In Sect. 2, we elaborate our system model. We then propose a resource allocation scheme based genetic algorithm for D2D communications and evaluate the capacity of D2D communications and the average transmission power of CUEs in Sect. 3. Simulation results are presented in Sect. 4, and the conclusion is drawn out in Sect. 5.

2 System Model

2.1 Network Model

In cellular networks such as frequency division duplex long term evolution (FDD-LTE), at most one CUE can be allocated to a single sub-channel generally. We assume that the communication system only provides N sub-channels. The means that the communication system can accommodate up to N CUEs. Let us consider a single cellular network, where N CUEs and M DUE pairs coexist, as illustrated in Fig. 1. Every DUE pair consists of a D2D transmitting user equipment (DTUE) and a D2D receiving user equipment (DRUE). Meanwhile, we consider that the CUE and the DTUE follow a uniform distribution in the cell with the radius of R and the DRUE uniformly locates in the circle with center at the DTUE and radius equal to L (the allowed maximum communication distance for D2D communications). Every CUE occupies one sub-channel, and M DUE pairs share the total sub-channel resources. To full use of the superiority introduced by D2D technology, we analyze the resource allocation problem under the condition that the number of DUE pairs is far than that of CUEs. Because it is advantageous to use uplink resources for the D2D link, we only focus the case that the D2D links use uplink cellular resources in this paper.

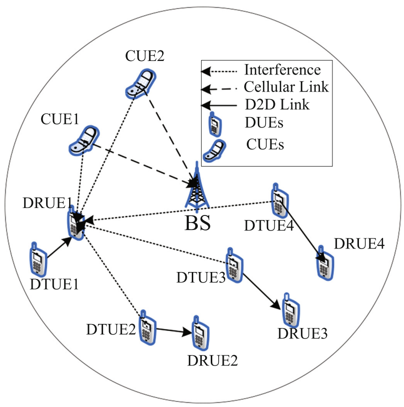

Fig. 1. System model of D2D communications

2.2 Channel Model

In conventional cellular network, power-control scheme is applied into CUEs. Given the complexity of implementation for D2D communication, power-control scheme is not applied into DUE pairs. Here we assume that the transmitting powers for all DTUEs are the same and denoted as P_T. Meanwhile, we assume that the UE links follow a median path loss model having the form $P_r/P_t = 1/r^{\alpha}$ [27]. Here P_r is the received power at the UE or BS, P_t is transmitting power of the UE, r is the distance between the transmitter and receiver of a pair of DUEs, α is path loss exponent.

3 Problem Formulation and Solution

As mentioned above, N CUEs and M DUE pairs share total sub-channel resources. Let $S = (N, M)$. In cellular networks such as frequency division duplex long term evolution (FDD-LTE), at most one CUE can be allocated to a single sub-channel in general. We assume that there are N sub-channels. Then each CUE is allocated one sub-channel, and all DUE pairs share total sub-channels. For the convenience, we assume that CUE

i use ith sub-channel. Now, we can consider one sub-channel as one package. Then there are N packages. What we need to do is to allocate all DUE pairs to N packages. The goal we pursue is the maximum capacity. The ith package is denoted as $\Re_i$, $i = (1, 2, \cdots, N)$. The diagram below shows an example of $S = (3, 8)$ (Fig. 2).

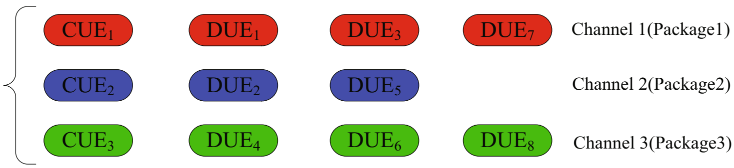

Fig. 2. An example of channel resource allocation

The genetic algorithm can be divided into five main steps:

1. *Coding*
   For CUEs, CUE i is allocated to ith sub-channel (package i) by default. For DUE pair j, the corresponding gene-bit is the sequence number of the assigned package for DUE pair j. Then every chromosome is coded as a M dimensional row vector like $G = (g_1, \cdots, g_j, \cdots, g_M)\, g_j \in (1, 2, \cdots, N)$.
   For example of $S = (3, 8)$ as shown above, the corresponding chromosome is $(1, 2, 1, 3, 2, 3, 1, 3)$. That means DUE pair 1, 3, 7 are allocated to package1, DUE pair 2, 5 are allocated to package2 and DUE pair 4, 6, 8 are allocated to package3.
2. *Population Initialization*
   We initiate the population number as $10 * N$. For every chromosome, the element g_j in G is a discrete random variable between 1 and N. We define the probability mass function $p(a)$ of X by $p(a) = P\{X = a\}$. We assume that the every DUE pairs is equivalent. For g_j, we have

$$p(1) = p(2) = \cdots = p(M) = 1/M \tag{1}$$

3. *Set Fitness Function*
   In D2D communications, we need to get the maximum capacity. To guaranty the QoS of UEs, the signal to interference plus noise ratio (SINR) value should greater than SINR threshold. Therefore, for the CUE i, the SINR can be written as

$$\beta_i = \frac{P_i/r_i^\alpha}{\sum\limits_{k \in \Re_i} P_T/d_k^\alpha + N_0} \tag{2}$$

   Here, P_i is the transmitting power of CUE i, r_i is the distance between CUE i and the BS, P_T is the transmitting power of the DTUE k, d_k is the distance between DTUE k and the BS, α is the path loss exponent, N_0 is noise power.
   At the same time, for the DRUE j, the SINR can written as

$$\gamma_j = \frac{P_T / l_j^{\alpha}}{P_m / d_{m,j} + \sum\limits_{\substack{k \in \Re_m \\ k \notin m}} P_T / d_{k,j}^{\alpha} + N_0} \tag{3}$$

Here, l_j is the distance between DTUE j and DRUE j, $d_{m,j}$ is the distance between CUE m and DRUE j, $d_{k,j}$ is the distance between DTUE k and DRUE j.

Obviously, the total capacity consists of two parts: CUEs and DUE pairs. For CUE i, the capacity is written as

$$Cc_i = B \log_2(1 + \beta_i) \tag{4}$$

Here, B is the bandwidth of one sub-channel.

Similarly, for DUE pairs, we consider that DUE pairs j is belong to package m, i.e. $j \in \Re_m$. Then, we have

$$Cd_j = B \log_2(1 + \gamma_j) \tag{5}$$

Therefore, the fitness function is denoted as

$$C(U_x) = \sum_{i=1}^{N} Cc_i + \sum_{j=1}^{M} Cd_j = B \sum_{i=1}^{N} \log_2(1 + \beta_i) + B \sum_{j=1}^{M} \log_2(1 + \gamma_j) \tag{6}$$

Here, U_x represent some chromosome.

4. *Breeding Process*

   The population of genetic algorithm evolves toward the optimal solution by breeding process, which consists of 4 steps: selection, crossover, mutation, amendment.

   (1) Selection

   Based on classical roulette wheel selection scheme, individual U_{k} is selected with probability $p(U_{\mathrm{k}})$ which is denoted as

$$p(U_k) = \frac{C(U_k)}{\sum\limits_{x=1}^{10*N} C(U_x)} \tag{7}$$

   (2) Crossover

   The function of crossover is to get the better next-generation. A single point crossover operator is adopted in our algorithm. The crossover point of the chromosome is selected randomly, and the right parts of points of two parent chromosomes are exchanged to generate next-generation. We denote the crossover probability as P_0. The algorithm of crossover is as follows:

```
Begin
    k=0;
    While k < 10*N
            if random number < P_0 then
                    U_k is selected as the parents for crossover.
            End
            k = k + 1
            End
    End
```

The crossover point is randomly selected between 1 and M.

(3) Mutation

We denote the probability of mutation as P_1. If the value of the gene bit is x, then the mutated value is randomly selected from the set $\bar{x}$ (The universal set is $S = 1 \cdots N$).

(4) Amendment

To guaranty the QoS of UEs, the SINR value must be greater than SINR threshold ($\beta_i \geq \Gamma$ for $i = 1 \ldots N$, $\gamma_j \geq \Gamma$ for $j = 1 \ldots M$, here Γ is the SINR threshold). Sometimes, for one chromosome, the corresponding channel allocation result maybe violates the QoS conditions. This can happen during three statuses: population initialization, mutation, amendment. Therefore, we need repeat the relative process to amend the chromosome.

(5) Stopping criteria

Usually, by iterating for *Num* generations, the population will eventually evolve to a convergence. Finally, we get the best chromosome and calculate the optimal result.

4 Simulations and Discussions

In this section, we discuss some important observations obtained from the simulation results. In our simulations, we assume that CUEs and DTUEs follow a uniform distribution in the cell with the radius of R and the DRUEs uniformly locates in the circle with center at the corresponding DTUE and radius equal to L. Simulation parameters are summarized in Table 1.

Table 1. Simulation parameters

Parameter	Value	Parameter	Value
Cell radius (R)	600 m	Crossover probability P_0	0.2
L	20 m	The number of DUE pairs	10
Path loss factor (α)	4	The maximum transmission power of CUE	2 W
SINR threshold (β)	6 dB	The transmission power of DTUE	0.001 W
N_0	−105 dBm	The number of CUEs	3
Iteration number	50	Probability of mutation as P_1	0.2

Figure 3 shows the capacity comparisons of D2D communications among these three algorithms. Obviously, exhaustive algorithm can get the maximum capacity because every feasible solution is calculated. The capacity performance based on genetic algorithm is very close to the optimal value based on the exhaustive algorithm, and far greater than that based on random algorithm. Meanwhile, it can be seen that the proposed genetic algorithm has fast convergence speed. We can get the objective function's optimal value only go through about 11 iterations.

Similarly, Fig. 4 demonstrates the average transmission power of CUEs based on the three algorithms. The genetic algorithm proposed in this paper can get the minimal average transmission power of CUEs compared with exhaustive algorithm and random

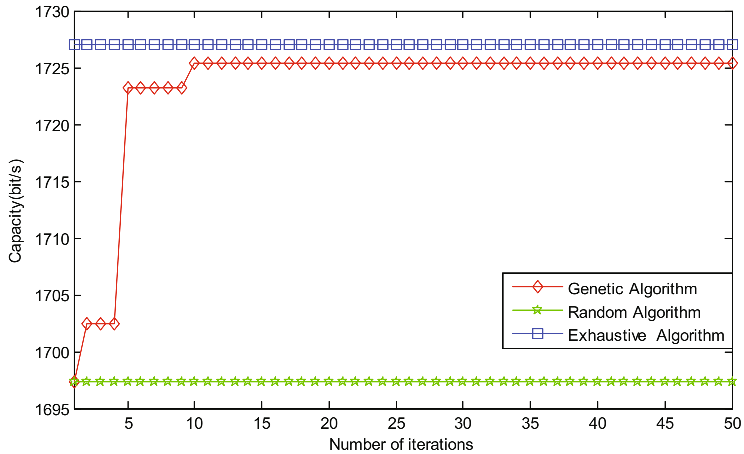

Fig. 3. The capacity of D2D communications

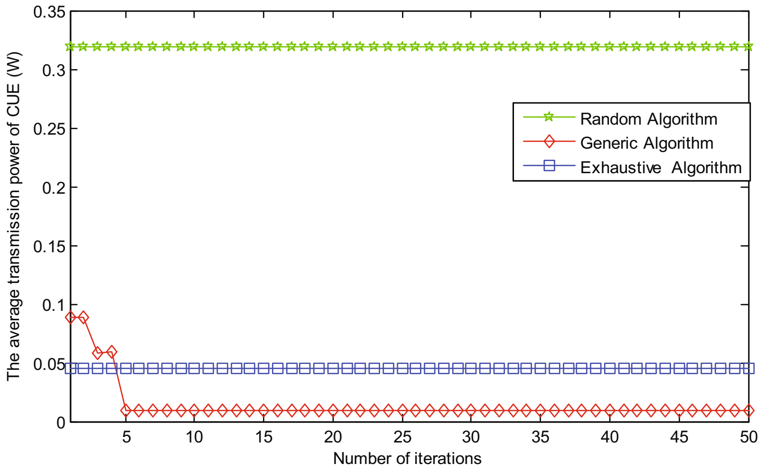

Fig. 4. The average transmission power of CUEs

algorithm. This is because the power control scheme for CUEs is applied into our algorithm. Likewise, the proposed genetic algorithm can obtain very fast convergence speed.

5 Conclusions

In this paper, D2D system model where M DUE pairs and N CUEs coexist is described. Then the resource allocation problem based on genetic algorithm is formulated and analyzed. Next, a resource allocation scheme based on genetic algorithm is proposed. Finally, the analysis and simulation results show the performance of proposed scheme outperform that of random algorithm and is close to that of exhaustive algorithm. This result can be applied for design and optimization of D2D communications.

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