Allocation Optimization Based on Multi-population Genetic Algorithm for D2D Communications in Multi-services Scenario

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Abstract. For D2D Communications in Multi-services scenario, fast resource allocation optimization is a crucial issue. In this paper, a resource allocation optimization method based on the multi-population genetic algorithm for D2D communications in Multi-services scenario is proposed. Due to the interference between the cellular user equipment (CUE) and D2D user equipment (DUE) which share the same frequency, the complexity of resource allocation increases. Firstly, the interference model of D2D communications is analyzed. Then the resource allocation problem is formulated and discussed. Next, a resource allocation scheme based on Multi-population genetic algorithm is presented. Finally, the analysis and simulation results show the Multi-population genetic algorithm can converge faster compared with standard genetic algorithm. Therefore, the Multi-population genetic algorithm is more suitable to the Multi-services scenario where the data rate demand varies quickly and frequently.

Keywords: D2D communications · Cellular network
Multi-population genetic algorithm · Resource allocation

1 Introduction

With the rapid development of modern communication technology, the demand for wireless data is increasing rapidly. The wireless spectrum becomes a scarce resource [1]. Device to Device (D2D) communications can effectively improve spectrum efficiency by licensed frequency sharing between the cellular user equipments (CUEs) and D2D user equipments (DUEs) [2]. D2D communication using the licensed band can guarantee the quality of communication [3]. The establishment of D2D communication link is divided into two modes: One is centralized mode, with the intervention of base station (BS). The BS can control the interference between the links by power control, resource allocation and other ways to achieve reasonable optimization. The other one is

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distributed mode. DUE pairs may bypass the BS and establish the link directly, but this approach requires more complex D2D devices to achieve the discovery and connection between the D2D pairs.

Recently, most researches mainly focus on resource allocation [4], interference coordination [8], power control [11] and so on. In paper [4], the authors propose a new resource allocation scheme to obtain higher throughput and save significant amount of energy. In order to maximize the sum rate of the cellular system while meeting the rate requirements of all users, an alternating optimization method is proposed in paper [5]. In paper [6, 7], the authors make full use of the spectrum resources through optimal power allocation to improve the system performance. Considering the capacity and power saving, the authors propose an incentive mechanism encouraging terminals to organize themselves into an optimal number of clusters and achieve a significant gain in terms of costs while increasing the capacity of the whole cell in [6]. The authors propose an algorithm which converges quickly, have low overhead, and maximizes network throughput, while maintaining the quality of CUEs in [7]. In order to improve the spectrum efficiency and the energy efficiency of the D2D-aided networks, a proper interference coordination scheme is proposed in [8]. In paper [9], the authors introduce the non-negligible distance of the interference between D2D pairs and the non-reusable distance of CUE, and propose a method which allocated the resource based on graph theory, and improve the total system capacity. In paper [10], the authors optimize the resource allocation of DUE and CUE one-to-one by genetic algorithm, and increase the total system throughput. The authors also use the genetic algorithm to reduce the transmission power and the energy consumption in [11]. Based on the genetic algorithm, the wireless frequency hopping technology with a reasonable resource allocation of DUE is adopted to reduce the interference between the same sub-channel in paper [12]. In paper [13], the authors define the interference limited region and control the D2D transmission power so as to improve the channel capacity. The authors formulate the joint power control and mode selection problem for D2D communications in LTE-A network to minimize the aggregate transmit power of users subject to a minimum target throughput for each cellular and D2D user in paper [14]. In paper [15], a two-stages relay selection and resource allocation joint method for relay-assisted D2D communication is proposed to maximize the total throughput of cellular uplink (UL) and D2D link. It can guarantee the quality of service (QoS) of the two links simultaneously [16–20].

However, few papers and works had been contributed to resource allocation optimization based on intelligent algorithm for D2D communications in multi-services scenario. To guarantee the QoS of all UEs, we need to allocate the applicable channel resources for UEs. In multi-services scenario, the service type of the UEs maybe transit from low data rate service to high data rate service. Then the resource allocation scheme needs to be adjusted frequently and rapidly. Therefore, a quick convergence algorithm needs to be presented. Based on above, a resource optimization scheme based on multi-population genetic algorithm for D2D communication in multi-services scenario is proposed. The proposed algorithm can rapidly allocate the channel resources for multi-services. And the performance of the algorithm is evaluated.

The structure of this paper is as follows. In Sect. 2, the system model is presented. Based on the system model, a resource optimization scheme based on multi-population genetic algorithm for D2D communication in multi-services scenario is proposed in Sect. 3. The simulation results are analyzed in Sect. 4. Finally, we summarize this work in Sect. 5.

2 System Model

In cellular networks, there are two types of mobile terminals: conventional cellular network mobile terminal CUEs and D2D mobile terminal DUEs. DUEs are in pairs, and a pair of DUEs includes a D2D transmitting mobile terminal DTUE and a D2D receiving mobile terminal DRUE. In a FDD network, each CUE is assigned a separate and mutually orthogonal sub-channel, and multiple DUE pairs can simultaneously share a sub-channel resource. This paper assumes that N CUEs and M DUEs share all channel resources. Figure 1 shows the application scenario that a D2D communication system in which N CUEs and M DTUEs are randomly distributed in a cell with the radius of R. DRUE uniformly locates in the circle with center at the DTUE and radius equal to L (the allowed maximum communication distance for D2D communications). The same colors in the figure represent that the users' spectral resources are the same.

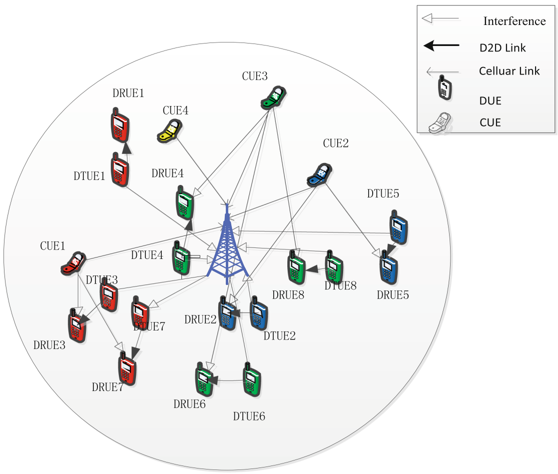

Fig. 1. D2D communications system model in multi-services scenario

Due to the complexity that power control scheme is applied to the D2D communications, we only consider that the power control scheme is applied to CUEs and the fixed transmission power is applied to DUEs. In other words, the transmitting powers for all DTUEs are the same and denoted as P_T. Next, we assume that the UE links follow a median path loss model with the form of $P_r/P_t = 1/r^{\alpha}$. Here P_r is the received power at the UE or BS. The transmitting power of UE denoted as P_t. r is the distance between the transmitter and receiver. α is path loss exponent.

In D2D communications, the SINR of CUE i can be written as

$$SINR_{c_i} = \frac{P_i / r_i^{\alpha}}{\sum\limits_{k \in \Re_i} P_T / d_{k,i}^{\alpha} + N_0} \tag{1}$$

Here, P_i is the transmission power of CUE i, r_i is the distance between CUE i and the BS, $d_{k,i}$ is the distance between DTUE k and the BS, $\Re_i$ is ith package which includes the DTUEs using the same frequency with CUE i.

Similarly, the SINR of DRUE j can be written as

$$SINR_{d_j} = \frac{P_T / l_j^{\alpha}}{P_m / d_{m,j}^{\alpha} + \sum\limits_{k \in \Re_m} P_T / d_{k,j}^{\alpha} + N_0} \tag{2}$$

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

Next, we can get capacity of CUE i

$$R_{c_i} = \log_2(1 + SINR_{c_i}) \tag{3}$$

In the same way, the capacity of DUE j can be calculated

$$R_{d_j} = \log_2(1 + SINR_{d_j}) \tag{4}$$

Therefore, the fitness function is denoted as

$$C(U_x) = \sum_{i=1}^{N} R_{c_i} + \sum_{j=1}^{M} R_{d_j} \tag{5}$$

Here, U_x represents some chromosome.

3 Resource Allocation Optimization Based on Multi-population Genetic Algorithm

In Multi-services Scenario, to satisfy the demand for varying transmission rate of UEs, we need to adjust the resource allocation schemes rapidly. As shown in Fig. 1, when the CUE4 requires a higher date rate, the DUE pair 7 which reuses the spectrum resources of CUE4 may be kicked out. DTUE7 sends a request to BS, and BS reallocates the other sub-channel resources to DTUE7. So we need a quick and effective resource optimization algorithm to reallocate channel resources. Then a resource optimization scheme based on multi-population genetic algorithm for D2D communication in multi-services scenario is proposed. The proposed algorithm can rapidly allocate the channel resources for multi-services.

Because a sub-channel can only be assigned to one CUE, and multiple DUEs can share a sub-channel, N CUEs and M DUEs need at least N sub-channels. We denote the set of sub-channels as $\Re_i (i = 1, 2 \ldots N)$. For CUEs, CUE i is allocated to ith sub-channel (package i). For DUE pair j, the 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 $N = 4$ and $M = 8$, chromosome (1,2,1,3,2,3,4,3) means that DUE pairs 1 and 3 share sub-channel 1 with CUE1, DUE pairs 2 and 5 share sub-channel 2 with CUE2, DUE pairs 4, 6 and 8 share sub-channel 3 with CUE3, DUE pair 7 share sub-channel 4 with CUE 4, as illustrated in Fig. 2.

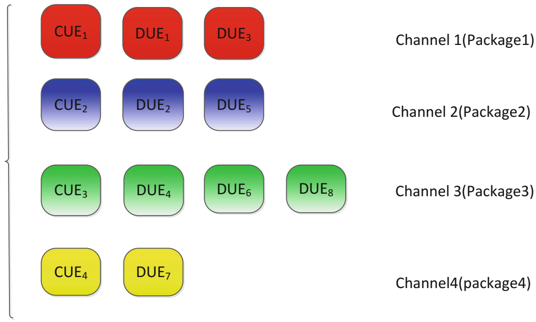

Fig. 2. Original channel resource allocation scheme

In multi-services scenario, the service type of the UEs is likely to change from low data rate service to high data rate service. Then we need to frequently and rapidly adjust resource allocation scheme. For example, DUE 2 needs higher data rate, and it maybe forces DUE 5 to change sub-channel from 2 to 4, as shown in Fig. 3.

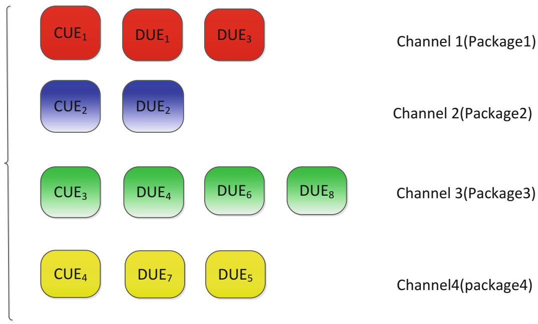

Fig. 3. Channel re-allocation scheme

The resource optimization scheme based on multi-population genetic algorithm can be divided into five main steps:

1. Parameter Initialization

We initialize system parameters including the radius of the cell, the threshold of SINR, the maximum power of CUE and DUEs, the number of UEs, and the positions of UEs.

2. Population Initialization

We initiate the number of populations as 10. Every population includes 30 chromosomes. For every chromosome, the element is a discrete random variable which takes value between 1 and N based on the equal probability.

3. Breeding Process

The population of multi-population genetic algorithm improves the system performance by the breeding process, which consists of five steps: selection, crossover and mutation, immigration, amendment and elite strategy.

(1) Selection

Generally, the rotation gambling method is selected as selection algorithm [10]. But the competitiveness of individual is not strong. Based on this, a new sorting and selection algorithm is proposed as follows:

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Algorithm 1 Selection algorithm
Begin
    {Sorting the chromosomes in the population according to their fitness function
    value from largest to smallest, denoting the values as set A(i) (i = 1…30)}
    i = 1; j = 1;
    While j <= 30 do
    {B(j) = B(j+1)=A(i); j = j + 2; i = i + 1}
    Based on classical roulette wheel selection scheme, selecting the chromosome.
End
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(2) Crossover and Mutation

We set the crossover probability as P_c, which is different depending on the different populations. The value of crossover probability and mutation probability determines the ability of global search and local search. Multi-population genetic algorithm co-evolves through multiple populations with different parameters, so it can get the optimal value faster.

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

(3) Immigration

Immigration operator is adopted in the multi-population genetic algorithm. It introduces the optimal individual of each population in the evolution process into other populations periodically to realize the information exchange among the populations.

The multi-population genetic algorithm can achieve fast convergence by the introduction of immigration operator.

(4) Amendment

If we can't guarantee the QoS of UEs whose SINR must be greater than SINR threshold, we should repeat the process as mentioned above.

(5) Elite Strategy

The elite strategy is introduced into Multi-population genetic algorithm. In each generation of evolution, the best individuals of every population are selected and stored in the elite set. The individuals in elite set don't participate in crossover and mutation to ensure that the optimal individuals will not be affected by the following changes such as damage or loss.

4. Iteration Termination Condition

We set a minimum generation value Γ for optimal individual. The iterative process is terminated if optimal individual doesn't change in Γ iterations. Compared with standard genetic algorithm in which a fixed maximum generation value is set, Multi-population genetic algorithm has faster convergence ability.

4 Simulation and Discussion

In our simulations, we assume that there are four CUEs and thirty DUEs which follow a uniform distribution in the cell with the radius of R and DTUEs uniformly located in the circle with center at the corresponding DRUE and radius equal to L. Simulation parameters are as shown in Table 1.

Table 1. Simulation parameters

Parameter	Value
Cell radius (R)	600 m
The number of CUEs	4
Path loss factor (α)	4
SINR threshold (β)	6 dB
N_0	−105 dBm
L	20 m
The number of D2D pairs	30
The maximum transmission power of CUE	0.02 W
The transmission power of DTUE	0.001 W

Figure 4 shows the convergent speed comparison between standard genetic algorithm and Multi-population genetic algorithm. The Multi-population genetic algorithm can converge faster compared with standard genetic algorithm. This is because that migration and elite strategy are introduced into the Multi-population genetic algorithm.

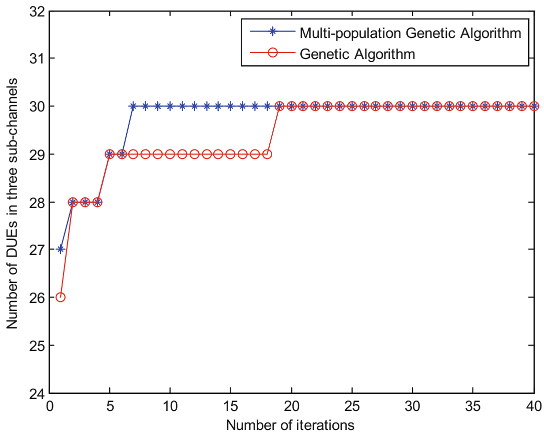

Fig. 4. Convergent speed comparison (standard genetic algorithm vs Multi-population genetic algorithm)

Migration ameliorates the diversity of populations, and elite strategy maintains the optimality of populations. Therefore, the Multi-population genetic algorithm is more suitable to the Multi-services scenario where the data rata demand varies quickly and frequently.

At the same time, Fig. 5 shows the capacity based on the two algorithms. We can get a slightly better capacity based on Multi-population genetic algorithm compared with that based on standard genetic algorithm. This is because that the introduction of elite strategy can maintain the better individual in population. Meanwhile, Multi-population genetic algorithm also has faster convergence ability.

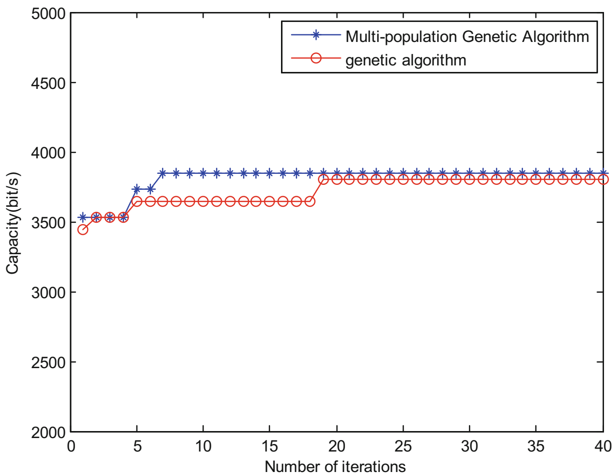

Fig. 5. The capacity of D2D communications

5 Conclusion

In this paper, the resource allocation problem for D2D Communications in Multi-services scenario is described and analyzed. Based on the analysis of interference model of D2D communications, the resource allocation problem in Multi-services scenario is formulated and analyzed. Then a resource allocation scheme based on Multi-population genetic algorithm is proposed. Finally, the analysis and simulation results show the Multi-population genetic algorithm has faster convergence ability compared with standard genetic algorithm. So, it is more suitable to the Multi-services scenario where the data rate demand varies quickly and frequently. This result can be applied for design and optimization of D2D communications in Multi-services scenario.

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