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# Joint Optimization of Device to Device Resource and Power Allocation Based on Genetic Algorithm

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**ABSTRACT** Device-to-device (D2D) communication plays an important role in the next generation of communication systems. Enabling D2D communication decreases latency and expands the coverage of a cell in cellular networks. In addition, D2D underlying cellular users benefit from high spectral efficiency. However, it creates interference to cellular communications. In this paper, we propose a genetic algorithm-based method to minimize the interference and maximize the spectral efficiency. One of the advantages of genetic algorithm is that it escapes from local maximums and evolves toward global maximum by searching different parts of search space simultaneously. Since D2D underlay cellular network degrades the signal-to-interference plus noise ratio (SINR), a minimum SINR is considered for cellular users. Numerical evaluations demonstrate the superior performance of the proposed technique in terms of spectral efficiency and interference mitigation.

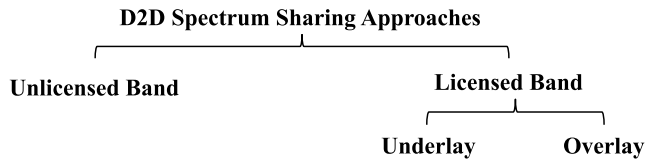
**INDEX TERMS** Channel prediction, device to device (D2D) communication, genetic algorithm, spectral efficiency, optimization.

## I. INTRODUCTION

Next generation of mobile communication systems comprises of wide variety of applications. Internet of things (IoT) is one of these applications that connects a tremendous number of devices and users to each other [1]. By increasing the number of IoT-based applications, communicating through a base station (in cellular network) imposes a huge load on the network. It also increases the latency of the communication and decreases the quality of service. Device to device (D2D) communication is proposed to overcome these problems. This type of communication allows the nearby devices to communicate directly, independent of base station, to each other [2]–[4]. Therefore, D2D communication decreases the load of the network and expands the coverage of the base station by enabling multi-hop transmission.

D2D communication in spite of simplicity has some challenges. Choosing the spectrum for D2D communications is one of the challenges [5], [6]. Based on the used spectrum by D2D users and their impact on the cellular users, D2D communication can be classified as shown in Figure 1 [7].

One approach is that D2D users use unlicensed spectrum such as TV white space [8], [9]. In this case, there is no interference from D2D users to cellular users using licensed spectrum and vice versa. However, due to the limited rules over the unlicensed spectrum, it is difficult to control it and usually not preferable. The other approach is that D2D users along with cellular users utilize the licensed spectrum [10]. This category is also classified into two subgroups of overlay and underlay. In overlay, the D2D users and cellular users utilize orthogonal time/frequency resource blocks (i.e. the smallest unit of resources that can be allocated to a user) [11], [12]. In other words, the resources are divided into two groups, one for cellular users and the other one for D2D users. Due to the orthogonality of the resources, there is no interference from one user to other users. However, in the overlay, the spectrum is not utilized efficiently, because there might be some unused resources in one group while there are not enough resources in the other group. Despite the overlay, in underlay, D2D users utilize the same spectrum as the cellular users [13]–[17]. Therefore, more users can be served within a fixed spectrum compared to the overlay. Note that although the spectrum



**FIGURE 1.** Classification of D2D communication based on the spectrum sharing.

is used more efficiently in underlay, there is interference between the communications who share the same resource blocks. Thus, the importance of an interference management and intelligent resource allocation method is increased. Interference mitigation results in efficient spectrum utilization.

In the literature, a significant effort has been done related to the resource allocation and interference mitigation in underlay D2D communication [15]–[28]. Yu *et al.* [15] presented a joint mode selection, channel assignment and power control to maximize the spectral efficiency. They proposed three different modes under which a D2D pair can either reuse a resource of a cellular user or a use a dedicated resource. In the case of reusing, only one D2D pair shares a resource block with a cellular user which restrict the number of served user. In the other hand, the maximization is done in two steps: 1) power control 2) channel assignment. These two steps are done independently which results in not a very optimized solution.

In [16], a greedy algorithm is proposed for resource allocation for D2D undelaying cellular networks. The authors assumed that the number of cellular users is larger than the D2D pairs which is not a realistic assumption for the new generation of communications. Yu *et al.* [17] greedy algorithm is presented which is used only for resource allocation. However, the users either transmit with the maximum power or they do not have a transmission. In other words, the effect of transmission power on the interference is not considered. Also, the authors assumed that a single pair of D2D users can only share the resource block with a cellular user. Thus, the number of served users is also limited. Furthermore, the greedy algorithms often stuck in local optimum solutions and do not evolve toward the global optimum solutions.

The purpose of the resource allocation in [18] is to have longer battery life at each device. Resource allocation is done to enable the users to transmit with a minimum power. However, efficient spectrum usage is not considered. Wang *et al.* [19] resource allocation method for increasing the energy efficiency and battery life of user equipment is suggested. For this purpose, an iterative combinatorial auction algorithm is used where D2D pairs and cellular users are as bidders and auctioneer, respectively.

Zhong *et al.* [20] suggested to use different algorithms for resource allocation in multiple input multiple output (MIMO) systems under different conditions. First, they proposed an algorithm based on random search that search a huge search space randomly for finding a sub-optimal solution. Then, the use of game theory is suggested for the cases that users

has incomplete information. Moreover, an iterative algorithm based on best response dynamic structure and an algorithm using sum-rate reinforcement mechanism is proposed as alternatives for solving the game theoretic problem.

Algedir and Refai [21] minimized the interference while maximizing the spectral efficiency using only resource allocation and does not consider transmission power. Moreover, only one D2D pair is allowed to share a resource block with a cellular users.

Hassan *et al.* [22], used resource allocation done by a proposed two-phased algorithm, to minimize the interference for a given spectral efficiency. Thus, the result is not the optimum solution in terms of spectral efficiency.

Ali *et al.* [23] aimed to maximize spectral efficiency per unit network power consumption. Authors formulated the optimization problem as a non-linear fractional programming problem. Then, They converted it to the concave optimization problem using Charnes-Cooper transformation. In order to solve the concave optimization problem outer approximation algorithm is proposed. Therefore, in [23] maximizing the over all spectral efficiency is not considered.

Janis *et al.* [24] suggest minimizing the interference from D2D users to the cellular by decreasing the power of D2D users, and the interference from the cellular users to D2D users by choosing the best resource. In their research one resource block can be shared with one cellular user and one device to device user at most, which can prevent using the resources efficiently.

In [25], multiple different game algorithms for resource allocation are presented. The non-cooperative and cooperative behaviors of mobile users are analyzed to control the transmission power for underlay D2D communication. Then, the power control is done by a non-cooperative static game profiting from Game theory. Additionally, Stackelberg game is used for resource allocation while the resources for cellular users are assumed to be known. Authors also proposed combinatorial auction for resource allocation of both cellular users and D2D users. However, a suitable resource allocation highly depends on the transmission power of the user. Therefore, since the resource allocation is done independent of the power control, the result is not well-optimized.

Stackelberg game is also suggested in [26] to coordinate the resource allocation and power assignment. The authors used the downlink resources. However, due to the heavy load of download links and high power of base station, sharing downlink resources is not preferable. Also sharing a cellular user resource block with only one D2D pair is considered which restricts the number of served users.

Xu *et al.* [27] suggested to use sequential second price auction as a method for resource allocation. However, the result is not an optimal solution because in the resource allocation, the effect of assigning different resources to cellular users is not considered. In other words, the resource allocation for cellular users is done before the optimization.

In [28], a genetic algorithm-based joint resource allocation and user matching scheme (GAAM), is proposed. Genetic

algorithm, unlike the greedy algorithms, escapes from the local maximums by adding some randomness to the search space. The probability of the added randomness should be small. Otherwise, the search gets similar to a random search. However, huge mandatory randomness is added in the algorithm in [28] which degrades the performance of the algorithm. Also, GAAM shares a resource block of a cellular user with only one D2D pair without power control.

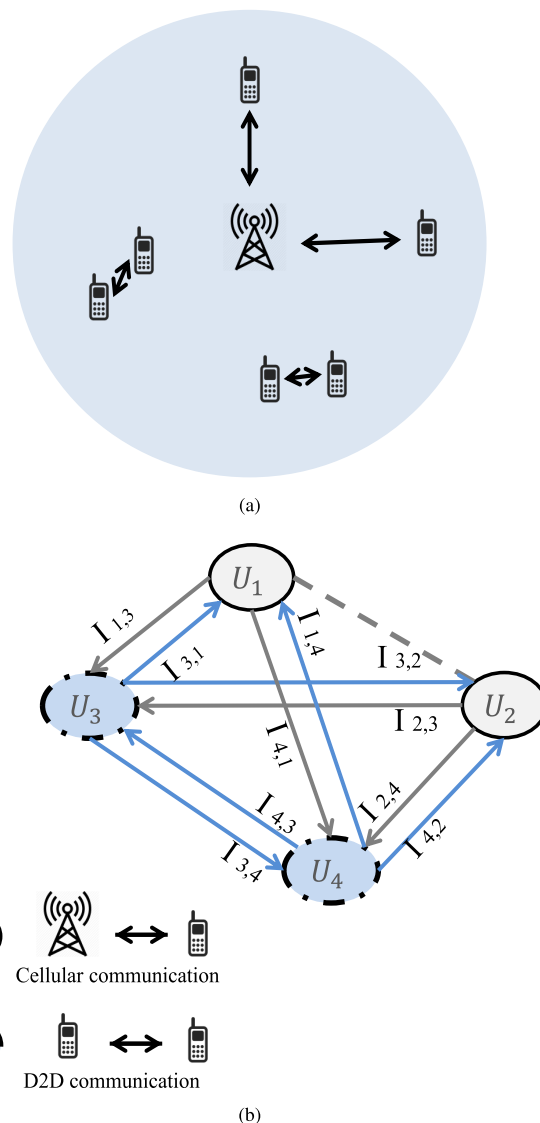
All of the mentioned algorithms are in the category of the interference aware algorithms. They require knowledge of global channel state information (CSI) between different pairs at all the transmission time intervals (it is usually obtained by feedback from users to base station). Achieving this information causes a huge load on the network. Although authors in [16]–[23], [26]–[28] did not highlight this problem, a periodically update method for CSI is suggested in [24]. However, it makes the information not useful due to delay caused by feedback or collecting the information periodically which affects the performance of the algorithms. Also in [25], a method based on local CSI is proposed, but in the next generation of communications, there is a huge number of users and devices even in local areas. Therefore, the number of channels required to be known and imposed load due to it are still huge.

In this paper, we propose a joint optimization for resource allocation and power assignment based on the genetic algorithm to maximize the spectral efficiency of the network. Moreover, a minimum SINR for the cellular users is guaranteed. Also, there is no restriction on the number of D2D users that can share a resource block with a cellular user. Furthermore, in order to reduce the overhead of CSI knowledge, we suggest to use a channel prediction method to reduce the overhead significantly while the performance is preserved.

The rest of the paper is as follows. In Section II, the system model is described. Then, the proposed algorithm is described in Section III. In Section IV, channel prediction is explained. The numerical simulation results are presented in Section V. Finally, the conclusions of the paper are given in Section VI.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

A cellular cell with one base station in the center and a number of users are considered as shown in Figure 2 (a). The users are randomly distributed around the base station. Users are classified into two groups of cellular users and D2D users. Although the cellular users communicate through the base station, in D2D communication, a device communicates directly to another close by device. Two communicating devices form a D2D pair. The set of communications are defined as  $\mathbf{N} = \{U_1, U_2, \dots, U_V, U_{V+1}, \dots, U_{V+K}\}$ , where  $U_i$  shows the  $i^{th}$  communication.  $V$  and  $K$  are the total number of cellular users and D2D pairs, respectively. Therefore, the first  $V$  elements are cellular users and the next  $K$  elements are D2D pairs. In other words, the set of cellular users is denoted by  $\mathbf{M} = \{U_1, U_2, \dots, U_V\}$  and the set of D2D pairs is defined by  $\mathbf{D} = \{U_{V+1}, U_{V+2}, \dots, U_{V+K}\}$ . The bandwidth is divided into narrow resource blocks.



**FIGURE 2.** A cell and the graph based on it. A cellular user communicates through base station while a D2D user communicates to another nearby D2D user. (a) A cell with two cellular users and two D2D pairs. (b) Interference graph based on the topology of the network.

$\mathbf{R} = \{RB_1, RB_2, \dots, RB_Q\}$  indicates the set of the resource blocks.  $RB_i$  and  $Q$  denotes the  $i^{th}$  resource block and total number of resource blocks, respectively. Also,  $\mathbf{A} = \{a_{i,r}\}$ ,  $\mathbf{A} \in \{0, 1\}^{(V+K) \times Q}$  is resource assignment matrix.  $a_{i,r} = 1$  means  $i^{th}$  user utilizes  $r^{th}$  resource block and  $a_{i,r} = 0$  shows that the  $r^{th}$  resource block is not used by  $i^{th}$  user. It is also worth mentioning that since the downlink resources are almost fully occupied by high power transmitted signals from base station to the cellular users, the uplink resources of the cellular users are shared with D2D users in the proposed algorithm.

In Figure 2 (b), a directed graph based on the cell in Figure 2 (a) is created. The graph shows the interference between each pair of communications. Nodes in this graph represent a communication, either a cellular or a

D2D communication. The edges are interference between two connected nodes.  $I_{i,j}$  is the edge weight which indicates the set of interference value from  $i^{th}$  node to  $j^{th}$  node at different resource blocks which is defined as:

$$I_{i,j} = \{I_{i,j,1}, I_{i,j,2}, \dots, I_{i,j,Q}\}, \quad (1)$$

where  $I_{i,j,r}$  is the interference from  $i^{th}$  node to  $j^{th}$  node at  $r^{th}$  resource block. It is worth mentioning the dashed line between  $U_1$  and  $U_2$  shows that sharing a resource block between two cellular users is not allowed. Since their receiver is the base station, if they share a resource block the receiver cannot differentiate the signals. Thus, there is no interference between cellular users.

Maximum spectral efficiency of  $i^{th}$  communication at  $r^{th}$  resource block, either cellular user or D2D pair, is denoted by  $Se_{i,r}$  and defined based on Shannon formula as

$$Se_{i,r} = \log_2(1 + SINR_{i,r}), \quad (2)$$

where  $SINR_{i,r}$  is the signal to interference plus noise ratio. The  $SINR_{i,r}$  in (2) is expressed as

$$SINR_{i,r} = \frac{a_{i,r}p_{i,r}g_{i,i,r}}{\sigma^2 + I_i^r}. \quad (3)$$

In (3),  $p_{i,r}$  is the transmission power of the  $i^{th}$  node at  $r^{th}$  resource block and  $g_{i,j,r}$  is the channel gain between transmitter of the  $i^{th}$  node and receiver of the  $j^{th}$  node at  $r^{th}$  resource block.  $\sigma^2$  denotes the noise power.  $I_i^r$  is the total interference from other nodes to  $i^{th}$  node which can be written as

$$I_i^r = \sum_{j=1, j \neq i}^{V+K} a_{j,r}I_{j,i,r} = \sum_{j=1, j \neq i}^{V+K} a_{j,r}p_{j,r}g_{j,i,r}. \quad (4)$$

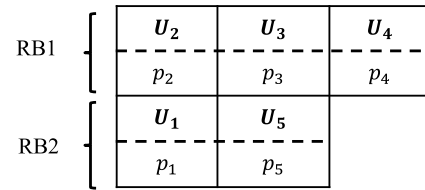
By substituting (4) in (3), we obtain

$$SINR_{i,r} = \frac{a_{i,r}p_{i,r}g_{i,i,r}}{\sigma^2 + \sum_{j=1, j \neq i}^{V+K} a_{j,r}p_{j,r}g_{j,i,r}}. \quad (5)$$

The goal is to maximize the spectral efficiency of the network, which can be written as

$$Se_{network} = \sum_{i=1}^{V+K} \sum_{r=1}^Q Se_{i,r} = \sum_{i=1}^{V+K} \sum_{r=1}^Q \log_2(1 + SINR_{i,r}). \quad (6)$$

As (6) shows,  $Se_{network}$  depends on  $SINR_{i,r}$ . Moreover, as shown in (5), in addition to resource allocation which determines the interfering users, transmission power of the users determines the amount of the interference and affects the  $SINR$  and consequently the spectral efficiency. Therefore, optimizing the transmission power of the users helps maximizing the spectral efficiency of the network and managing the interference. It is also evident that both cellular users and D2D users, have an upper limit for their transmission power. Cellular users also should meet a minimum  $SINR$  to prevent a severe reduction in spectral efficiency while sharing



**FIGURE 3.** A sample chromosome representation:  $RB_1$  is shared by  $U_2$ ,  $U_3$  and  $U_4$  with power of  $p_2$ ,  $p_3$  and  $p_4$ , respectively. Also  $RB_2$  is shared by  $U_1$  and  $U_5$  with power of  $p_1$  and  $p_5$ , respectively.  $M = \{U_1, U_2\}$  and  $D = \{U_3, U_4, U_5\}$  are cellular users and D2D pairs, respectively.

their resource block. Thus, maximization problem can be formulated as follows

$$\begin{aligned} \mathfrak{S} &= \arg \max_{p,a} \sum_{i=1}^{V+K} \sum_{r=1}^Q \log_2(1 + SINR_{i,r}) \\ &= \arg \max_{p,a} \sum_{i=1}^{V+K} \sum_{r=1}^Q \log_2 \left( 1 + \frac{a_{i,r}p_{i,r}g_{i,i,r}}{\sigma^2 + \sum_{j=1, j \neq i}^{V+K} a_{j,r}p_{j,r}g_{j,i,r}} \right) \end{aligned} \quad (7)$$

$$\text{subject to} \begin{cases} C_1 : \sum_{i=1}^V a_{i,r} \leq 1, & i \in M, \forall r \in R \\ C_2 : p_i < p_{d,max}, & i \in D \\ C_3 : p_i < p_{c,max}, & i \in M \\ C_4 : SINR_{i,r} \geq SINR_{min}, & i \in M, \forall r \in R \end{cases} \quad (8)$$

where  $C_1$  shows that there is at most one cellular user in each resource block.  $C_2$  and  $C_3$  limit the power of the users to their upper limits.  $p_{d,max}$ ,  $p_{c,max}$  are maximum transmission power of D2D users and cellular users, respectively.  $C_4$  shows that  $SINR_{min}$  is minimum  $SINR$  for the cellular users. It is worth mentioning that there is no restriction in the number of D2D users in one resource block as long as  $C_4$  is met.

Finding a solution for an optimization problem with more than one constraint, similar to (7), is not possibly practical. Exhaustive search also is not applicable in engineering implementations due to the huge size of the search space. Therefore, to solve the constrained optimization problems, Genetic algorithm is a well known method [29]. In the next section, a new Genetic algorithm-based method is proposed to solve the multi-constrained problem in (7).

### III. ALGORITHM DESCRIPTION

Genetic Algorithm emulates the process of natural selection. The algorithm starts with a set of candidate solutions (chromosomes). A chromosome presents dedicated powers and resource blocks to communications. Figure 3 shows a sample chromosome, where two resource blocks are dedicated to five communications ( $V = 2$  and  $K = 3$ ), each with a specific transmission power. Additionally, each chromosome should satisfy the constrains of the optimization problem in (7). The set of chromosomes is called a generation. The generations are changed iteratively. At each iteration, chromosomes of the

current generation are chosen to be parents and produce the children (offspring) for the next generation. The fitter chromosome, in terms of spectral efficiency, has higher chance to be selected as a parent. After series of iterations, the generation evolves toward the optimal chromosome. Moreover, the algorithm works with three operators to form a new generation based on the current generation: 1) *proportional selection*, 2) *crossover*, 3) *mutation*.

In the following, first, a metric for the fitness of a chromosome is given. Then, the operators based on the problem in (7) are defined.

**A. DETERMINING FITNESS FUNCTION AND POWER ASSIGNMENT**

**1) FITNESS FUNCTION**

Fitness function measures the fitness of a chromosome. Since the purpose of the algorithm is maximizing spectral efficiency of the network, the fitness value of a chromosome equals to spectral efficiency of the network with respect to the chromosome. Therefore, fitness value of a chromosome can be written as

$$f_{\text{chromosome}} = \sum_{i=1}^{V+K} \sum_{r=1}^Q \log_2 \left( 1 + \frac{a_{i,r} p_{i,r} g_{i,i,r}}{\sigma^2 + \sum_{j=1, j \neq i}^{V+K} a_{j,r} p_{j,r} g_{j,i,r}} \right) \tag{9}$$

**2) POWER ASSIGNMENT**

Power of the users is also optimized during calculating fitness value. For this purpose, at each iteration, one D2D communication in each resource block (if there is any) is selected randomly. Power of the selected communication is optimized to maximize spectral efficiency of the desired resource block. Furthermore, the *SINR* of the cellular user of the resource block (if there is any) is set to  $SINR_{min}$  in order to serve more D2D users. Then, the power of  $i^{th}$  cellular user at  $r^{th}$  resource block is assigned based on (5) as

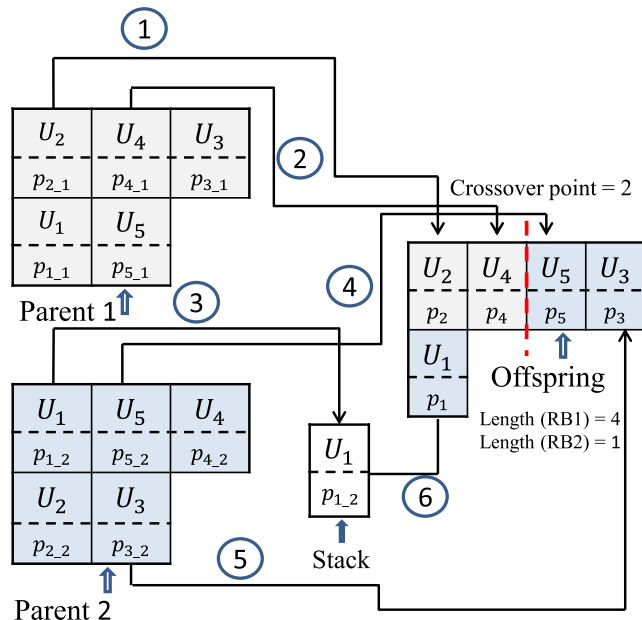
$$p_{i,r} = SINR_{min} \times \frac{(\sigma^2 + \sum_{j=1, j \neq i}^{V+K} a_{j,r} p_{j,r} g_{j,i,r})}{a_{i,r} g_{i,i,r}} \tag{10}$$

Additionally, if a resource block is used by only one communication, the transmission power of the communication is set to its maximum value. Algorithm 1 shows the pseudocode for fitness calculation and power assignment. Inputs to the algorithm are a chromosome (resource allocation matrix and transmission power vector). Also, the outputs are fitness value of the chromosome and optimized transmission power vector.

Next, we focus on mentioned operators and show that how they fit in the framework of our proposed method.

**B. PROPORTIONAL SELECTION**

Proportional selection operator selects the chromosomes based on their selection probabilities to be parents of



**FIGURE 4. Crossover operation. Parent 1 and Parent 2 produce offspring. crossover point randomly is selected and equals to 2. Moreover, length of two resource blocks, which are randomly selected, equal to 4 and 1, respectively.**

next generation. The selection probability of a chromosome is based on its fitness value and can be expressed as

$$pr_s(x, t) = \frac{f_{\text{chromosome}}(x)}{\max(\text{fit}(t))} \tag{11}$$

where  $x$  is a chromosome and  $pr_s(x, t)$  is the probability of selecting  $x$  at  $t^{th}$  generation as a parent.  $f_{\text{chromosome}}(x)$  is the fitness value of the chromosome  $x$ . Additionally,  $\text{fit}(t)$  is the set of fitness values at  $t^{th}$  generation as

$$\text{fit}(t) = \{f_{\text{chromosome}}(x_1), f_{\text{chromosome}}(x_2), \dots, f_{\text{chromosome}}(x_{N_t})\} \tag{12}$$

where  $x_i$  and  $N_t$  are  $i^{th}$  chromosome and the total number of chromosomes in  $t^{th}$  generation, respectively.

**C. CROSSOVER OPERATION**

Crossover operator combines two parents and produces offspring for the next generation. At the beginning, a random length is dedicated to each resource block of the offspring where the sum of the lengths must be equal to total number of communications. This length shows the number of potential communications that can be supported in the intended resource block. Also, a random number in the range of  $[1, V+K]$  is selected which is called *crossover point*. It determines the number of communications which are taken from each parent (e.g *crossover point* = 3 means three communications and their transmission powers are taken from parent 1 and the others are taken from parent 2). Figure 4 shows an example of crossover operation, where  $p_{i,j}$  shows the transmission power of  $i^{th}$  user of  $j^{th}$  parent. In the figure,  $\mathbf{M} = \{U_1, U_2\}$ ,  $\mathbf{D} = \{U_3, U_4, U_5\}$  and lengths of resource blocks in the offspring are randomly selected to be 4 and 1,



**Algorithm 1** Fitness Calculation and Power Assignment

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```

1: procedure Fit_Calc (resourceVector, powerVector)
2:   Output fitness_value, powerVector
3:   Initialization: sum_vector =  $\emptyset$ ; cellVector =  $\emptyset$ ;
4:   for RB_member each row in resourceVector
5:     if there is any D2D pair in RB_member
6:       Select optd randomly among D2D pairs of
7:       RB_member
8:       for All possible values popt for power of optd
9:         temp  $\leftarrow$  powerVector
10:        Update temp with popt for optd
11:        if there is any cellular user in RB_member
12:          cell  $\leftarrow$  cellular user in RB_member
13:          p(cell)  $\leftarrow$  required power for SINRmin
14:          Add p(cell) to cellVector
15:          if p(cell)  $\leq$  Pc,max
16:            Update temp with p(cell)
17:            rate  $\leftarrow$  sumrate of RB_member
18:            with respect to temp
19:          else
20:            rate  $\leftarrow$  -infinity
21:          end if
22:        else
23:          rate  $\leftarrow$  sumrate of RB_member with
24:          respect to temp
25:        end if
26:        Add rate to sumVector
27:      end for
28:      sumrate(RB_member)  $\leftarrow$  max(sumVector)
29:    else
30:      p(cell)  $\leftarrow$  Pc,max
31:      Update powerVector with p(cell)
32:      sumrate(RB_member)  $\leftarrow$  sumrate of
33:      RB_member with respect to powerVector
34:    end if
35:  end for
36:  fitness_value  $\leftarrow$  sum(sumrate)

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respectively. Also, the *crossoverpoint* equals to 2. Therefore, first  $U_2$  and  $U_4$  are chosen from parent 1 and as the results of first and second moves, the two communications are set as the first two communications of the first resource block of the offspring. Other communications of offspring are taken from the second parent. First element of second parent is  $U_1$ , but it cannot be set as the third communication of the offspring. The reason is that there is another cellular user ( $U_2$ ) at the first resource block. Thus, in the third move,  $U_1$  is added to the stack. As fourth move,  $U_5$  is added to the offspring as the third communication. Since  $U_4$  and  $U_2$  already exist in the offspring, they are not added again. The last element in second parent is  $U_3$  which as fifth move will be set as fourth communication of the offspring. The communications of the first resource block of the offspring is completed. The next communication is at the second resource block. Although

**Algorithm 2** Crossover

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```

1: procedure Crossover (Parent1, Parent2)
2:   Output offspring
3:   Initialization: i = 1 and done = 0
4:   select Len = {len(1), len(2), ..., len(Q)} randomly in a
5:   way that len(1) + len(2) + ... + len(Q) = V + K.
6:   crossover_point  $\leftarrow$  random number 1 to V + K.
7:   for rb = 1 to Q
8:     while done = 0
9:       if i  $\leq$  crossover_point
10:        temp  $\leftarrow$  ith communication of the Parent1.
11:       else
12:        temp  $\leftarrow$  (i - crossover_point)th communication of
13:        the Parent2.
14:       while temp is already taken from Parent1
15:         i  $\leftarrow$  i + 1
16:       temp  $\leftarrow$  (i - crossover_point)th communication of
17:       the Parent2.
18:       end while
19:       for pos = 1 to len(rb)
20:         if pos is for a D2D pair and temp is a D2D pair
21:           offspring(rb, pos)  $\leftarrow$  temp
22:           i  $\leftarrow$  i + 1
23:           done = 1
24:         else if pos is for a D2D pair and temp is a cellular
25:         user
26:           Add temp to the Cell_Stack
27:           i  $\leftarrow$  i + 1
28:         else if pos is for a cellular user and temp is a cellular
29:         user
30:           offspring(rb, pos)  $\leftarrow$  temp
31:           i  $\leftarrow$  i + 1
32:           done = 1
33:         else if pos is for a cellular user and temp is a D2D
34:         pair
35:           if Cell_Stack is not empty
36:             offspring(rb, pos)  $\leftarrow$  Cell_Stack(1)
37:             Delete the first element in Cell_Stack.
38:             done = 1
39:           else
40:             offspring(rb, pos)  $\leftarrow$  0
41:             done = 1
42:           end if
43:         end if
44:       end while
45:     end for

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there is no remaining elements in parent 2, the stack has one element. Thus, in the sixth and the last move, the element in the stack will be the only communication of the second resource block of the offspring. Moves are shown by numbers in the Figure 4. The pseudocode of crossover operation is given in Algorithm 2. Two chromosomes (parents) are the inputs to the algorithm and produced offspring is the output.

**Algorithm 3** Select and Reproduce

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```

1: procedure Sel_Rep (gen, fit)
2:   Output new_gen
3:   max_fit  $\leftarrow$  max(fit)
4:   for each chromosome in gen
5:     prs(chromosome) =  $\frac{fit(chromosome)}{max\_fit}$ 
6:   end for
7:   for chr = 1 to  $N_t$ 
8:     p1, p2  $\leftarrow$  choose two parents based on the probability
9:     new_in  $\leftarrow$  Crossover(p1, p2)
10:    mut  $\leftarrow$  random number 0 to 1
11:    if mut < 0.2
12:      mut_gen  $\leftarrow$  Choose two cellular users or two
13:      D2D pairs and swap them
14:      Add mut_gen to new_gen
15:    else
16:      Add new_in to new_gen
17:    end if
18:  end for

```

---

**D. MUTATION**

In order to escape from local optimum solutions, the genetic algorithm adds a random change to chromosomes with a low probability [29]. For applying a random change in a chromosome, two users are selected randomly and swapped. In order to follow the first constraint in (8) ( $C_1$ ), if the first selected user is among the D2D pairs (cellular users), the second one should also be selected among the D2D pairs (cellular users). Note that the probability of the mutation should be low to prevent a random search.

Combination of proportional selection, crossover operation and mutation is called select and reproduce. The pseudocode of select and reproduce function is given in Algorithm 3.

**E. OPTIMIZATION USING GENETIC ALGORITHM OPERATORS**

The optimization algorithm, as shown in Algorithm 4, starts with a random generation. Random generation generate  $N_t$  random chromosomes as the first generation. Power of the users is set to their upper limit in the beginning. Then, fitness value of all the chromosomes in the generation is calculated. Next, the select and reproduce function is called. In the function, parents are selected according to their fitness value and then, offspring are produced. Mutation is also applied on the offspring at this step. Therefore, generation is updated and algorithm is repeated *rep* times. Tuning the mutation rate and crossover rate is usually done by means of trail-and-error [30].

In order to assign the resource blocks and transmission power of users efficiently, having the prior knowledge of interference between the users is required. In other words, CSI is required to be known prior to the resource and

**Algorithm 4** Optimization

---

```

1: procedure Optimization (rep)
2:   Output best_individual
3:   Initialization::
4:   (initial_generation)  $\leftarrow$  random generation
5:   i  $\leftarrow$  1
6:   do:
7:     fit =  $\emptyset$ 
8:     for each chr in next_gen:
9:       (fit_chr, Power)  $\leftarrow$ 
10:      Fit_Calc(chr.resourceVector, chr.powerVector)
11:      chr.powerVector  $\leftarrow$  Power
12:      Add fit_chr to fit
13:     end for
14:     nextgen  $\leftarrow$  Sel_Rep(fit, next_gen)
15:     i  $\leftarrow$  i + 1.
16:   while i < rep
17:   best_individual  $\leftarrow$  max(fit)
18:

```

---

power allocation. In the following section, we describe a channel prediction algorithm which results in a lower transmission overhead.

**IV. CHANNEL PREDICTION**

Performance of adaptive communication systems depends heavily on knowledge of CSI. Interference aware resource allocation is also an adaptive system. Knowledge of the CSI in adaptive systems, is usually provided through feedback. After establishing a connection between the intended users, the receiver estimates the channel and then, feeds it back either to the transmitter or the base station. This process does not only result in a huge load on the network, but also the fed back information can be outdated due to delay caused by the feedback. An error in CSI or an outdated information results in a wrong decision in the system. Thus, instead of feeding back the CSI from each user or using outdated CSI by periodically collecting CSI, a prediction method at the base station for CSI is used [31]–[36].

In our system model, we assume a flat fading channel. The reason lies in dividing the bandwidth into small and narrow bands. Therefore, users experience a flat fading channel. Taps of a channel act as sum of the sinusoids [37]. This sum of sinusoids can be modeled as an autoregressive (AR) process. Let  $y_t$  denote the received data at the  $t^{\text{th}}$  time.  $h_t$  is the complex quantity of time-based channel impulse at  $t^{\text{th}}$  time instance and  $b_t$  is the transmitted modulated data (e.g. BPSK).  $y_t$  can be defined as:

$$y_t = h_t b_t + z_t, \quad (13)$$

where  $z_t$  is the Added White Gaussian Noise (AWGN). Then, predicting the  $(n + 1)^{\text{th}}$  sample based on the previous  $L$

TABLE 1. System numerical parameters.

System Parameters	Corresponding value
Cell radius	500 m
Channel model	Winner model
Carrier frequency	1.8 GHz
Bandwidth of resource blocks	180 KHz
Number of resource blocks	8
Number of cellular users	4
Maximum distance between D2D pairs	10 m
Maximum power of D2D transmitters	23 dBm
Maximum power of cellular users	23 dBm
Noise power density	-174 dBm
Number of repetition in genetic algorithm	50

samples can be done using a linear prediction.

$$h_{n+1} = \sum_{i=1}^L w_i h_{n+1-i}, \quad (14)$$

where the  $w$  is the predictor coefficient and is calculated as

$$w = R^{-1}r \quad (15)$$

where  $R$  is the autocorrelation matrix with coefficient  $R_{ij} = \mathbf{E}[h_{n-i}h_{n-j}^*]$  and  $r$  is the autocorrelation vector with coefficient  $r_j = \mathbf{E}[h_n h_{n-j}^*]$  [36].

In the next section, the performance of the algorithm is evaluated using numerical simulations.

### V. SIMULATION RESULTS

In this section, the performance of the algorithm under different scenarios is evaluated. The evaluations include: A) network spectral efficiency evaluation, B) cumulative distribution function (CDF) comparison, C) network interference power evaluation. In all the simulations, radius of the cell is assumed to be 500 m. There is a base station in the center of the cell. The users are distributed randomly around the base station. Maximum distance between D2D pairs is set to 10 m [38]. Carrier frequency, resource blocks bandwidth and maximum power of users (D2D transmitters and cellular users) are set as in long term evolution (LTE) to 1.8 GHz, 180 kHz and 23 dBm, respectively [39]. The parameters used in simulation results are given in Table 1, unless otherwise specified. Each user is assumed to have an omni-directional antenna. Without loss of generality for the case of simplicity, for all the scenarios, an indoor channel model according to Winner model is considered. In the case of outdoor, due to the significant difference in antenna height for base station and users (cellular and D2D users) two different channel models should be considered, one for cellular users and one for D2D users. The channel gain consists of large scale pathloss and small scale fading. Large scale pathloss, denoted by  $PL$ , based on Winner model is defined [40] as

$$PL(dB) = 22.7 \log_{10} d + 27 + 20 \log_{10} f_c. \quad (16)$$

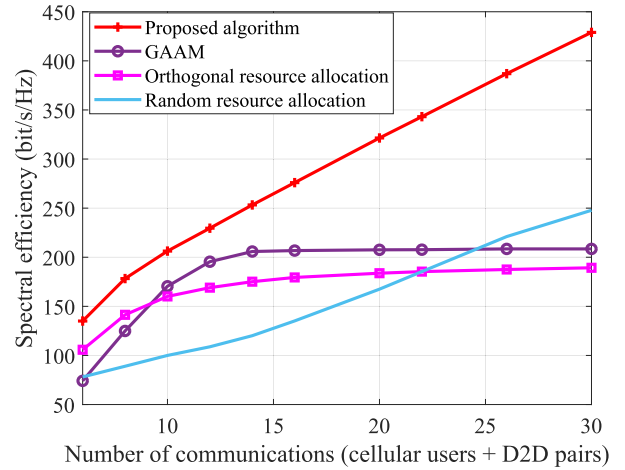


FIGURE 5. Spectral efficiency for different number of resource blocks.

The small scale fading is assumed to be Rayleigh fading and is modeled by jakes model as

$$h_I(t) = 2 \sum_{n=1}^{N_0} (\cos \phi_n \cos w_n t) + \sqrt{2} \cos \phi_N \cos w_d t \quad (17)$$

and

$$h_Q(t) = 2 \sum_{n=1}^{N_0} (\sin \phi_n \cos w_n t) + \sqrt{2} \sin \phi_N \cos w_d t, \quad (18)$$

where  $h_I(t)$ ,  $h_Q(t)$ ,  $\phi_n$  and  $\phi_N$  are the real and imaginary components of channel at  $t^{th}$  time instance, initial phases of the  $n^{th}$  doppler shifted sinusoid and maximum doppler frequency ( $f_m$ ) shifted sinusoid, respectively and  $w_d = 2\pi f_m$  with  $w_n = w_d \cos \phi_n$  [41]. The model is used to obtain  $L$  channel samples and the next samples are predicted using (14).

#### A. NETWORK SPECTRAL EFFICIENCY EVALUATION

This subsection is divided into three comparisons. The first is the comparison of the throughput of the proposed algorithm, GAAM [28], orthogonal [11], and random resource allocation. Figure 5 shows the outperformance of the proposed algorithm compared to GAAM, orthogonal, and random resource allocation. In this figure,  $Q = 8$ ,  $V = 4$  and  $K$  is varied from 2 to 18. In GAAM, a resource block is shared by a cellular user and a D2D pair. Thus, when  $Q$  equals to 8 at most 8 cellular users and 8 D2D pairs are served. Since  $V = 4$ , the maximum number of served communications is  $4 + 8 = 12$ . Thus, the curve for GAAM is increasing until number of communications equal to 12, and after that it is almost constant. In the orthogonal resource allocation, first, the 4 of 8 resource allocation is assigned to 4 cellular users. Then, the other resources are assigned to random D2D pairs. Therefore, after 8 number of communications, the slope of the curve decreases significantly. In the random and the proposed algorithm, as the number of communications increases, the spectral efficiency increases as well. The reason lies in having flexible number of D2D pairs in a resource block. It is



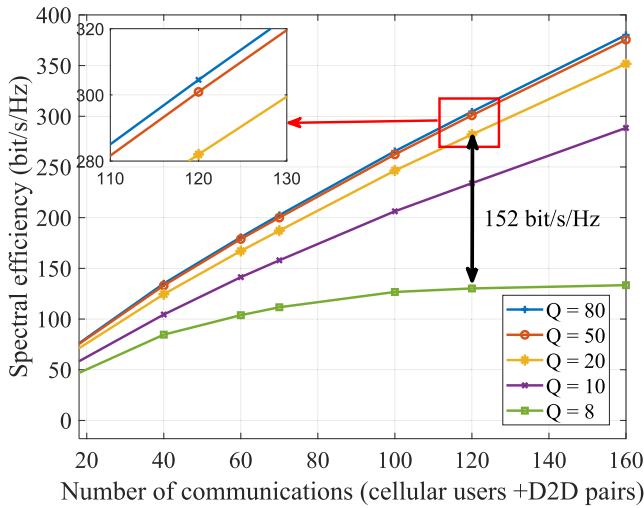


FIGURE 6. Spectral efficiency with respect to the number of available resource blocks.

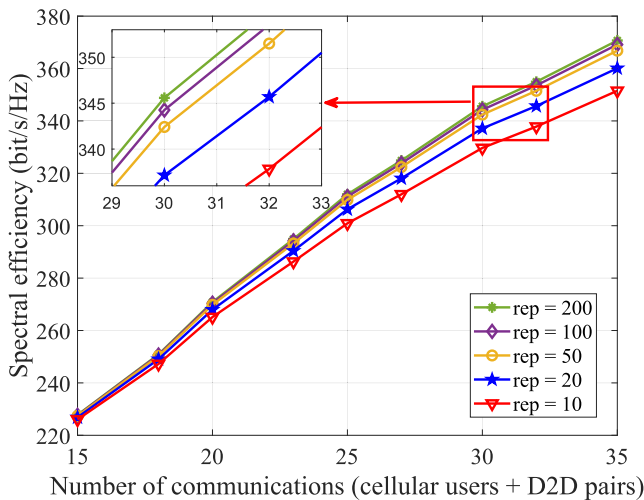


FIGURE 7. Spectral efficiency for different number of repetitions.

shown that even the random resource allocation can do better than GAAM and orthogonal resource allocation in dense and crowded environment.

The second comparison in this subsection evaluates the effect of number of resource blocks on the spectral efficiency. In Figure 6, the number of cellular users is fixed,  $V = 8$  and  $K$  is varying from 7 to 152. It is shown that as the number of resource blocks -  $Q$ - increases, the spectral efficiency increases. The reason is that as more resource blocks results in less interference between the users. The difference in spectral efficiency for lower number of  $K$  is less than higher numbers of  $K$  due to the minimum  $SINR$  that each cellular user should met. There is a trade-off between having better performance or lower number of resource blocks. Having more resource blocks leads to higher cost and better performance. The trade-off depends on the minimum expected spectral efficiency and number of communications expected to be served.

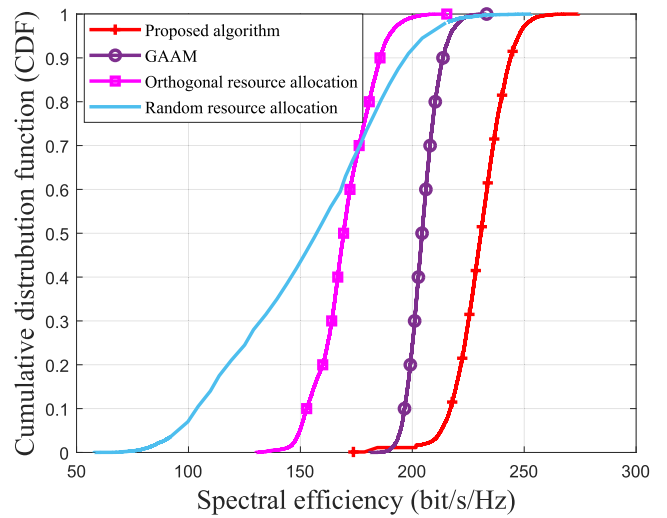


FIGURE 8. Cumulative distribution function of spectral efficiency.

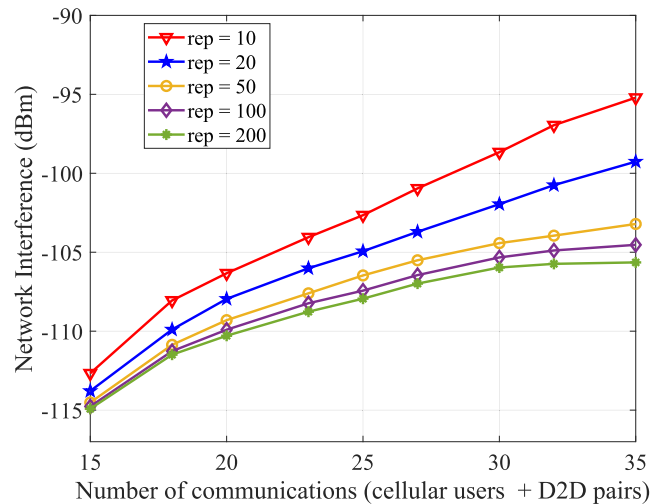


FIGURE 9. Network interference for different number of repetitions.

Third comparison is with respect to the repetition parameter of the genetic algorithm, denoted by  $rep$ . The parameter shows the number of produced generations. In Figure 7, spectral efficiency for different values of  $rep$  is shown. As  $rep$  gets larger, algorithm results in a better optimization. Higher number for repetition makes the algorithm finds a better solution but the algorithm needs to be run longer. Therefore, there is another trade-off between having higher performance or lower number for repetition. However, when  $rep$  is large enough, e.g.  $rep = 50$ , result of the algorithm is an acceptable solution and good enough. As the figure shows the curves for  $rep = 50, 100, 200$  are very close.

### B. CDF EVALUATION

Figure 8 shows the CDF curves of the proposed algorithm, GAAM [28], orthogonal [11] and random resource allocations. In the simulations,  $Q, V$  and  $K$  are assumed to be 8, 4 and 8, respectively. The CDF curves shows the ranges of the

output algorithms. As Figure 8 shows, the proposed algorithm outperforms the other methods. It also shows that random resource allocation can even perform better than orthogonal resource allocation. Moreover, random resource allocation has the widest range.

### C. INTERFERENCE EVALUATION

Figure 9 shows the amount of the intra-cell interference for the proposed algorithm with different repetitions. The parameters for this simulation is the same as Figure 7. It is shown that for higher number of repetition, There is less interference. In other words, at each iteration a better and more optimized solution is found. Considering Figures 7 and 9, the proposed algorithm results in higher spectral efficiency at each iteration by mitigating the interference.

### VI. CONCLUSION AND FUTURE WORK

In this paper, a novel genetic algorithm-based method is proposed to optimize the resource allocation and power assignment of D2D communication underlying cellular communication. Contrary to orthogonal resource allocation and GAAM, the algorithm is presented with respect to the flexible number of D2D and cellular communications. Therefore, larger number of users can be served with a limited number of resource blocks. Also, a minimum SINR is considered for the cellular communications to guarantee the quality of service of them. Moreover, despite GAAM, operators of the genetic algorithm are defined to produce an acceptable offspring at each iteration. Therefore, no additional randomness is added to the algorithm. It results in superior performance and fast converging of the proposed method compared to GAAM. In this paper, we consider only users in one cell and we assume there is no interference from adjacent cells. However, adjacent cells may effect SINR of the users inside the cell. Taking the interference of the adjacent cells into account in resource allocation algorithm is left for future work.

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