Relay Selection Exploiting Genetic Algorithms for Multi-hop Device-to-Device Communication

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Abstract. Device-to-device (D2D) communication allows a direct transmission between two devices. In this way, cellular user equipment's are not always obliged to route the data conventionally through a cellular base station. This paper focuses on multi-hop D2D communication, where D2D relays are exploited to delivery of data from a source to a destination. We propose a novel algorithm that finds the most suitable path between the D2D source and destination so that the capacity of multi-hop communication is maximized. The appropriate route is found via Genetic Algorithm (GA) with an ordered crossover. The simulation results show that the proposed algorithm improves the capacity of multi-hop D2D communication from a source to a destination compared to an existing relay selection algorithm by 20–61%. We also show that the proposed solution converges fast enough to be beneficial even in realistic mobile networks.

Keywords: D2D communication · Genetic Algorithm · Relay selection

1 Introduction

New generation of cellular networks introduces a plethora of technological advancements with respect to 4G, such as ultra-dense (heterogeneous) networks, mobile edge computing, Internet of Things, vehicular networks, drones (UAVs), intelligent transportation systems, or device-to-device (D2D) communication. Contrary to conventional cellular networks, the D2D communication allows a direct communication between two or more devices without intervention of a base station (BS) [1]. The benefits of D2D communication can be fully exploited in the relay-based communication scenario, where two devices may communicate with each other through one or several relays [2,3].

The relay(s) exploited by the D2D communication can be either a fixed relay station, which is part of the network infrastructure, or other User Equipment (UE). Fixed relay is considered, for example, in [4] where the authors propose a full-duplex scenario for D2D system in two-hop networks. The paper assumes

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multiple potential full-duplex decode-and-forward relays can assist the transmission between two D2D UEs. The UE acting as a relay between two D2D UEs is considered, e.g., in [5]. The authors apply a relay to D2D communication in order improve cellular downlink throughput. Most of the works, however, focus on the one-hop or two-hop scenarios, i.e., only UE within the one-hop or two-hop range can communicate with each other. The use of multi-hop communication can overcome extend communication range and/or enhance the capacity of the whole network [6]. In this respect, enabling the multi-hop D2D communication can significantly expand opportunities of the D2D communication in cellular networks, especially for UE that are relatively far from each other and cannot communicate directly or through just one relay.

The fundamental challenge in multi-hop enabled D2D communications is to find a suitable set of D2D relay UEs between the D2D UE acting as a source and the D2D UE acting as a destination while maximizing the overall capacity. The multi-hop D2D communication is considered in, e.g., [7–9]. The paper [7] proposes a multi-hop D2D communication in order to extend the coverage of BS. In this case, the D2D relays retransmit data between the BS and the UEs out of BS coverage. The multi-hop D2D communication also can be used to offload data from network backhaul, as investigated in [8]. The authors analyze the problem of relaying data through multiple relay UEs and also sharing resources allocation from cellular UEs. For each D2D communication pair, the algorithm finds the optimal shortest path using Dijkstra's algorithm based the distance. However, the Dijkstra's algorithm often cannot be used, because it is too computationally demanding for practical implementations.

Several optimization algorithms based on the machine learning, such as Genetic Algorithm (GA), have been developed in order to reduce computation complexity of the relaying algorithms. In [9], the GA is used to find shortest path from the source to the destination and to reduce complexity. The authors exploit standard single-point crossover to determine new routing options. Since the standard crossover leads to the creation of loops between source and destination, the authors propose a loop elimination algorithm. In [10], a multi-population GA with immigrant's scheme is proposed to solve the dynamic shortest path routing. The GA is also exploited in wireless networks to find a suitable path from cluster head to the base station, as suggested in [11]. The GA with spanning tree topology is implemented to maximize the usage of the network [12]. In [13], the GA is used to solve the shortest path routing problem with an adaptive routing. Nevertheless, this method needs a routing table to find a link communication between the source and destination.

The GA can be also exploited in the area of D2D communication. For example, the GA-based resource allocation and power control for the network optimization is proposed in [14]. The scheme is designed to mitigate the intra-cell interference and to enhance the system throughput by means of proper resource allocation. A relay-aided D2D with the single-point crossover is implemented in [15]. The paper proposes joint resource allocation for relay aided underlay D2D communication in cellular networks. Nevertheless, none of these papers consider the multi-hop D2D communication, which extend the coverage area and opportunities related to optimizing the capacity.

In this paper, we target to maximize the overall network throughput via multi-hop D2D communication. We propose an algorithm based on the GA to enhance the capacity for multi-hop D2D communication in the presence of co-channel interference, where the D2D relays use the same radio resources. As the conventional GA would lead to redundant use of relays, we exploit ordered crossover to reduce interference, and, thus, increase the communication capacity. We show that the proposed D2D relay selection based on the ordered crossover scheme overcomes the existing solutions in terms of capacity between D2D source and destination.

The rest of this paper is organized as follow. System model and problem formulation is defined in Sect. 2. The proposed relay selection scheme exploiting genetic algorithms with the ordered crossover is described in Sect. 3. Section 4 presents the simulation scenario and results. Last, major conclusions and findings are summarized in Sect. 4.3.

2 System Model and Problem Formulation

This section describes first the system model and then, we formulate the problem of relay selection for D2D communication.

2.1 System Model

In this section, we introduce a general system model for multi-hop D2D communication. We assume that the D2D communications is carried in dedicated resources. Therefore, there is no interference to conventional cellular UEs. We assume one D2D source (S) is sending data to one D2D destination (D). We assume R relay UEs deployed between the S and the D as shown in Fig. 1. The capacity between the S and D without any relays is calculated as:

$$C_{sd} = B\log_2\left(1 + \frac{P_s g_{sd}}{BN_o}\right) \tag{1}$$

where P_s is the transmission power of S, g_{sd} is the channel gain between the S and D UEs, N_o is the thermal noise with a spectral density of $-174\,\mathrm{dBm/Hz}$, and B is the channel bandwidth used for the communication. Notice that for the direct communication, there is no interference to the D, since only the S is transmitting while all potential relays are idle.

To calculate the capacity of each link in the multi-hop D2D communication from any i-th D2D source to any j-th D2D destination is calculated as:

$$C_{ij} = B\log_2\left(1 + \frac{P_i g_{ij}}{BN_o + I_j}\right) \tag{2}$$

where P_i is the transmission power of the i-th UE, g_{ij} is the channel gain between the i-th and the j-th UE, and I_j is the interference to the j-th UE (i.e., the one who receives data from the i-th UE) expressed as:

$$I_j = \sum_{i \in N, j \in N, i \neq j} P_i g_{i,j} \tag{3}$$

where N is the number of UEs, P_i is the transmission power of the i-th UE while interference from the i-th UE is not considered as this UE transmits data to the j-th UE. The interference from an idle mode (i.e., potential relays that are not used for relaying) is not included as these do not transmit any data.

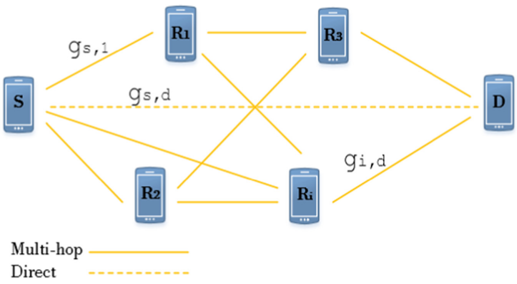


Fig. 1. System model with D2D source (S), destination (D), and relays (R)

2.2 Problem Formulation

This section is focused on problem formulation. Our objective is to maximize capacity in multi-hop D2D communication from the source UE (S) to the destination UE (D) by incorporation of the relays. Since the capacity of multi-hop communication is determined as a minimum capacity on all involved hops, the objective can be formulated as:

$$\begin{aligned} & C^* = \arg\max_{y \in R}(\min\{C_y\}) \\ & s.t \\ & 4a. \quad h_{\max} - 1 \leq R \\ & 4b. \quad \forall y_{s,R_i,d}, y_{s,R_j,d} : i \neq j : R_i \neq R_j : i, j \in \{1 \cdots n\} \end{aligned} \tag{4}$$

where y the set sequences of multi hop communication from S to D, h_{max} is the maximum number of hops and R is the number of all relays. Note that in the sequence of combination, S is always in the first and D is in the end of communication chain. The constrain (4a) ensures that the number of hops is less or equal than the number of relays. The constrain (4b) ensures that the relay UE cannot be used more than once in the whole communication chain.

3 Proposed Relay Selection

In this section, we present the proposed solution for selection of relays to increase the capacity of the link between the S and the D. We exploit the genetic algorithm with the ordered crossover as used in [16] to select the most suitable relays. In the common genetic algorithm, the relays are selected completely randomly. Then, such solution allows to choose any arbitrary set of relays including those with repeating relays (loops). Avoidance of loops is straightforward and can be solved by a simple removal of relays that appears twice or more. However, still, the order of relays in the communication chain is crucial a common genetic algorithm cannot guarantee a right order of the relays. Reordering of the relays after each randomly generated set would lead to confusion in fitness function, in our case represented by capacity achieved for give ordered set of relays.

The fitness function (f) is formulated as:

$$f = \max\left\{C^{h}_{s,R_{(i,j)},d}\right\} \tag{5}$$

Thus, we propose to use ordered cross-over instead of the common one. The process of the proposed genetic algorithm for the relay selection is described as follows.

– Step 1. We start with an initial population constituted of only a direct communication between the S and the D. For this case, the capacity $C^1_{s,d}$ is estimated from the known channel quality. If the capacity using direct communication from S to D results in the highest capacity compared to all possible relay UEs $C^1_{s,j}$,$C^1_{s,d} > C^1_{s,j}$, then relay selection process is finished. We do not need to follow the next step because the direct communication is always the option with the maximum capacity from S to D.
– Step 2. If there is at least one relay that leads to solution that is better than the direct communication,
$$C^1_{s,d} < C^1_{s,j} \tag{6}$$
the ordered crossover operation is initialized. The ordered crossover operation combines two members of the populations (denoted as parents) to create a new path from the S to the D. In other words, the path via relay(s) represented by the Parent $P1$ (one possible and good performing combination of relays between S and D) and the Parent $P2$ (another good performing set of relays from S to D) is randomly generate. The new, can be expressed as follow:
$$\begin{aligned}
&P1 = y^{h}_{s,Ri,d}\\
&P2 = y^{h}_{s,Rj,d}\\
&\downarrow\\
&O1 = y^{h}_{s,R_{(i,j)},d} : i \neq j : R_{(i,j)} \neq R_{(j,i)}\\
&O2 = y^{h}_{s,R_{(j,i)},d} : j \neq i : R_{(j,i)} \neq R_{(i,j)}
\end{aligned} \tag{7}$$
where y is the set sequences of relay UEs in the communication link between S and D, $O1$ and $O2$ are the offspring of the new communication link,

i and j denote the relays based on the ordered crossover process by choosing the high capacity (2).
To preserve diversity in the population, a mutation m is exploited besides the crossover operation. The mutation $M1$ is used to get a new set of the relays from the S to the D. The mutation is expressed as:

$$O1 = y^h_{(s,R_j,d)} \rightarrow M1 = y^h_{(s,R_m,d)} : m \neq j \tag{8}$$

where m is any UEs except the relay j included in the communication link from the S to the D.

– Step 3. The process of ordered crossover starts from single hop to h relay hops so with each new population, one more relay is added to the communication chain between the S and the D. New population is generated based on the previous population (following ordered cross-over explained in previous step), but a random new relay (out of these not used so far) is integrated into the communication chains. Note that each parent can integrate any random new relay not used so far.
If an inclusion of one more relay into the communication chain improves performance, the whole process is repeated, but one more relay is added (i.e., the number of hops is increased by one). Of course, if all the of UEs have already been used for relaying, the process is stopped. If the inclusion of the new relay does not lead to any improvement in the capacity, the process is stopped. The final communication path is selected as the one leading to the highest estimated capacity out of all members of the previous population (i.e. with one less relay).
Note that each new generation is determined based on channels estimation, so the time duration required for the whole process is negligible (in order of milli or microseconds).

The pseudo code of the algorithm is shown in Algorithm 1.

4 Performance Evaluation

In this section, the simulation scenarios and main simulation parameters are described, then, the simulation result are presented and discussed.

4.1 Simulation Scenario

The multi-hop relay D2D communication scenario is evaluated by simulation in MATLAB software. We consider simulation distance from S to D from 100–1000 m. Within the distance, R relay UEs are randomly distributed. We consider two deployment scenarios assuming either 5 or 10 relay UEs. Note that the number of relays used between S and D is usually less than maximum number of relays in the area. Thus, we also evaluate the impact of number of relays, we investigate the capacity and number of relays actually used for multi-hop D2D communication. In order to see the impact of distance on the number of

Algorithm 1. Relay Selection for Multi-hop D2D Communication with GA

Choose initial population
Calculate capacity (C) acc. to (6)
Determine $y \leftarrow 1 < i < j < n$;
Apply ordered crossover via (7) and acc. to (2),
$t_1 = t_2 = v = j + 1$
for $h = 1, ..., h_{max}$
  for $w = 1, ..., n$
    if $P_{1,w} \notin \{P_{2,i} \dots P_{2,j}\}$ **then** $O_{1,t_1} = P_{1,v}; t_1 + +;$
    if $P_{2,w} \notin \{P_{1,i} \dots P_{1,j}\}$ **then** $O_{2,t_1} = P_{2,v}; t_2 + +;$
    $v = v + 1$
    $O_1 = [O_{1,1} \dots O_{1,i-1} P_{2,i} \cdots P_{2,j-1} O_{2,i} \dots O_{1,i-1}]$
    $O_2 = [O_{2,1} \dots O_{2,i-1} P_{1,i} \cdots P_{1,j-1} O_{2,i} \dots O_{2,i-1}]$
    Apply mutation M via (8)
    Calculate capacity (C) via (2)
  end for
  Select highest capacity (f) via (5).
end for

relays, we also investigate the difference range distance from D2D source and D2D destination. The simulation results are investigated and averaged out over 100 simulation drops in each scenario.

The transmission power of all UEs is set to the same level equal to $23dBm$. All UEs (S, and all active relays) also use the same channel frequency and bandwidth. Thus, the interference can have a significant impact on the quality of the relay links. The path loss between all communicating UEs is calculated according the indoor propagation models defined by ITU standards [17].

The simulation compares the proposed ordered crossover with the others previous solutions. To be more specific, we simulate the proposed ordered crossover in Genetic Algorithm (OGA) with SGA in [15], IGA in [9], and Dijkstra based distance in [8]. The SGA method uses the random one- and two-point crossover. The crossover method that is implemented in IGA is the same as in SGA methods, but the methods can mutate the relay UEs with the same number. Consequently, IGA method is able to remove the looping problem of the D2D links. We also compare our proposed algorithm with the conventional shortest path method, i.e., Dijkstra based distance and direct communication (no relays in communication route). Table 1 shows the list of major parameter scenario that is used in this paper.

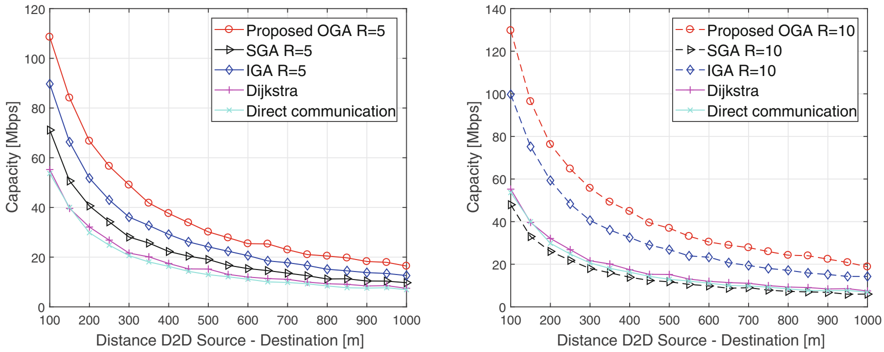
4.2 Simulation Result and Discussion

Figure 2 illustrates the capacity performance of the proposed method for different sizes of the distance. Note that the S and D are positioned at the same place and, thus, distance between them is always fixed over all drops. Figure 2 shows that the capacity is gradually decreased with increasing of the distance between S and D is increased as well. First, we investigate the proposed OGA methods

Table 1. Simulation parameter

Parameter	Value
UE transmit power	23 dBm
Bandwidth	100 MHz
Distance	100–1000 m
Number of relay/ D2D link	5 and 10 Relays
Carrier frequency	2000 MHz
Noise power spectral density	−174 dBm/Hz
Path-loss model	ITU indoor propagation [17]

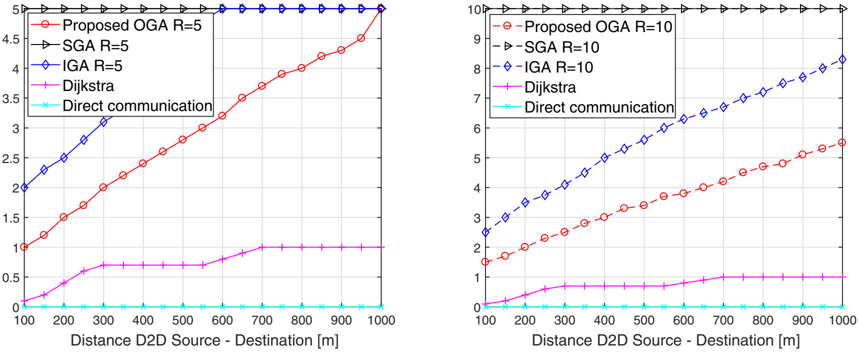
with 5 relay UEs in the network between S and D. If the distance is 100–1000 m, the OGA method achieves an average capacity gain between 10%–20%, 20%–36%, and 40%–54% in comparison to the IGA, SGA, and Dijkstra based distance, respectively. In 10 relay cases, the OGA still outperforms the IGA, SGA, and Dijkstra based distance, by up to 20%–30%, 40%–61%, and 50%–57% respectively. In this case, SGA gives the worst performance because all relay UEs are used in D2D communication and significant interference among transmitters occur.



(a) R=5 relays (b) R=10 relays

Fig. 2. Capacity over distance between S and D for scenario with R = 5 (a) and R = 10 (b) relays

Figure 3 investigate how many relays are exploited on average, if the distance increases proportionally with the distance between S and D similarly as in Fig. 2. Since the SGA method uses the same length of communication link (i.e., the same number of relays) in the crossover methods, the number of relays used is always the maximum number deployed in the simulation (i.e., 5 or 10). In the previous IGA method, there is a difference in the number of relay uses at each distance



(a) R=5 relays

(b) R=10 relays

Fig. 3. Probability of relay usage

compare to SGA, because IGA methods removes the looping where there is a same relay UE in the link, but it does not consider the relay selection. Since our proposed OGA method selects the relays from the first hop, therefore the number of relays in the multi-hop D2D networks can be minimized and the capacity can be maximized. Figure 3 also demonstrates that Dijsktra achieves the lowest number of relays on average since only up to one relay is always used. This is, however at the cost of low capacity as shown in Fig. 2.

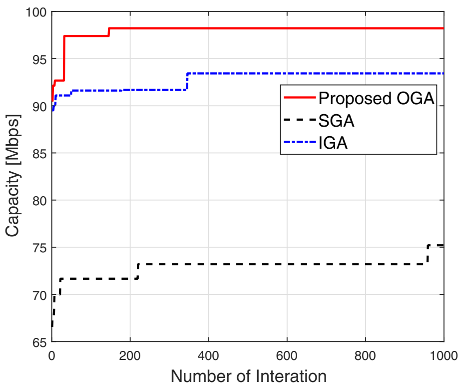


Fig. 4. Evolution of the communication capacity over iterations of the algorithm, R = 5

Figure 4 shows a sample of the capacity performance characteristic for a designated number of generations. In this case, the OGA not only converges fast to get its best solution (i.e. only roughly 150 iterations are needed) but also outperforms IGA and SGA method by almost 6% and 22%, respectively. Still, it is worth mentioning that already after first generation is created, the OGA outperforms both SGA and IGA.

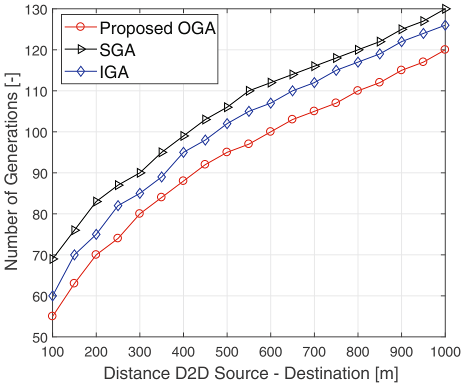


Fig. 5. Number of generations to reach the highest capacity, R = 5

Figure 5 takes a closer look at how many generations are needed if distance is changing. We can see that the all methods can reach the high capacity in fewer generations if there is a short distance between S and D. With increase of distance, more crossover operations need to be performed to achieve satisfactory results. In other words, more relays should be in communication path between S and D to obtain good performance. Nevertheless, disregarding the distance the proposed ordered crossover still outperforms both the SGA and IGA methods.

4.3 Conclusion

In this paper, we have presented a novel algorithm for relay selection to improve capacity between the D2D source and the D2D destination in multi-hop D2D communication. The objective is to find the communication path via relays by choosing suitable relaying UEs between the source and the destination UEs. The proposed solution is based on the genetic algorithm with ordered crossover. The simulation results show that the proposed algorithm improves the communication capacity up to 57%, 61%, and 30% in the distance up to 1000 m with respect to the Dijkstra based distance, SGA, and IGA, respectively. At the same time, the OGA converges faster than IGA and SGA and outperforms existing solutions even the first iteration.

Future work should address a problem of resource allocation in scenario with multiple source UEs transmitting data to their respective destinations but sharing the relaying UEs.

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