D2D Communication Underlaying LTE Cellular Network

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Declaration of Authorship

This is to certify that the work presented in this thesis is the outcome of the analysis and experiments carried out by **Faisal Hussain** and **MD. Yeakub Hassan** under the supervision of **MD. Sakhawat Hossen**, Assistant Professor of Department of Computer Science and Engineering (CSE), Islamic University of Technology (IUT), Dhaka, Bangladesh. It is also declared that neither of this thesis nor any part of this thesis has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

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Abstract

Device-to-Device (D2D) communication underlaying cellular network, introduced in LTE-Advance, is a very promising feature. Using this feature user equipments (UEs) can communicate directly where in traditional cellular communication, all UEs need to communicate via base station. UEs in close proximity can act as D2D pair and communicate reusing the Resource Blocks (RBs) of existing cellular network infrastructure. This D2D communication is supervised by eNodeB (Base station in LTE) and the supervising eNodeB is also responsible for the allocation of RBs for the D2D pairs.

This thesis is concerned with the resource allocation algorithm aiming different goals like maximize the total system capacity, minimizing total interference etc. These resource allocation algorithm will be used by the supervising eNodeB to allocate appropriate RBs to the D2D pairs (shared with existing cellular UE) to attain the goals satisfying certain quality of service (QoS) requirements.

There are three approaches depending on the degree of sharing namely "One to One Sharing", "One to Many Sharing" and "Many to Many Sharing" approaches for **"maximization of sum rate"** and each of the existing algorithms follows one of these. This thesis book proposes algorithm for each of the approaches and shows the comparison analysis. Among these, algorithm for "One to One Sharing" and "One to Many Sharing" approaches is optimal which is theoretically proved.

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Chapter 1

Introduction

1.1 Overview

D2D communication is rapidly becoming a familiar term in personal communications. As a technology, it is becoming popular for different types of inter device applications. Therefore, spectrum requirement for D2D communication is increasing day by day. Again user equipments (UEs) in close proximity need less amount of transmission power in direct communication rather than communicating via eNodeB (eNB, base station in LTE) [1], [2]. Instead of communicating in traditional manner, these UEs can reuse appropriate RBs of existing cellular network and communicate as D2D communication which will generate minimal interference. Moreover, this technique increases spectral efficiency and system capacity of traditional cellular network, as well as reduces traffic load of eNB and power consumption of UEs. To enjoy these advantages D2D communication underlaying to cellular networks is introduced in Long Term Evolution (LTE). However, choosing ill-fitting RBs ends up in catastrophic level of interference in the existing cellular network [3].

1.2 What is D2D Communication

D2D communication in cellular networks is defined as direct communication between two mobile users without traversing the Base Station (BS) or core network. D2D communication is generally non-transparent to the cellular network and it can occur on the cellular spectrum (i.e. inband) or unlicensed spectrum (i.e. outband).

1.3 D2D Communication Underlay to Cellular Network

D2D communication underlay to a cellular network implies the very thing that, the UEs can reuse the existing cellular spectrum (i.e. inband) or licensed band. This feature is enabled in LTE-Advance and it comes with some questions and challenges.

- Who will be responsible to allocate the resources to these D2D pair for reusing?
- How the D2D pair will start a communication?
- Will the primary user face any difficulties?
- What are the advantages of this feature?

Following sections contain the answers of above questions.

1.4 Traditional Cellular Communication

In traditional cellular communication, the major responsibilities are imposed on the eNB. In normal scenario the cellular UEs exchange control information with the eNB. The eNB and cellular UEs set their signal strength for communication depending on these control information. Base station also allocates RBs for both uplink and downlink communication where the cellular UE send the signal to eNB using uplink RBs and eNB send the signal to cellular UE using downlink resources. Both caller and callee send and receive data via eNB.

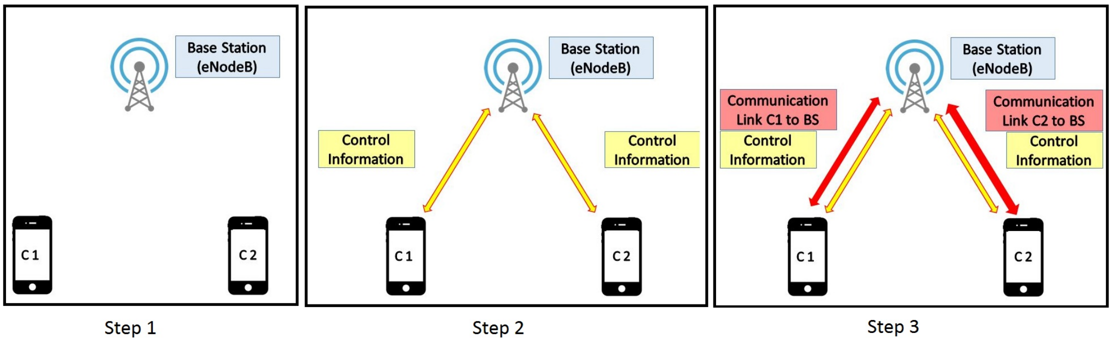

FIGURE 1.1: Traditional Cellular Communication

1.5 How D2D Communication Underlay Cellular Network works

In this scenario, D2D transmitter send a request to supervising eNodeB for allocation of RBs along with the information of the receiver. Supervising eNB allocate RBs to this D2D pair after running some Resource Allocation (RA) algorithm. After that eNB sends the information of RBs to the D2D pair by the control packet. D2D pair then communicate using allocated RBs. It should be noted that these RBs are already using by the existing cellular network. Thus D2D pairs are sharing these RBs.

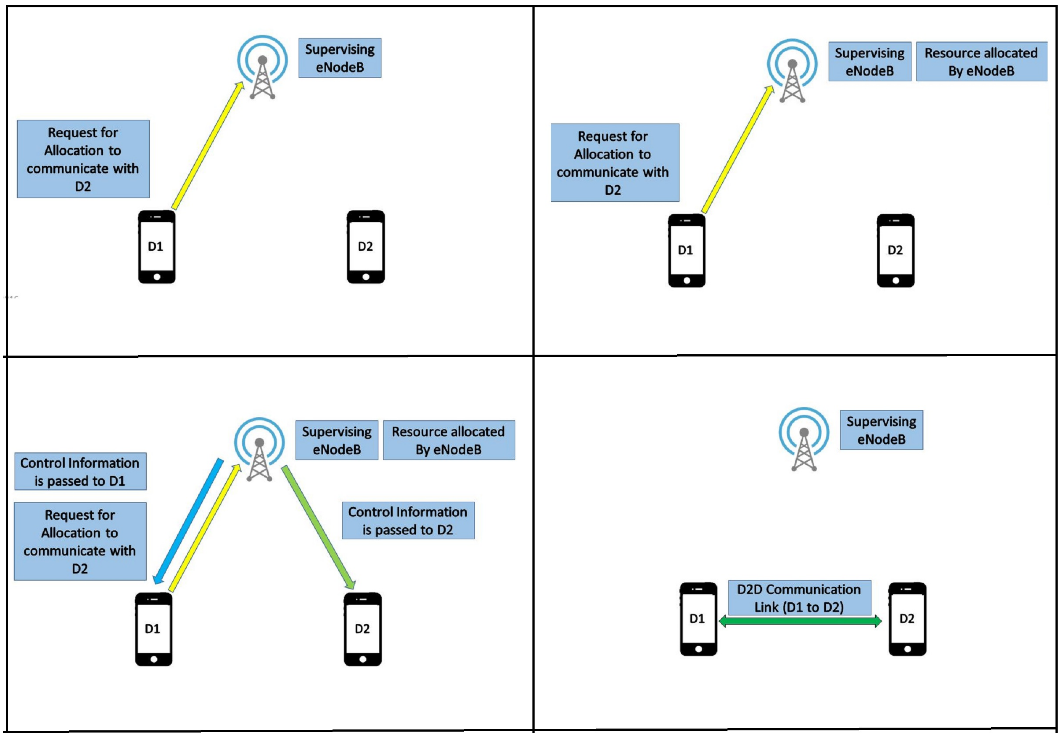

FIGURE 1.2: D2D Communication Underlay a Cellular Network

1.6 Benfits of D2D communication

This new mode of personal communication is also attracting the network operators as it offers following benefits [2],[4] .

- Bit-rate Gain: As the distance between receiver and sender is decreasing for D2D pair, bit-rate increases.
- Reuse Gain: As both D2D devices and cellular UEs simultaneously use the common radio resources.

- Hop Gain: As D2D communication uses a single link rather than using uplink and downlink resources for sending and receiving devices.
- Coverage Gain: D2D communication can be possible at some place where signal strength of eNB is too low for cellular communication.
- Energy Efficiency: D2D communication consumes less power than communicating via eNB.

So several research works are focusing on different aspects like maximizing sum rate, minimizing interference, management of transmission power etc.

1.7 Problem Statement

D2D pairs can communicate by reusing appropriate Resource Blocks (RBs) of the existing cellular network which increases system capacity and spectral efficiency. To utilize this opportunities in full length, It is compulsory to use an efficient resource allocation algorithm. It needs to minimize the interference in the system as well as increase the system capacity. The problem can be divided into two branches:

- Sum rate maximization.
- Interference minimization while maintaining a target system sum rate.

Detailed problem formulation will be discussed in the respective chapters.

1.8 Thesis Objectives

An efficient resource allocation technique can assign suitable RBs to D2D pairs to avoid above mentioned problem. A number of resource allocation algorithms exists in literature [5],[6],[7],[8],[9] aiming to increase system sum rate and to reduce interference level. However, there are scopes to improve these approaches. Some approaches [5],[6],[7] do not allow a D2D pair to share RBs of multiple cellular UEs, thus losing chances to increase more system capacity. Authors in [6],[7], propose algorithms that allow to reuse such RBs that reduces the system capacity than the traditional network. Moreover these approaches choose sub-optimal RBs which increase less amount of system capacity. The objective of this thesis is to design resource allocation algorithms which serve the purpose of maximizing the system sum rate or minimizing the total interference introduced maintaining a fixed system sum rate.

1.9 Thesis Contributions

For maximization of system capacity proposed approach maintains the minimum QoS constraint like Signal-to-Interference-plus-Noise-Ratio (SINR) for both D2D pairs and cellular UEs. The contribution of this paper is to eradicate the shortcomings of the existing algorithms. Our algorithm remove those D2D pair which can not increase the system capacity from the candidate set. After that optimal bipartite matching algorithm is used to find appropriate RBs for a D2D pair. Later remaining unassigned RBs of cellular UEs is distributed among the D2D pairs. In this case we provide options for both considering and not considering fair assignment of RBs to the D2D pairs.

For minimization of total introduced interference maintaining a sum rate, our approach showed different options which gives better result than the existing algorithms.

1.10 Organization of The Thesis

The rest of the thesis is organized in the following manners. Chapter 2 canvasses prior works related to our topic of interest. Chapter 3 discusses different aspects of system model and channel model. Chapter 4 discusses the "Maximization of System sum rate" policy with performance evaluation. Chapter 5 discusses the "Minimization of System Interference" policy with performance evaluation. Finally, chapter 6 draws the conclusion.

Chapter 2

Literature Review

2.1 Related Work

Numerous research works have been conducted on various resource allocation problems of D2D communication underlaying cellular networks. An analysis of D2D communication on both spectrum overlay and underlay of existing cellular network with ad hoc networks is discussed in [10]. They apply a technique called successive interference cancellation (SIC), which generates good transmission capacity. Huang et al. propose that frequency separation of cellular network and ad hoc network overlaying cellular network would give maximum transmission capacity rather than spatial diversity, i.e. disjoint sets of sub-carriers are used by the ad hoc network [11]. The performance of D2D underlay communication is analyzed in [12]. They reduce the performance degradation of existing cellular network by controlling the transmitting power of D2D transmitters.

A greedy heuristic resource allocation algorithm is discussed in [13] where the cellular UEs are sorted in decreasing order depending on the Channel Quality Indicator (CQI). A D2D pair with the lowest channel gain which is not yet assigned is selected for a cellular UE which has higher CQI if QoS constraints are maintained. However, provided algorithm may not terminate in some cases. A cellular UE with higher CQI is coupled with a D2D pair with the lowest channel gain can maximize the SINR of cellular UEs. However, it is not the optimal choice for maximizing the total system capacity. Some D2D pair might be missed out to be allocated or some D2D pairs are selected for earlier cellular UE which might give better sum rate to cellular UEs chosen later on.

A simple local search algorithm is designed in [6] to solve the same resource allocation problem (maximizing system sum rate while maintaining some QoS) that we are considering. The result of the greedy heuristic [13] is considered as the initial feasible solution of this algorithm. After that, the algorithm checks whether improvement can be found if a D2D pair choose a new cellular UE. If there is improvement and it also satisfies the minimum SINR constraints then sharing is swapped. However, the final result of the heuristic might miss out some assignments of D2D pairs which is considered in the optimal solution. These D2D pairs can also be missed out in the final assignments returned by this local search algorithm and in practice the local optima of this algorithm can be far away from the global solution. Moreover, as local search is an iterative improvement technique, it might take much more time to reach the solution and cannot be very useful in LTE networks.

A deferred acceptance based resource allocation algorithm (DARA) is proposed in [7] to solve the discussed problem following the stable matching algorithm presented in [14]. Preferences for both cellular UEs and D2D pairs are calculated depending on the location of D2D pairs and cellular UEs. On the basis of given preferences, a cellular UE is selected to be coupled with a D2D pair share RBs. Typically a stable matching algorithm [14] gives an optimal result to the initiator, which does not necessarily provide the optimal results to the overall system. In this algorithm, preference is calculated on the basis of distance between a D2D pair and a cellular UE only. But distance is not the only factor behind better sum rate. There are other factors like transmission power, RBs allocated to a cellular UE etc. It is assumed that a lower distance is preferred over a higher distance. However, a cellular UE experiences more interference from a assigned D2D pair and we encounter such observations in our simulations. So a reasonable weight to calculate the preferences would give better result. Different scenarios is discussed in section 4.2.

A graph based algorithm in [15], is proposed to solve a resource allocation problem which is similar to our problem. However, they do not consider QoS requirements. They propose to assign RBs of multiple cellular UE to a D2D pair whenever possible. The admissibility of a D2D pair is calculated depending on the transmission range of D2D pairs and cellular UEs [5]. In first phase of this algorithm it formulates an estimation process of required power for both D2D pair and cellular UE. After that it adopts the maximum weighted bipartite matching algorithm to calculate the feasible solution. However, in this approach some D2D pairs can be considered in admissible set which reduces the system capacity.

Huang et al. [16] propose a game theory based resource allocation mechanism where the information about the transmission parameter is incomplete. Janis et al. [17] introduce an interference aware algorithm where they propose a method for generating local awareness of the interference between D2D pairs and cellular UEs. They also exploit multiuser diversity of the cellular network to minimize the interference. Interference limited area [18] for cellular UEs has been suggested where D2D devices can share the uplink medium. On the other hand, a restricted zone is also modeled in downlink medium in [8]. Both find a candidate set of D2D pairs for allocation. But the allocation of candidate D2D pairs is not optimal.

Chapter 3

System And Channel Model

3.1 System Model

We consider a cell area consisting of only one eNB, some D2D pairs and some cellular UEs.

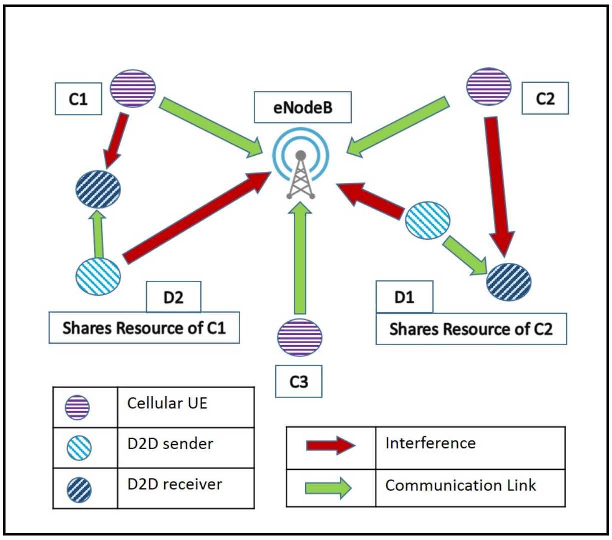

FIGURE 3.1: System Model (Uplink)

To keep the model simple, we assume that both eNB and cellular UEs are equipped with omni-directional antenna. The eNB is in charge of allocating RBs and fixing the allowed maximum transmission power for both cellular UEs and D2D pairs, to avoid unwanted interference and higher gain in system capacity. In normal scenario, the number of cellular UEs is much higher than the number of D2D pairs. Our work considers the similar scenario that is considered in [6], [7], [13]. We consider n cellular UEs and m D2D pairs, where $n >> m$. The set of cellular users is represented as $C = \{c_1, c_2, c_3, ..., c_n\}$, whereas the set of D2D pair is represented as $D = \{d_1, d_2, d_3, ..., d_m\}$. A D2D pair $d_i \in D$ contains a receiving device d_r and a transmitting device d_t.

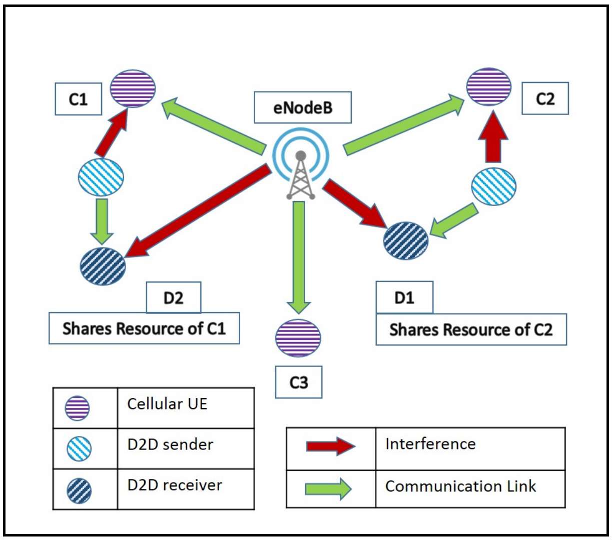

FIGURE 3.2: System Model (Downlink)

3.2 Channel Model

LTE network consists of both uplink (UL) and downlink (DL) resources. In our work, we consider the sharing of DL resources which uses Orthogonal Frequency Division Multiple Access technique[1]. In case of OFDMA, inter-cell interference can be reduced with the help of power control and resource scheduling [19]. Thus our model only considers the intra-cell interference. As the eNB transmits signal to cellular UEs using DL resources, cellular UEs only experience interferences from their shared D2D transmitters whereas D2D receivers encounter interferences from the eNB.

We consider an Urban Micro System, which follows the Rayleigh fading path loss model [6],[7], [13]. The path loss (dB unit) equation is

$$PL = 36.7\log_{10}(dist) + 22.7 + 26\log_{10}(f_c), \tag{3.1}$$

where $dist$ (meter) is the distance between transmitter and receiver and f_c (GHz) is the medium frequency. Now, the channel gain between these two devices is

$$G^{x,y} = 10^{-PL^{x,y}/10}, \tag{3.2}$$

where x and y are the two devices i.e. transmitter and receiver and $PL^{x,y}$ is the distance dependent path loss between x and y.

Chapter 4

Sum Rate Maximization

4.1 Problem Formulation

The SINR of a receiver is the ratio between the received signal power and interference with noise power. In a downlink interference model, the SINR value of a cellular UE depends on the transmitting power of the eNB, channel gain between a eNB and a cellular UE as well as the intra channel interference. Let us consider the individual transmitting powers of an eNB, a cellular UE and a D2D device are P^{eNB}, P^c and P^d, respectively. Thermal noise which is also known as the energy of Additive White Gaussian Noise (AWGN) introduced at the receiver end is denoted by T. As only intra-channel interference needs to be considered, interference occurs at a cellular UE whenever one or more D2D pairs share RBs with that cellular UE. So, the SINR of cellular UE in DL phase [13] can be represented as

$$SINR_c^{DL} = \frac{P^{eNB} G^{eNB,c}}{T + \sum_d x_d^c P^d G^{d_t,c}}. \tag{4.1}$$

where a binary variable x_d^c indicates whether the D2D pair d shares RBs with the cellular UE c or not. $G^{d_t,c}$ implies the channel gain between the D2D transmitter and a cellular UE. In the denominator of equation (4.1), summation refers to the total interferences to the cellular UE c introduced by signal from all D2D pairs, sharing RBs with c. If no D2D pair shares RBs of the cellular UE c, no intra cell interference is incurred. So the SINR of such cellular UE is

$$SINR_{c_0}^{DL} = \frac{P^{eNB} G^{eNB,c}}{T}. \tag{4.2}$$

Similarly, the SINR at the D2D receiver [13] is

$$SINR_d^{DL} = \frac{\sum_c x_d^c P^d G^{d_t,d_r}}{T + P^{eNB} G^{eNB,d_r}}, \tag{4.3}$$

where, G^{d_t,d_r} denotes the channel gain between D2D transmitter d_t and D2D receiver d_r. The summation in the numerator of the equation (4.3) indicates the total signals incurred from a D2D pair d for different cellular UE sharing the same D2D d.

The aim of this paper is to maximize the total system sum rate contributed by all individual cellular UEs and D2D pairs. According to Shannon's Capacity formula, the sum rate for a given receiver r is

$$R = B \log_2(1 + SINR_r), \tag{4.4}$$

where B is the bandwidth used to communicate and $SINR_r$ is the SINR at the receiver.

Suppose the sum rate contributed by an individual cellular UE and a D2D pair are R_c^{DL} and R_d^{DL} (using one RB) respectively. Then the objective function satisfying the QoS requirements can be formulated as

$$\max \left(\sum_c^C R_c^{DL} N_c + \sum_c^C \sum_d^D x_d^c R_d^{DL} N_c \right) \tag{4.5}$$

subject to,

$$\frac{P^{eNB} G^{eNB,c}}{T + \sum_d x_d^c P^d G^{d_t,c}} \geqslant SINR_{c,min}^{DL}, \; \forall\, c \in C \tag{4.6}$$

$$\frac{\sum_c x_d^c P^d G^{d_t,d_r}}{T + P^{eNB} G^{eNB,d_t}} \geqslant SINR_{d,min}^{DL}, \; \forall\, d \in D \tag{4.7}$$

$$x_d^c = \{0, 1\}\,, \quad \forall\, c \in C \quad \text{and} \quad \forall\, d \in D, \tag{4.8}$$

where, N_c denotes the number of RBs allocated to a cellular UE c. In case of D2D pairs, a D2D pair might share RBs with multiple cellular UEs. Double summation covers all of them.

Several constraints need to be satisfied while sharing the RBs to maintain QoS requirements. Each device requires a target SINR for maintaining normal transmission rate. $SINR_{c,min}^{DL}$ and $SINR_{d,min}^{DL}$ in (4.6) and (4.7) are the minimum SINR value for a cellular UE c and a D2D pair d, respectively.

4.1.1 Solution Approaches

Depending on the variant modes of RB sharing among the cellular UEs and D2D pairs we present three different of approaches to maximize the objective function (4.5). For easy reference, we name the approaches as

i. One to One Sharing,

ii. One to Many Sharing and

iii. Many to Many Sharing.

One to One Sharing implies that, one D2D pair can share RBs of only one cellular UE provided that no other D2D pair shares the RBs of that cellular UE yet. So the objective function needs to satisfy the following two new constraints for this category.

$$\sum_{d}^{D} x_d^c \leqslant 1\ , \quad \forall\, c \in C \tag{4.9}$$

$$\sum_{c}^{C} x_d^c \leqslant 1\ , \quad \forall\, d \in D. \tag{4.10}$$

One to Many Sharing implies that, one D2D pair can share RBs of multiple cellular UEs provided that no other D2D pair shares the RBs of those cellular UEs. In this case the objective function needs to satisfy constraint (4.9) but constraint (4.10) is relaxed as follows (number of cellular UE in the system is n)

$$n \geqslant \sum_{c}^{C} x_d^c \geqslant 0\ , \quad \forall\, d \in D \tag{4.11}$$

Many to Many Sharing implies that, D2D pairs can share RBs of multiple cellular UEs and different D2D pairs can share RBs of same cellular UE. In this case the objective function needs to satisfy constraint (4.11) but constraint (4.9) is relaxed as follows

$$m \geqslant \sum_{d}^{D} x_d^c \geqslant 0\ , \quad \forall\, c \in C \tag{4.12}$$

Algorithms for all of these approaches are discussed in following sections. Comparison with other algorithms is also be included in those section for better understanding.

4.2 One to One Sharing

We translate our resource allocation problem for "One to One sharing" approach into a maximum weighted bipartite matching problem where each D2D pair needs to be assigned to only one cellular UE. This assignment needs to satisfy necessary constraints. The goal of the assignment is to attain maximum system capacity. The procedure for this approach is discussed in 4.2.1 - 4.2.4. Simulation environment and performance evaluation will be presented after that.

4.2.1 Candidate Selection

Sharing of RBs might decrease the system capacity in some cases due to greater interference in the system. Such kind of sharing needs to be avoided to maximize the objective function (4.5). So we should only share when shared sum rate is greater than non-shared sum rate. Shared sum rate implies total sum rate attain by the D2D pair and the cellular UE when they share RBs. And non-shared sum rate means the sum rate attain by the cellular UE provided that no D2D pair share its RBs. So to be a candidate of D2D pair d following constraint should be satisfied

$$R_c + R_d > R_{c_0}, \tag{4.13}$$

where R_{c_0} denotes the sum rate attained by cellular UE c alone (no D2D pair shares its RBs), R_c denotes the sum rate attained by cellular UE c (D2D d shares its RBs) and R_d denotes the sum rate attained by D2D pair d (it uses RBs of cellular UE c).

Thus A cellular UE can not be a candidate for a D2D pair to share RBs in following cases.

i) After sharing RBs, if either the D2D pair or the cellular UE does not satisfy the constraints (4.6) and (4.7).

ii) If sharing of RBs of the cellular UE by the D2D pair does not increase the sum rate.

So candidate set of cellular UEs for a D2D pair d is $Q_d = \{c \mid c$ *and* d *can share RBs satisfying eqs. (4.6),(4.7) and (4.13)* $\}$

4.2.2 Formation of Bipartite Graph

The bipartite graph is constructed of two disjoint sets i) set of existing cellular UEs C and ii) set of all D2D pairs D^{new}. In second set there are $n-m$ dummy D2D pairs which is required for matching algorithm discussed in subsection 4.2.4. So $D^{new} = D \cup D^{dummy}$ where D is the set of existing D2D pairs and D^{dummy} is the set of all dummy D2D pairs needed.

4.2.3 Weight Calculation

The weight of an edge is crucial to find the best matching. In our case the weight of the edges represent the sum rate contribution of that D2D pair and cellular UE when they shares RBs. Edges of the constructed graph can be categorized into three groups.

i) Edges between D2D pair $d \in D$ and cellular UE $c \in Q_d$ defined in section 4.2.1.

ii) Edges between D2D pair $d \in D$ and cellular UE $c \in Q_d^{'}$, where $Q_d^{'} = C - Q_d$. Here C is the set of all cellular UEs in the system.

iii) Edges between D2D pair $d \in D_{dummy}$ and cellular UE $c \in C$.

Any D2D pair d sharing RBs with a cellular UE c of its candidate set Q_d increase the system sum rate. So the weight of the edges in the first group is $R_c + R_d$ as it is their contribution to the system sum rate. On the other hand, any D2D pair d sharing RBs with a cellular UE $c \in Q_d^{'}$ decrease the system sum rate or fails to satisfy the constraints. Such sharing should be avoided. Again an edge with any dummy D2D pair represents that the cellular UE is not sharing its RBs. So edges of second and third group has a weight of R_{c_0}.

4.2.4 Matching Algorithm

For optimal bipartite matching algorithm we use the Hungarian algorithm [20] for maximization. Hungarian algorithm is optimal depending on the weight matrix with polynomial time complexity. Though classic Hungarian algorithm is intended for minimization, but with simple modification this can be used for maximization also. Hungarian algorithm works on square weight matrix, where elements of the matrix depict the weight of the associated row and column which is a non negative value. As we have $n >> m$, we make the matrix square by adding $n - m$ dummy D2D pairs at the time of constructing bipartite graph in 5.3.1. The pseudo code of our algorithm is described in Algorithm 6.

We introduce an $n \times n$ matrix named S in line 2 of Algorithm 6 as the weight matrix. The rows represent D2D pairs and columns represent cellular UEs. The matrix is populated as discussed in 5.3.2.

Algorithm 1 Resource Allocation Algorithm (OneToOne)

1: **procedure** OneToOneSharingRA($D(d_1, d_2, \ldots, d_m), C(c_1, c_2, \ldots, c_n)$) ▷ An allocation from C(cellular UEs) to D(D2D pairs)
2: Let $S[1 \ldots n][1 \ldots n]$ be a new Matrix ▷ $S_{i,j}$ is the weight of the edge between d_i and c_j
3: Assign weight in S, as described in section 5.3.2
4: Let $M[1 \ldots n][1 \ldots n]$ be a new matrix ▷ a boolean matrix, a true value in i, j index depicts, d_i is assigned to c_j
5: M = Hungarian(S) ▷ Optimal bipartite matching algorithm which will return a boolean matrix
6: **for** $i = 1$ to m and $j = 1$ to n **do**
7: **if** $M_{i,j} = TRUE$ and $c_j \in Q_{d_i}$ **then**
8: assign RBs of c_j to d_i
9: **end if**
10: **end for**
11: **end procedure**

In line 5, the weight matrix is passed to the Hungarian algorithm for the maximum weighted bipartite matching. This algorithm returns a boolean matrix ($M_{i,j}$) containing assignments between cellular UEs and D2D pairs depending on the weight matrix. In line 7, if $M_{i,j}$ is true and c_j is a candidate cellular UE of d_i then D2D pair d_i is assigned the RBs of cellular UE c_j. The reason of this check is that Hungarian algorithm take decision from the weight matrix and has no idea about the candidacy of a D2D pair. So we should check the validity of that assignment before assigning . It is to be noted that only m rows of M is checked. Because the rest rows are for dummy D2D pairs.

Hungarian algorithm dominates the other parts of the algorithm 6 in terms of the running time which is $O(n^3)$ [20]. So the total running time of our algorithm is also $O(n^3)$ where n is the number cellular UEs.

We can derive the following lemmas and theorem from algorithm 6.

Lemma 1 : If R_{ij} is the sum rate contribution of a cellular user c_i and d_j after they share RBs and R_i is the sum rate of a cellular user c_i without sharing of RBs, then in an optimal solution, c_i and d_j can not share RBs *iff* $R_i > R_{ij}$.

Lemma 2: If an algorithm gives an optimal solution for a weighted bipartite matching problem then it will also give the optimal solution of the problem that we consider in this paper. Hence, the problem can be solved in polynomial time exactly.

Theorem 1: Our algorithm gives us the optimal solution.

4.2.5 Simulation Environment

We simulate different scenarios to evaluate the efficiency of our algorithm. We use C++ programming language to build our simulator that support the LTE system. We use the same simulation parameters used in [13], [6], [7] (Table 4.2.5). A single cell network is considered in our simulations. We consider two distributions of cellular UEs and D2D pairs; i) Cellular UEs and D2D pairs are uniformly distributed in the cell area and ii) cluster distribution model of D2D pairs discussed in [5] where the D2D pairs are uniformly distributed in a random cluster with a maximum radius of 15 meter. Each of the simulation results presented is an average of 20 different runs for a particular scenario. In the next subsection, the description and the performance of different other resource allocation (RA) algorithms compared to our algorithm is explained. To measure the performance we assume three metrics: system sum rate, total interference introduced and total SINR produced in the system.

Parameter	**Value**
Cell Radius	1000 meters
Cellular Users	250
D2D pairs	10 to 250(increments of 10)
Maximum D2D pair distance	15 meters
Cellular user transmit power	20 dBm
D2D transmit power	20 dBm
eNB transmit power	46 dBm
Noise power (AWGN)	−174 dBm
Carrier Frequency	1.7 GHz for LTE
$SINR^{DL}_{c,target}$	Random
$SINR^{DL}_{d,target}$	Random

Table 4.1: Simulation Parameters

4.2.6 Performance Evaluation

To evaluate the performance of our algorithm we compare our algorithm with some existing algorithms that address the same issue. Among them, some selected algorithm is discussed briefly in the following

4.2.6.1 Greedy Heuristic Resource Allocation Algorithm (Greedy)

A greedy heuristic resource allocation algorithm is discussed in [13] where the cellular UEs are sorted in decreasing order depending on the Channel Quality Identifier (CQI). A D2D pair with the lowest channel gain not yet assigned is selected for a cellular UE which has higher CQI if QoS constraints are satisfied. However, this algorithm may not terminate in some cases. We modify that portion of the algorithm without altering the main theme for our comparison study. A cellular UE with higher CQI is coupled with a D2D pair with the lowest channel gain can maximize the $SINR_c^{DL}$ (4.1). However, it might not be an optimal choice. Some D2D pairs might be missed out to be allocated or some D2D pairs are selected for earlier cellular UE which might give better sum rate to cellular UEs chosen later on.

4.2.6.2 Deferred Acceptance Based Algorithm for Resource Allocation (DARA)

DARA [7] follows the stable matching algorithm presented in [14]. Preferences for both cellular UEs and D2D pairs are calculated depending on the location of D2D pairs and cellular UEs. Depending on the given preference, a D2D pair selects a cellular UE to share RBs. If the preference is calculated correctly, there will be no pair of assignment which can be swapped to get more system sum rate. In this algorithm, preference is calculated on the basis of distance between a D2D pair and a cellular UE only. But distance is not the only factor behind better sum rate. It is assumed that a lower distance is preferred over a higher distance. However, a cellular UE experiences more interference from a nearby assigned D2D pair and we encounter such observations in our simulations. Moreover, in some cases, a cellular UE and D2D pair can be matched even though QoS are not satisfied.

4.2.6.3 Local Search Based Resource Allocation Algorithm (LORA)

LORA [6] uses the allocation given by the greedy algorithm [13] as the initial feasible solution. Then it swaps assignment between a pair of D2D pairs, and cellular UEs only if the swapping improves the objective function and the constraints (4.6) and (4.7) are satisfied. LORA can also face the similar problem encountered in the greedy algorithm [13]. So, a particular D2D pair can be unassigned at the end of the local search algorithm. It is very easy to find an example, where such a D2D pair can be assigned in the optimal solution.

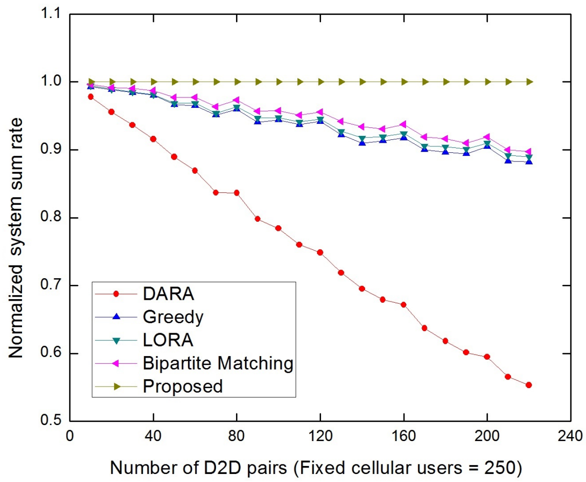

FIGURE 4.1: Normalized system sum rate of RA algorithms for uniform distributions (Normalized with respect to the proposed algorithm)

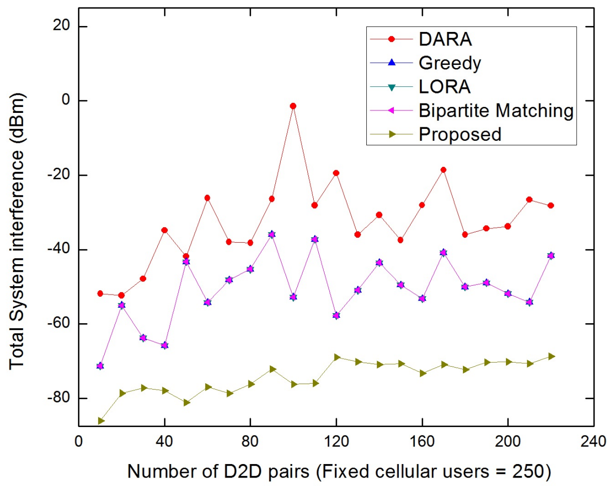

FIGURE 4.2: System interference of RA algorithms (in uniform distributions)

4.2.6.4 Weighted Bipartite Matching Algorithm

Weighted bipartite matching based algorithms are used in [5, 15] for similar resource allocation problem in D2D communications. In our simulation and performance evaluation, we also consider a similar algorithm [20].

In simulation graphs, our algorithm is named as “proposed”.

4.2.6.5 Result Comparisons and Explanation

In case of One to One Sharing approach we compare our proposed algorithm with Greedy [13], LORA[6], DARA[7] and normal Bipartite matching[5]. Figures 5.5 and 4.3 represent the total system sum rate returned by RA algorithms. To get a comparative view, we normalize all results with respect to the system sum rate of our proposed algorithm.

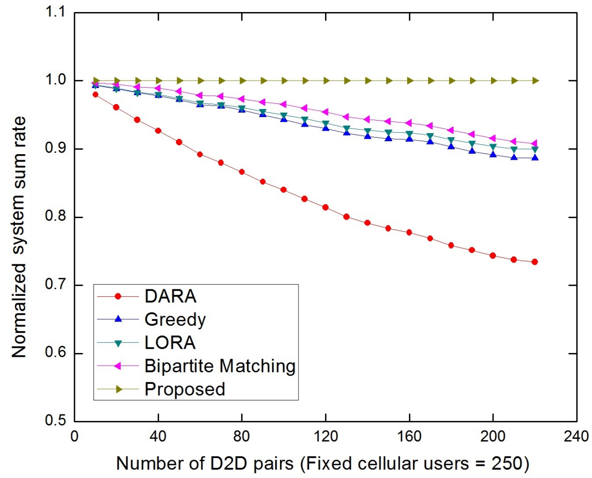

FIGURE 4.3: Normalized system sum rate of RA algorithms for cluster distributions (Normalized with respect to the proposed algorithm)

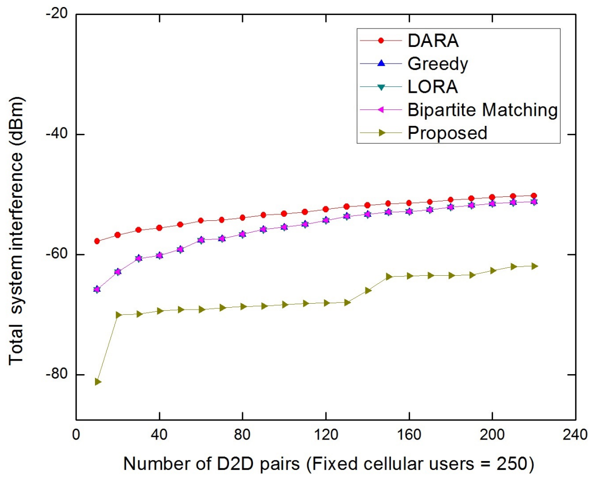

FIGURE 4.4: System interference of RA algorithms (in cluster distributions)

Figure 5.5 shows the comparison result for the scenario where D2D pairs are distributed uniformly while Figure 4.3 represents the comparison result for the cluster distributions as discussed in [5].

Simulation results show that our algorithm outperforms other algorithms in terms of the system sum rate and differences get significant with the increased number of D2D pairs for a fixed number of cellular UEs. LORA always performs better than the greedy approach as it uses greedy heuristic as the initial feasible solution and then tries to improve result. On the other hand, bipartite matching performs better than LORA. However, all the three algorithms do not consider the possibility of decreasing the sum rate by assigning a D2D pair to a cellular UE. So, if we ignore this possibility then the weighted bipartite matching always outperforms other algorithms as our results confirm. Weighted bipartite matching algorithm always gives us the optimal assignment for the given weight. But the algorithm should not select such assignments which will produce negative contribution. We consider this scenario in our algorithm in the process of candidate selection described in 4.2.1 and then use weighted bipartite matching algorithm. We also find that DARA performs the worst among all algorithms as it uses the increasing order of proximity in assigning preferences for both cellular UEs and D2D pairs which causes a lot of interference and system sum rate gets affected.

Figures 4.2 and 4.4 indicate the comparison of performances in terms of the interference introduced in the system due to sharing of RBs. Our proposed algorithm introduces the minimum interference among all other algorithms as depicted in the figures. Again DARA performs worst and all other algorithms (LORA, greedy and bipartite) introduce similar interference.

We also find that our algorithm returns the best total SINR for both shared and non-shared cellular device after the assignments. On the other hand, all the other algorithms produce similar total SINR at a D2D pairs. From (4.3), it is certain that interference is introduced at a D2D pair only by eNB and signal strength is dependent on the distance between the transmitter and receiver of a D2D pair. Thus, SINR at the D2D pairs should be similar (small differences are there due to the fact that the number of assigned D2D pairs can be different in these algorithms) if the number of assigned D2D is same.

Our algorithm assigns fewer number of D2D pairs compared to other algorithms as assigning those D2D pairs can cause the degradation of the system sum rate. According to the original problem definition [13],[7],[6] our goal is to maximize the system sum rate by adding as many D2D pairs as possible. So, we should not add those D2D pairs which can not find any such cellular UE with whom it can share RBs and the sharing results in an improved system sum rate. If any network provider wants to maximize assignments of D2D pairs even compromising the system sum rate then it becomes a different optimization problem and the solution of that problem can be investigated differently which is not the scope of this paper.

4.2.6.6 LP Solver

We convert this problem (One to One Sharing approach) into a linear problem and solve it with Gurobi. The result of the LP solver is same as the result of proposed algorithm. This is on evidence that proposed algorithm indeed provides an optimal solution.

4.3 One to Many Sharing

In this approach one D2D pair can share RBs of multiple cellular UEs but different D2D pairs cannot share the RBs of same cellular UE. For this mode of sharing sum rate increased drastically as a D2D pair can reuse more RBs.

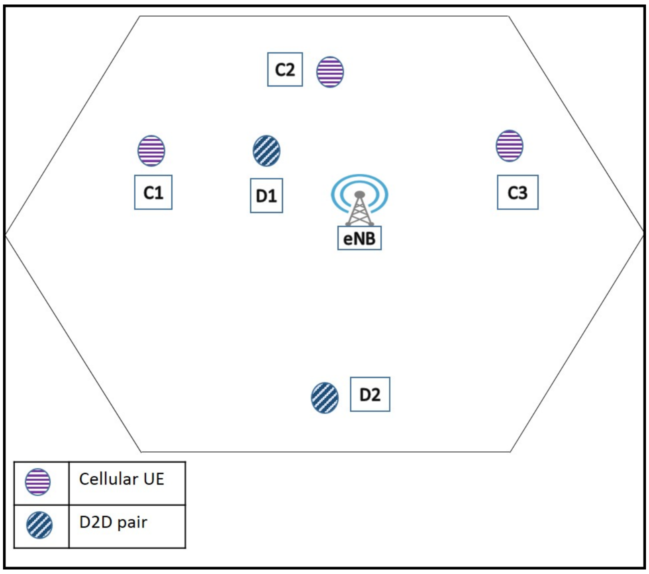

FIGURE 4.5: Examle scenario explaining fairness

This model creates two kind of solution. They are

i. Unfair Assignment and

ii. Fair Assignment.

We discuss both approaches in following subsections. For better understanding we use an example scenario showed in figure 4.5. There are two D2D pairs d_1 and d_2 and three cellular UE c_1, c_2 and c_3. d_1 is nearer to cellular UEs c_1, c_2 and c_3 than d_2. Assume that if d_2 share RBs of any cellular UE it will increase the system capacity more than if d_1 shares. Thus for one to many case scenario, if d_2 shares RBs of all cellular UEs, the system sum rate will be the highest. But it will deprive d_1 from communication.

If an RA algorithm ensures that, all D2D pairs, having non empty candidate set [see paragraph 4.2.1], will be allocated RBs then we term this as fair assignment. On the other hand, if the RA algorithm does not depend on this criteria then we term this as unfair assignment. Solution for both approach needs candidate selection method and calculation of weight of the edges discussed in section 4.2.

4.3.1 Unfair Assignment

In this approach, as single D2D pair can share RBs of multiple cellu6lar UEs, the highest weight needs to be selected for sharing each time. If Rbs of any cellular UE is shared then that cellular UE should be removed from all other D2D pairs' candidate set.

Algorithm 2 Resource Allocation Algorithm (OneToMany)

```
1:  procedure OneToManySharingRA(D(d_1, d_2, ..., d_m), C(c_1, c_2, ..., c_n), TYPE)
                                      ▷ An allocation from C(cellular UEs) to D(D2D pairs)
2:      Create candidate set of all d_j ∈ D, form graph and calculate the weight of all
    edges
                                                     ▷ Using the same method from 4.2
3:      if TYPE == FAIR then
4:          OneToOneSharingRA(D,C)
                            ▷ Using Hungarian Algorithm minimum constraint is satisfied
5:          Remove all the assigned cellular UE from candidate sets
6:      end if
7:      for i = 1 to n do
8:          if c_i is not yet shared by any D2D pair then
9:              Find d_j such that the edge between d_j and c_i has the highest weight
10:             assign RBs of c_i to d_j
11:             Remove cellular UE c_i from all D2D pairs' candidate set
12:         end if
13:     end for
14: end procedure
```

Algorithm 7 is the proposed One to Many Sharing algorithm. At first the candidate set of all D2D pairs is calculated in line 2. This candidate set represents the feasible cellular UEs one D2D pair might share RBs with. As well as in the same line weight is calculated for this sharing. As unfair approach does not care about the access rate of D2D pair in the medium, to maximize the system capacity highest weight is selected for every cellular UE in line 9. To maintain the constraint (4.9), assigned cellular UE is removed from candidate set of all D2D pairs in line 11. Though it is a greedy approach it is the optimal solution for this approach.

For unfair assignment the algorithm do not need to execute Hungarian algorithm. So the run time of the algorithm 7 becomes $O(mn)$ for unfair assignment. Where m is the number of D2D pairs and n is the number of cellular UEs in the system.

4.3.2 Fair Assignment

For this approach, all D2D pairs with non empty candidate set must be assigned RBs of at least one cellular UE. To ensure fairness we take the help from One to One RA method. Using Hungarian algorithm we choose the optimal one to one correspondence. After that we adopt the greedy approach to maximize the system capacity discussed in 4.3.1.

In algorithm 7 an argument named $TYPE$ is passed along with the set of cellular UEs C and set of D2D pairs D. If the $TYPE$ is $FAIR$ then it gets a special treatment in line 3 where algorithm 6 i.e. OneToOneSharingRA(D,C) is executed in line 4 to get the optimal sharing. It ensures that each D2D pair with non-empty candidate set is getting RBs. In line 5 the assigned cellular UEs are removed from all candidate sets to maintain the constraint (4.9). After that greedy approach discussed in 4.3.1 is executed to distribute the RBs of remaining cellular UEs among the D2D pairs.

Fair assignment approach needs to execute the Hungarian algorithm in line 4 and it dominates in term of running time. So for fair assignment approach the run time of algorithm 7 is $O(n^3)$.

4.3.3 Performance Evaluation

CORAL algorithm [18] tries to solve the maximization problem with this approach. We discuss the key points of CORAL algorithm in the next subsection. Later we discuss that how our algorithm performs better than the existing algorithm with the simulation result. We use same simulation environment discussed in section 5.4.

4.3.3.1 Capacity Oriented Resource Allocation Algorithm (CORAL)

CORAL algorithm [18] introduces the concept Capacity Oriented Restricted Region (CORE) where sharing of RBs gain negative system capacity. This CORE region is used to calculate the candidate set. CORAL algorithm has two phases. First phase finds out the highest ratio of channel gain of a cellular UE with the base station to the channel gain of a D2D pair with that cellular UE and assigns that D2D pair with the cellular UE. After assigning all the D2D second phase starts where remaining unshared cellular UEs are distributed among the D2D pairs for further capacity gain. It selects the lowest channel gain of D2D pair with any cellular UE and assign the RBs of that cellular UE to the D2D pair.

CORAL algorithm selects cellular UE for sharing RBs depending on the channel gain. But system capacity does not depend on the channel gain solely. It also depends on the transmission power, position of the receiver with respect to other transmitters using same RBs. In first phase CORAL selects the optimal cellular UE for each D2D pair and similarly in second phase it choose the optimal D2D pair for the remaining unshared cellular UEs. So it is observable that CORAL does not give overall optimal or best result rather it is a greedy approach.

4.3.3.2 Result Comparisons and Explanation

In case of One to Many Sharing approach we compare our proposed algorithm with CORAL algorithm [8] mainly. We modified some existing One to One Sharing algorithms

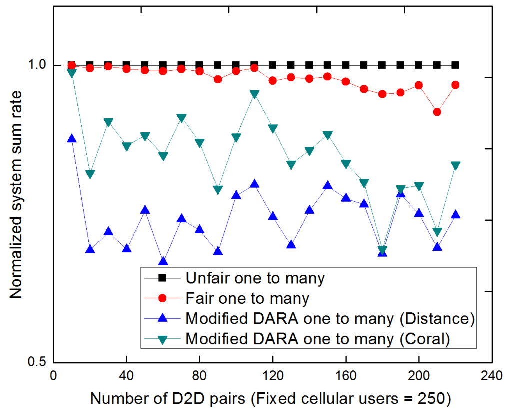

FIGURE 4.6: Normalized system sum rate of RA algorithms (One to Many Sharing)for uniform distributions (Normalized with respect to the unfair onetomany algorithm)

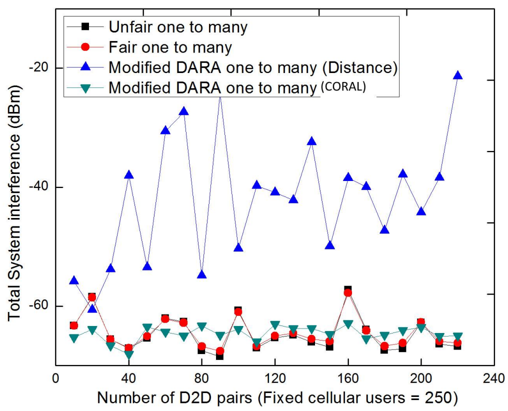

FIGURE 4.7: System interference of RA algorithms (One to Many Sharing)(in uniform distributions)

to find out their performance in this approach. The modification is to run the One to One Sharing algorithm multiple time. After each run the assigned cellular UE is removed from the list and the new list is passed to the next run as input. We use variants of DARA by taking different factors into account. We make the preference matrix depending on the weight described in CORAL.

Figures 4.6 and 4.8 represent the total system sum rate returned by RA algorithms in One to Many Sharing approach. To get a comparative view, we normalize all the results with respect to the system sum rate of our proposed "unfair One to Many Sharing" algorithm. Figure 4.6 shows comparison results for the uniform distribution of the D2D pairs whereas figure 4.8 represents the comparison result for the cluster distribution.

Figures suggest that "unfair One to Many Sharing" algorithm produces the highest sum rate as discussed in 4.3.1. However the access rate of D2D pairs might be very

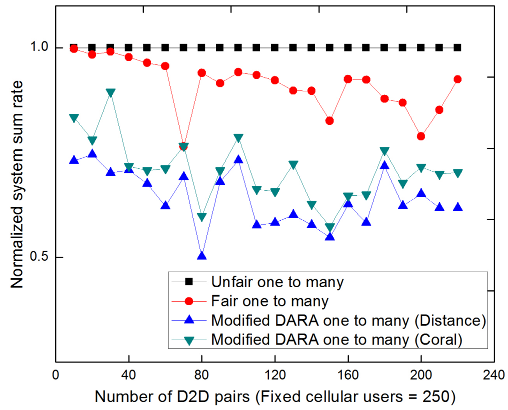

FIGURE 4.8: Normalized system sum rate of RA algorithms (One to Many Sharing) for cluster distributions (Normalized with respect to the unfair One to Many Sharing algorithm)

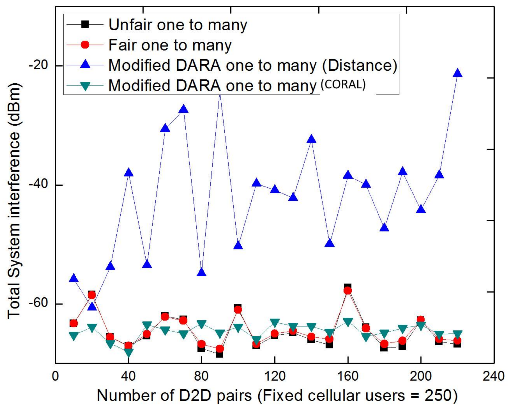

FIGURE 4.9: System interference of RA algorithms (One to Many Sharing)(in cluster distributions)

low. Just below this curve the curve of the "fair One to Many Sharing" algorithm is residing. In some cases there are downward spikes in this curve. The reason is that in those random cases, for fair assignment, some D2D pairs are allocated which reduces the system sum rate. We run multiple time DARA with higher distance higher preference. We use the weight discussed in CORAL to make the preference matrix as well and run DARA algorithm with that matrix. It performs better than that with the distance based preference matrix. The reason is that in case of CORAL weight we only assign whenever the cellular UE is in the candidate set of the D2D pair as discussed in 4.2.1.

Figures 4.7 and 4.9 show the interference introduced by different RA algorithm for One to Many Sharing along with our proposed algorithms.

4.3.3.3 Access Rate

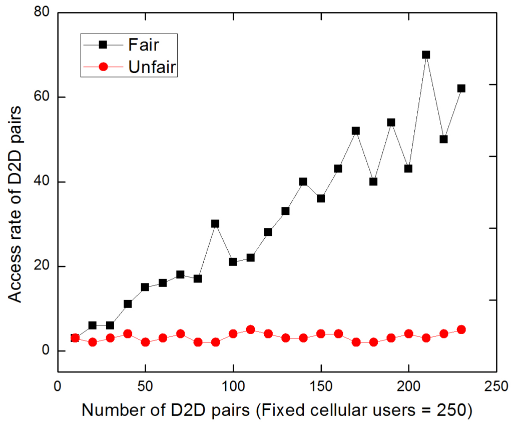

FIGURE 4.10: Access Rate (One to Many Sharing)

The access rate of D2D pairs in the system is different for fair and unfair assignment approach. Figure 4.10 depicts the access rate of the D2D pairs in the system where we can find that access rate of fair allocation is higher than unfair allocation and the difference gets significant with the increasing number of D2D pairs. It is to be noted that fair allocation does not allocate all the D2D pairs in the system. Rather it allocates all possible D2D pairs which increase the system sum rate.

4.3.3.4 LP Solver

We convert this problem (one to many unfair) into a linear problem and solve it with Gurobi. The result of the LP solver is same as the result of proposed algorithms. This is the evidence that our algorithm is indeed an optimal solution.

4.4 Many to Many Sharing

In "Many to Many Sharing" approach one D2D pair is allowed to share resources of multiple cellular UEs as well as different D2D pairs are allowed to share RBs of same cellular UE. This section mainly discusses an improved version of Graph Coloring Based Resource Allocation Algorithm (GOAL) discussed in [9]. We use same setup and graph formulation of GOAL algorithm. The graph formulation, neighbor construction, weight calculation and revised algorithm are discussed in the following subsections. The critical scenario is discussed after that where the revised algorithm improves the objective function. The revised algorithm is named as Multiple Allocation D2D (MAD) in the rest of the paper.

4.4.1 Graph Formulation

MAD resource allocation algorithm is devised on the basis of graph coloring approach. In this approach, vertex of a graph represents a D2D pair and edge represents that the connecting vertices are neighbor to each other. There might be significant amount of interference among the neighbors if they use same RBs. So the neighboring D2D pairs should not share RBs of same Cellular UE.

The cellular UEs are assumed to have different colors. D2D pairs very near to a cellular UE should not share the RBs as it creates huge interference to that cellular UE. Thus each vertex has its own candidate color set based on the distance of cellular UEs with respect to the D2D pair representing the vertex.

So a vertex can choose a color from it's candidate color set. After assigning the color, all the neighbors of that vertex need to remove the color from their candidate color set. Our goal is to assign all the colors to the vertices until candidate color sets of all D2D pairs are empty and to achieve maximum system sum rate.

Let us consider a graph $G = (V, E)$, where $V_j \in V$ represents a D2D pair and $e_{j,k} \in E$ implies V_j and V_k are neighbor to each other and they cannot share same RBs. Figure 4.11 represents the system model for Many to Many Sharing where vertices d_1, d_2, d_3 and d_4 represent the D2D pairs. Edge $e_{1,2}$ implies that d_1 and d_2 cannot share same RBs and similarly $e_{2,3}$ means d_2 and d_3 cannot share same RBs. c_1, c_2, c_3 represent three cellular UEs. From the figure 4.11 we can see that d_1 and d_2 has c_1, c_2 and c_3 in their candidate color set. Similarly d_3 has c_1 and c_2 and so on.

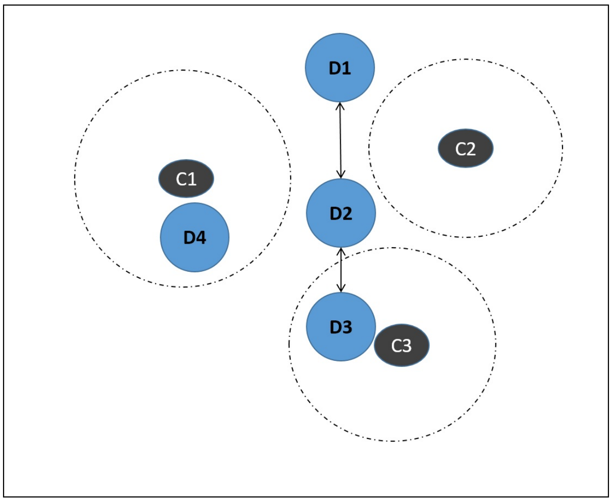

FIGURE 4.11: System Model for Many to Many Sharing

4.4.2 Neighbor Construction

GOAL algorithm introduce a term Interference Negligible Distance (INS) which dictates neighbor of a D2D. If two or more D2D transmitters using same RBs are very close to one of their receiver then that D2D receiver will face huge interference from those transmitters. It lowers the SINR at that D2D pair resulting lower system sum rate. This closeness is defined by INS. If the distance is above the INS then it is assumed that those D2D pairs can share same RBs without causing high interference to each other. There is an edge between D2D pairs if their distance is smaller than INS. INS is assumed to be fixed value in GOAL algorithm. MAD algorithm also follows this approach.

4.4.3 Candidate Color Set Formation

Another term named as SINR limited Area (SLA) is introduced in GOAL algorithm to form the candidate color set of each D2D pair. If a D2D pair close to a cellular UE shares RBs then cellular UE might face severe interference. To avoid this kind of sharing SLA is coined. So a D2D pair will not have a cellular UE in its candidate color set, if it resides in the SLA of the cellular UE. SLA for cellular UE c_i is an area where the $SINR$ at c_i is smaller than a minimum accpetable $SINR$. GOAL algorithm defines SLA by the following equation

$$SINR_i = \frac{P^{eNB} G^{eNB,c_i}}{P^d G^{d_t,c_i}} \leq SINR_{min} \tag{4.14}$$

The denominator is the interference introduced by a D2D transmitter d_t at cellular UE c_i. From the equation it is evident that GOAL algorithm does not consider the interference from multiple D2D pairs. It is possible to select multiple D2D pairs residing in the corner of SLA area, which will reduce the $SINR$ at the cellular UE. MAD algorithm also follows this approach but checks the constraints before assignment to satisfy the constraints.

4.4.4 Weight Calculation

GOAL algorithm puts a label to each vertex for each color. They use correlation degree in calculating the label. Correlation degree of a vertex j for color i is the number of neighboring vertices having the same color in their candidate set. Label is calculated using the following equation

$$L_{ij} = \frac{\log_2(1 + SINR_i) + \log_2(1 + SINR_j)}{\rho_{ij} + 1}, \tag{4.15}$$

where $SINR_i$ indicates the $SINR$ at cellular UE c_i, $SINR_j$ indicates the $SINR$ at D2D pair d_j and ρ_{ij} is the correlation degree.

However MAD algorithm does not use this label. Rather a revised label of the vertex j for color i is defined by following equations

$$W_{i,j} = R_{c_i}^{DL} + R_{d_j}^{DL} \tag{4.16}$$

$$L_{i,j}^{revised} = \sum_{h}^{X^j} W_{i,h} - W_{i,j}, \tag{4.17}$$

where X^j is the set of neighboring D2D pairs of d_j. This label implies the total loss the system incurs if it chooses d_j for the color i.

4.4.5 MAD Algorithm

MAD algorithm uses the same idea of neighbor construction, candidate color set formation of GOAL algorithm. The key differences are in weight calculation and assigning colors to the vertices.

Algorithm 3 Resource Allocation Algorithm (ManyToMany)

procedure MANYTOMANYSHARINGRA($D(d_1, d_2, \ldots, d_m), C(c_1, c_2, \ldots, c_n)$) ▷ An allocation from C(cellular UEs) to D(D2D pairs)
    create candidate color set for every D2D pair in the system ▷ It follows the procedure from 4.4.3
    create neighboring set of each D2D pair ▷ It follows the procedure from 4.4.2
    for each $c_i \in C$ **do**
        Let $N(n_1, n_2, \ldots, n_k) \in D$ containing c_i as candidate color set
        Let $W[1..k]$, $S[1..k]$ and $M[1..k]$ be three new Matrices
        for each $n_j \in N$ **do**
            $M_j = L_{i,j}$ ▷ Label is calculated using equation (4.17)
        end for
        while N is not empty **do**
            Let M_q is the lowest value ▷ Choosing the lowest loss from the labels
            if D2D pair d_q shares RBs of cellular UE c_i does not break the constraint (4.6) and (4.7) **then**
                assign color i to vertex q ▷ assigning RBs of c_i to d_q for sharing
                Remove color i from the vertex q and all the vertex neighboring to q
            else
                Remove color i from the vertex q
            end if
        end while
    end for
end procedure

In this approach, at first candidate color set for all D2D pairs are calculated in line 2 and the neighbors of all D2D pairs are calculated in line 3. This neighbor set is not changed throughout the algorithm, but the candidate color set of a D2D pair is updated in each cycle.

In line 4-19 a color is assigned to a suitable vertex. In line 8 label for each vertex M_j is calculated depending on the equation (4.17).

In line 11 the lowest label is selected for assignment but before assigning checking is done in line 12. Reason behind this checking is that, SLA and INS area could not give certainty about these constraints. Because SLA region does not consider multiple allocation in (4.14), and INS region is a fixed value set by the system administrator manually. So it can also break the constraints. If the constraints are satisfied, the color is assigned to the vertex in line 13 and the color is removed from all the neighboring vertices in line 14. But if the constraints does not hold then it is removed only from the selected assigned vertices.

4.4.6 Critical Scenario

In this subsection a critical scenario is discussed (shown in figure 4.12) where MAD algorithm performs better than GOAL algorithm. Let us consider, a cellular UE has three candidate D2D pairs d_1, d_2 and d_3 where d_1 has d_2 as neighbor, d_2 has both d_1 and d_3 as neighbor and d_3 has d_2 as neighbor. For that cellular UE, weights of d_1, d_2 and d_3 are a, $\frac{19a}{14}$ and b and assume that $a + b < \frac{19a}{14}$. In GOAL algorithm, it chooses d_1 at the very beginning as it gives the maximum value according to their equation. Later it chooses d_3 and total gain is $a + b$. But in case of MAD, it will choose d_2 at first as it gives the lowest in M and gain is $\frac{19a}{14}$ which is greater than $a + b$.

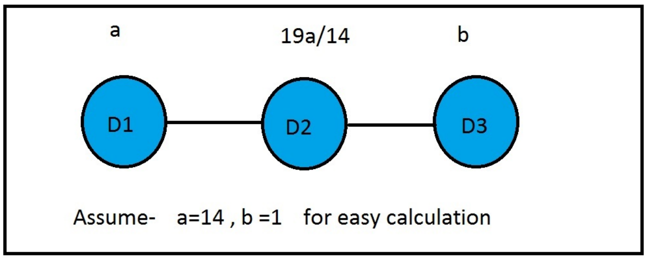

FIGURE 4.12: An Example of Critical Scenario in Many to Many Sharing

4.4.7 Performance Evaluation

We evaluate MAD algorithm by comparing with the GOAL algorithm. In normal scenario both algorithm give same result but GOAL algorithm could break constraints or give lower sum rate in some cases as discussed in subsection 4.4.6.

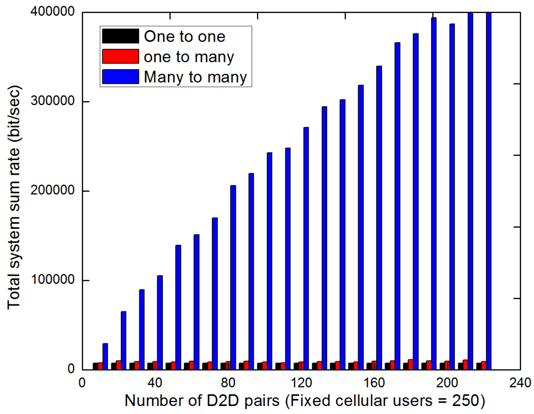

FIGURE 4.13: Comparison of the three approaches in terms of system sum rate for uniform distributions

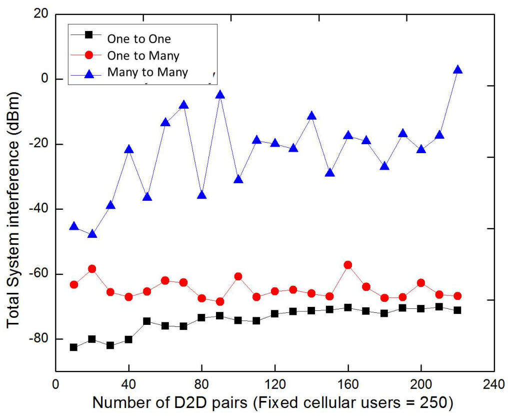

FIGURE 4.14: Comparison of the three approaches in terms of system sum rate for uniform distributions

In subsection 4.4.1, 4.4.2, 4.4.3 and 4.4.4 we have discussed the key points of the GOAL algorithm. GOAL algorithm differs from MAD at the time of selecting D2D pairs for a color when it calculates the label (4.15) and choose the highest label for assignment. However it does not check any constraints before this assignment. As discussed in earlier MAD algorithm rectifies some issues of graph coloring algorithm. MAD algorithm performs better in some critical scenario showed earlier with explanation. However we strongly discourage to follow the Many to Many Sharing approach to maximize the system sum rate. An error-nous allocation might produce a large interference in the cellular network, as multiple D2D pair is using RBs of same cellular UE.

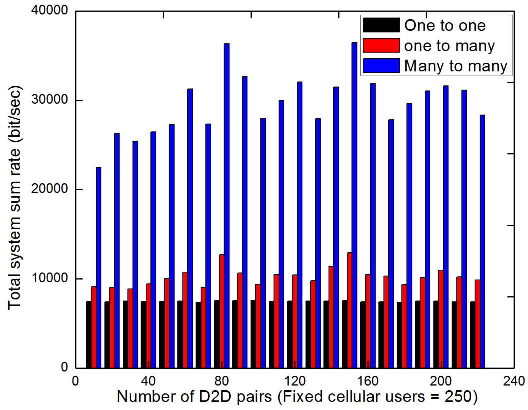

FIGURE 4.15: Comparison of the three approaches in terms of system sum rate for cluster distributions

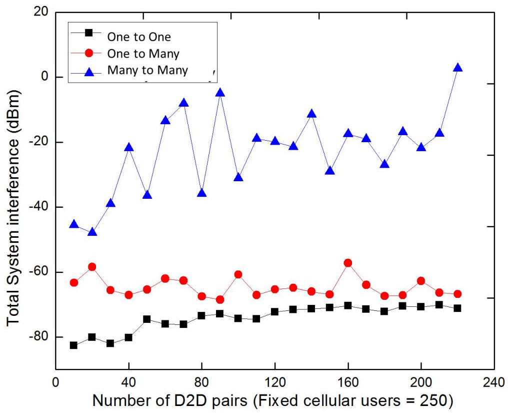

FIGURE 4.16: Comparison of the three approaches in terms of system sum rate for cluster distributions

4.5 Comparison among the Three Approaches

Figures 4.13 and 4.15 depicts the comparison of sum rate among the three approaches and figures 4.14 and 4.16 depicts comparison among th three approaches in terms of interference introduced. As expected the system sum rate and introduced interference of Many to Many Sharing approach is higher.

Summarizing above simulation results, we can conclude that our proposed algorithms returns the best overall system sum rate and the lowest total interference while satisfying the constraints in all approaches.

Chapter 5

Interference Minimization

5.1 Problem Formulation

The goal of this paper is to minimize the interference due to resource sharing while maintaining a system sum rate demand. Let us consider the transmission power of a cellular UE c_i, D2D transmitter d_j^t and eNB are P^{c_i}, $P^{d_j^t}$ and P^{eNB} respectively. We also consider T as the thermal noise at the receiver end, also known as the energy of Additive White Gaussian Noise and $x_{i,j}$ is a binary variable which indicates whether a D2D pair d_j shares RBs with a cellular UE c_i or not. It is noted that only one D2D pair can reuse the RBs of a cellular UE. Signal to Interference plus Noise Ratio (SINR) at the eNB in uplink phase while communicating with a cellular UE c_i (provided that D2D pair d_j is reusing the same RBs) is [21]

$$\gamma_{eNB,c_i,d_j} = \frac{P^{c_i} G^{c_i,eNB}}{T + P^{d_j} G^{d_j^t,eNB}} \tag{5.1}$$

where $G^{d_j^t,eNB}$ implies channel gain between the D2D transmitter d_j^t and eNB, $G^{c_i,eNB}$ implies the channel gain between the eNB and cellular UE c_i. If no D2D pair reuses the RBs, the equation (5.1) can be rewritten as

$$\gamma_{eNB,c_i,0} = \frac{P^{c_i} G^{c_i,eNB}}{T} \tag{5.2}$$

where the co-channel interference is zero because no D2D pair is sharing that resource. Similarly the SINR at D2D receiver reusing uplink resources is

$$\gamma_{d_j,c_i} = \frac{P^{d_j} G^{d_j^t,d_j^r}}{T + P^{c_i} G^{c_i,d_j^r}} \tag{5.3}$$

where $G^{d_j^t,d_j^r}$ denotes the channel gain between D2D transmitter d_j^t and D2D receiver d_j^r. Hence the total interference originates in the system due to sharing of resources by cellular UE c_i and D2D pair d_j is

$$I_{c_i,d_j} = P^{d_j^t} G^{d_j^t,eNB} + P^{c_i} G^{c_i,d_j^r}. \tag{5.4}$$

According to Shannon's capacity formula, sum rate contributed by cellular UE c_i (provided that D2D pair d_j is sharing the resources) can be represented as

$$S_{c_i,d_j} = B \log_2(1 + \gamma_{eNB,c_i,d_j}) + B \log_2(1 + \gamma_{d_j,c_i}) \tag{5.5}$$

where γ_{eNB,c_i,d_j} indicates the SINR at eNB while communicating with cellular UE c_i and γ_{d_j,c_i} indicates the SINR at D2D receiver d_j^r while communicating with D2D transmitter d_j^t and B is the bandwidth of the channel. It is noted that if no D2D pair reuses the RBs of cellular UE c_i, then the equation (5.5) can be written as

$$S_{c_i,0} = B \log_2(1 + \gamma_{eNB,c_i,0}). \tag{5.6}$$

So, the total system sum rate can be expressed as [13]

$$Z = \sum_{i=1}^{n} \sum_{j=1}^{m} \Big(x_{i,j} S_{c_i,d_j} + (1 - x_{i,j}) S_{c_i,0} \Big). \tag{5.7}$$

If we assume R as the target system sum rate then the objective function can be formulated as

$$\text{minimize} \sum_{i=1}^{n} \sum_{j=1}^{m} x_{i,j} I_{c_i,d_j} \tag{5.8}$$

subject to,

$$Z \geqslant R \tag{5.9}$$

$$\sum_{i=1}^{n} x_{i,j} \leqslant 1 \; ; \quad \forall\, d_j \in D \tag{5.10}$$

$$x_{i,j} \in \{0,1\} \; ; \quad \forall\, c_i \in C \quad \text{and} \quad \forall\, d_j \in D. \tag{5.11}$$

Sharing RBs of a single cellular UEs with more than one D2D pairs generate higher interference and sharing RBs of different cellular UEs by a single D2D pair makes the system complex. So in our proposed system multiple sharing is avoided. Constraint (5.10) implies a cellular UE can share RBs with maximum one D2D pair. A D2D pair can share RBs with one or no cellular UE. Depending on this case, we present two types of approaches to minimize the objective function (5.8). If a D2D pair must share RBs of one and only cellular UE, then we define it as **Fair Assignment resource allocation (FARA)**. It ensures the “fairness” property (same as TAFIRA). So, the following constraint is needed to add to the objective function for this category.

$$\sum_{j=1}^{m} x_{i,j} = 1 \, ; \quad \forall \, c_i \in C \tag{5.12}$$

In some cases, sharing RBs between a D2D pair and a cellular UE can also decrease the system sum rate [8]. A cellular UE c_i should not share RBs with a D2D pair, d_j if $S_{c_i,d_j} < S_{c_i,0}$, which concludes that a D2D pair shares RBs of maximum one cellular UE. We define it as **Restricted Assignment resource allocation (RARA)**. In this case, the following constraint is needed to add to the objective function.

$$\sum_{j=1}^{m} x_{i,j} \leqslant 1 \, ; \quad \forall \, c_i \in C \tag{5.13}$$

In this paper, we propose resource allocation algorithms for both the two approaches. So, our proposed problem is to minimize the total interference (5.8) while maintaining constraints (5.9)-(5.11) with additional constraint (5.12) for fair assignment and constraint (5.13) for restricted assignment.

5.2 Existing Algorithms

There are two existing algorithms TAFIRA [22] and MIKIRA [21] that consider the same problem formulation as we consider in this paper. MIKIRA uses the 0-1 minimum knapsack algorithm to allocate D2D pairs to available cellular UEs.

Theorem 5.1: In the worst case, MIKIRA provides an infeasible solution.
Proof: MIKIRA considers the interference of cellular UE (c_i) and a D2D pair (d_j) as an item (I_{c_i,d_j}) to be placed in the knapsack. If the solution of the minimum knapsack algorithm has the item I_{c_i,d_j}, then according to MIKIRA, c_i and d_j share RBs. MIKIRA does not prevent of having two items, I_{c_i,d_j} and I_{c_i,d_k} (where d_j and d_k are two D2D pairs and c_i is a cellular UE) in the final solution and same is true for I_{c_i,d_j} and I_{c_k,d_j} (where c_j and c_k are two cellular UEs and d_j is a D2D pair). Thus, MIKIRA fails to provide the guarantee of maintaining constraints 5.11 and 5.10 of the optimization problem that we consider. Figure 5.1 represents such a scenario where MIKIRA assigns both d_1 and

d_2 to c_1 as I_{c_1,d_1} and I_{c_1,d_2} are the two items which have minimum interference value. We can find a class of such bad examples in practice.

TAFIRA minimizes the interference while achieving the system sum rate demand by allocating all D2D pairs to the available cellular UEs. It is a two-phase auction based fair approach that satisfies sum rate demand while minimizing interference. In Phase-I, TAFIRA creates a bidding pool with all cellular UEs and a set of bidders with all D2D pairs. Each bidder has a greedy choice to bid for the cellular UE that produces minimum interference calculated from (5.4). Once all D2D pairs are allocated to cellular UEs, the algorithm calculates the total system sum rate according to the allocation. If the calculated system sum rate satisfies the sum rate demand according to (5.9), then TAFIRA terminates and reports the allocation as the final result. But if the demand is not satisfied in Phase-I, TAFIRA goes to Phase-II with the allocation formed in Phase-I where it releases a D2D pair and allocates it to any of the unallocated cellular UEs only if it improves the system sum rate. If TAFIRA fails to meet the sum rate demand in Phase-II, it reports that the allocation satisfying sum rate demand is not possible. Though TAFIRA can provide good solutions in average cases, the performance of the algorithm can be unbounded in the worst cases. Moreover, TAFIRA can return no solution even when it exists.

Theorem 5.2***:*** The performance of the TAFIRA, in the worst case, is unbounded.
Proof: Consider figure 5.2 where an edge between a cellular UEs (c_i) and a D2D pair (d_j) represents the interference (I_{c_i,d_j}) introduced if d_j is shared with c_i (M is a very large positive number, ϵ is a very small positive number and I_{c_1,d_1} is the smallest item among all). Now if we consider the target sum rate R, as 0 (any sum rate suffices as long as we can minimize the total interference) then TAFIRA returns the total minimum interference as $M + I_{c_1,d_1}$ (by sharing c_1 with d_1 and c_2 with d_2) whereas the optimal solution is $2(I_{c_1,d_1} + \epsilon)$ (by sharing c_1 with d_2 and c_2 with d_1). So the performance ratio of TAFIRA is unbounded (depends on the value of M).

Theorem 5.3***:*** TAFIRA can return no solution for the problem even when it exists.
Proof: Consider a similar example in figure 5.3. This graph also represents the system sum rates (sum rate contributions by any c_i and d_j due to sharing). It is to be noted that, sum rate does not only depends on the interference (5.1). Now, for this instance, TAFIRA gives total interference $2 \times I_{c_1,d_1}$, (by sharing c_1 with d_1 and c_2 with d_2) with total sum rate $2 \times S_{c_1,d_1}$, at the end of Phase-I of the algorithm. However, if the target sum rate (R) is $2(S_{c_1,d_1} + \epsilon)$, this solution is not feasible at the end of Phase-I. Even in Phase-II, the algorithm can not improve the system sum rate from $2 \times S_{c_1,d_1}$. Hence, TAFIRA can not provide any solution for this instance. However, there exists a solution (optimal) which shares c_1 with d_2 and c_2 with d_1 (total interference is $2(I_{c_1,d_1} + \epsilon)$ and the total sum rate is exactly the same as target sum rate which is $2(S_{c_1,d_1} + \epsilon)$).

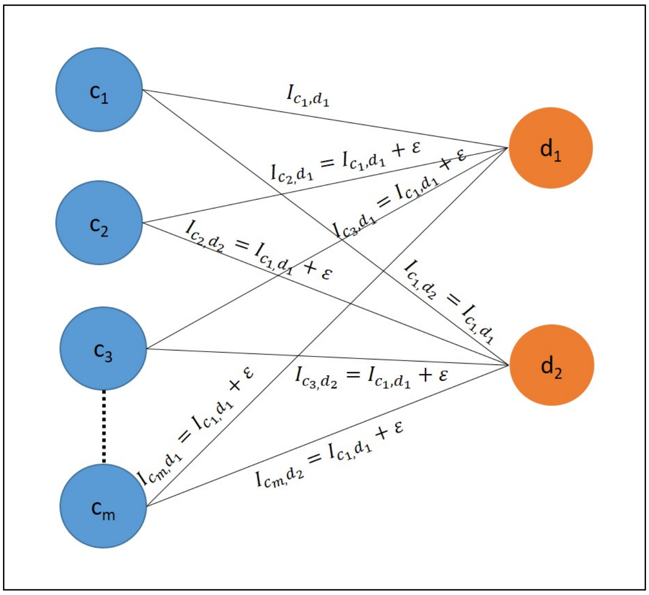

FIGURE 5.1: An infeasible solution by MIKIRA

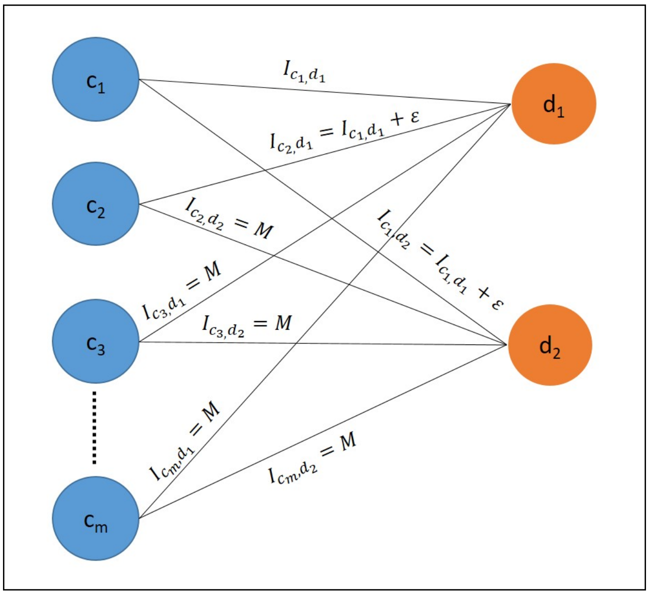

FIGURE 5.2: An unbounded solution by TAFIRA

5.3 Interference Minimization Resource Allocation Algorithm

We translate our resource allocation problem into a weighted bipartite matching problem. We propose resource allocation algorithms for both Fair Assignment and Restricted assignment. Formation of bipartite graph, calculation of the weight of edge between bipartite graph and two resource allocation algorithms are discussed in the following subsections.

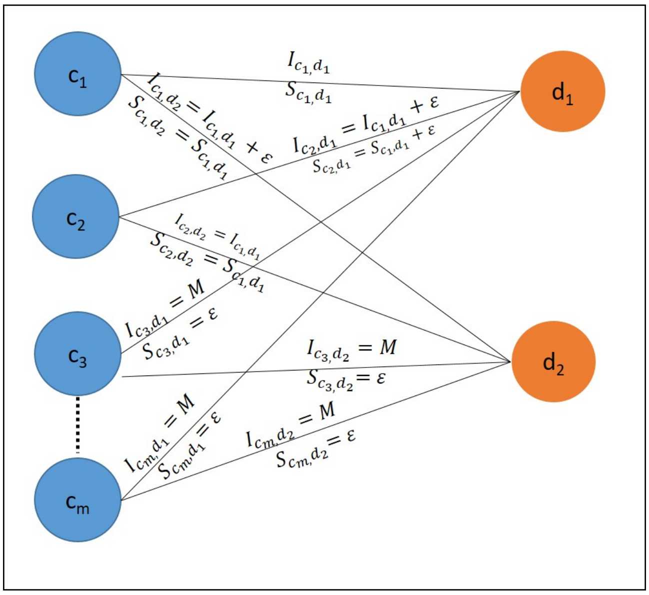

FIGURE 5.3: A failed case of TAFIRA

5.3.1 Formation of Bipartite Graph

The bipartite graph is constituted of two disjoint sets i) set of existing cellular UEs C and ii) set of D2D pairs D^{new}. In second set there are $n-m$ dummy D2D pairs which is required for matching algorithm discussed in subsection 5.3.3. So $D^{new} = D \cup D^{dummy}$ where D is the set of existing D2D pairs and D^{dummy} contains all dummy D2D pairs needed.

5.3.2 Weight Calculation

We consider cellular UEs $C(c_1, c_2, \ldots, c_n)$ and D2D pairs $D(d_1, d_2, \ldots, d_m)$ as the two sets of vertices of the matching problem where the edges between c_i and d_j represent the interferences and sum rate introduced due to the sharing of RBs between c_i and d_j. The weight of the edge is crucial to find the best matching. Initially, we run Hungarian algorithm [20] to find out the possible minimum total system interference amd possible maximum system sum rate by sharing RBs among a set of cellular UEs $C(c_1, c_2, \ldots, c_n)$ and a set of D2D pairs $D(d_1, d_2, \ldots, d_m)$.

We introduce a $n \times n$ matrix Y in algorithm 4, the input weight matrix for Hungarian algorithm (which represents the edges) where the rows are cellular UEs and columns are D2D pairs. As Hungarian algorithm deals with only square matrix, we add $(n-m)$ dummy D2D pairs in the weight matrix. In line 2-18, we calculate the value of weight matrix Y. In case of FARA algorithm, First m columns of Y holds the interference caused by c_i and d_j if they share RBs with each other and we assigned $infinity(\infty)$ to the remaining $(n-m)$ dummy D2D pairs in line 16 as we do not want them to be matched in the final solution. But in case of RARA algorithm, if (5.13) is not satisfied by any c_i and d_j then we assigned $infinity(\infty)$ to that edge as we also do not want them to be matched in the final solution.

Similarly, in algorithm 5 for sum rate maximization we need to calculate the input weight matrix for Hungarian algorithm (which represents the edges) where the rows are cellular UEs and columns are D2D pairs. A $n \times n$ matrix X is introduced for this matching algorithm. Here, in case of FARA algorithm, weight for first m columns is the system sum rate contributed by c_i and d_j if they share RBs with each other and for remaining $(n-m)$ dummy D2D pairs, the weight is calculated from (5.6) which ensures that dummy D2D pairs do not affect the selection of actual D2D pairs. On the other hand, for RARA algorithm, if (5.13) is not satisfied by any c_i and d_j then we assigned the value calculated from (5.6) to that edge as we also do not want them to be matched in the final solution.

Algorithm 4 Interference Weight Calculation

procedure INTERFERENCE($C, D, Y, Algo$) ▷ An allocation from C to D, Y is the interference matrix, $Algo$ is the algorithm name
    for all $i = 1 \dots n$ and $j = 1 \dots n$ **do**
        if $j \leq m$ **then** ▷ using (5.5) and (5.6)
            if $Algo = RARA$ **then**
                if $S_{c_i,d_j} > S_{c_i,0}$ **then**
                    $Y_{i,j} = I_{c_i,d_j}$ ▷ interference calculated from (**??**)
                else
                    $Y_{i,j} = \infty$
                end if
            else
                if $Algo = FARA$ **then**
                    $Y_{i,j} = I_{c_i,d_j}$
                end if
            end if
        else
            $Y_{i,j} = \infty$ ▷ As we do not want to allocate this pair
        end if
    end for
end procedure

5.3.3 Resource allocation algorithm

We translate our resource allocation problem for fair assignment approach into a weighted bipartite matching problem where each D2D pair needs to be assigned to one and only one cellular UE. The goal of the assignment is to attain minimum interference with maintaining a target system sum rate.

Algorithm 5 Sum Rate Weight Calculation

```
procedure SumRate(C, D, X, Algo)    ▷ An allocation from C to D, X is the interference matrix, Algo is the algorithm name
    for all i = 1...n and j = 1...n do
        if j ≤ m then    ▷ using (5.5) and (5.6)
            if Algo = RARA then
                if S_{c_i,d_j} > S_{c_i,0} then
                    X_{i,j} = S_{c_i,d_j}    ▷ interference calculated from (??)
                else
                    X_{i,j} = S_{c_i,0}
                end if
            else
                if Algo = FARA then
                    Y_{i,j} = S_{c_i,d_j}
                end if
            end if
        else
            X_{i,j} = S_{c_i,0}    ▷ As we do not want to allocate this pair
        end if
    end for
end procedure
```

Algorithm 6 Weighted Bipartite Matching (Phase-I)

```
procedure PHASE-I(C(c_1, c_2, ..., c_n), D(d_1, d_2, ..., d_m), R, Algo)    ▷ An allocation from C to D, R is the target system sum rate
    Let X[n][n], Y[n][n] be two new weight Matrices    ▷ X_{i,j}, Y_{i,j} is the sum rate and interference respectively when d_j shares RBs of c_i
    Interference(C,D,Y,Algo)
    HungarianMin(Y)
    Calculate Z from (5.7) using HungarianMin(Y)
    if Z ⩾ R then
        Allocate RBs of c_i to d_j for all TRUE value of M_{i,j}
        Return Current Allocation.    ▷ Optimal solution
    else    ▷ Phase-I failed
        SumRate(C,D,X,Algo)
        if R > HungarianMax(X) then
            Allocation satisfying R is not possible.
        else
            Allocate RBs of c_i to d_j using HungarianMax(X)
            Go to Local Search (Phase-II)
        end if
    end if
end procedure
```

We reduce the above optimization problem into a weighted bipartite matching problem where D2D pairs are assigned to cellular UEs. We pass the algorithm name *Algo* to our resource allocation algorithm that determines the execution of $FARA$ or $RARA$ algorithm. The difference between these two algorithm is only in weight calculation where algorithm 4 and 5 calculates the weights based on the algorithm name. In Phase-I, we find the minimum weight bipartite matching among cellular UEs and D2D pairs. If we find that the solution of the minimum bipartite algorithm meets the demand system sum rate then our algorithm is the optimal one. However, if the target sun rate (R) is not met then we use maximum bipartite matching algorithm to find out the possible maximum system sum rate of the system [23]. If the maximum possible system sum rate is less than the demand system sum rate then we can say that there exists no solution (demand sum rate is not achievable) for the problem. However, if we find that demand system sum rate can be achievable, then we calculate the total system interference from the assignment of the cellular users and D2D pairs returned by the maximum bipartite matching. Though maximum bipartite matching produces maximum system sum rate, but the total system interference calculated from this solution may not be the optimal one (maximum sum rate does not always imply the minimum interference). However, it is definitely a candidate (feasible) solution of our problem. So we consider this solution as an initial feasible solution of the local search algorithm (which is the Phase-II of our algorithm) and try to decrease the total system interference while maintaining the demand sum rate. The following subsections describe and analyze FARA.

5.3.3.1 Assignment Phase (Phase-I)

Initially, we run Hungarian algorithm [20] to find out the possible minimum total system interference by sharing RBs among a set of cellular UEs $C(c_1, c_2, \ldots, c_n)$ and a set of D2D pairs $D(d_1, d_2, \ldots, d_m)$. In the Hungarian algorithm, we only consider the minimization of the interference. We consider C and D as the two sets of vertices of the matching problem where the edges between c_i and d_j represent the interferences, I_{c_i,d_j} introduced due to the sharing of RBs between c_i and d_j. We introduce a $n \times n$ matrix Y in line 2, the input weight matrix for Hungarian algorithm (which represents the edges) where the rows are cellular UEs and columns are D2D pairs. We calculate the value of Y using algorithm 4 and weights are assigned based on the algorithm name. The Hungarian algorithm returns a boolean matrix ($M_{i,j}$) containing assignments between cellular UEs and D2D pairs. We calculate the system sum rate $currSum$ based on these assignments from the equation (5.7). If the system sum rate meets the target sum rate R, then we can consider this allocation as the optimal allocation of our problem (line 6). However, if the result of this minimization bipartite matching fails to met the target sum rate then we find the possible maximum system sum rate for the instance of the problem (using the maximum bipartite matching algorithm) to check whether there exist a solution or not. Please note that, we can do this checking at the start of the algorithm. However, we prefer this step later as we use the result of this step in the Phase-II of the algorithm. In line 11, our algorithm solves the maximum bipartite matching problem which gives us the optimal system sum rate. Similarly, a $n \times n$ matrix X is introduced for this matching algorithm. We calculate the value of X using algorithm 5 and weights are assigned based on the algorithm name. The boolean matrix $(N_{i,j})$ contains the optimal assignments between cellular UEs and D2D pairs considering the system sum rate and we calculate the total system sum rate from equation (5.7) by using these assignments. If the target sum rate is greater than calculated optimal system sum rate, then we can confirm that there exists no solution for the current instance of our allocation problem (line 11). However, if the target sum rate is lower than or equal to the calculated sum rate then we consider current allocation as a candidate solution. Phase-II of our algorithm is a local search technique, that takes this initial feasible solution and tries to decrease the total interference iteratively until it reaches the local optima.

Algorithm 7 Local Search (Phase-II)

1: **procedure** FARA-II
2:     **while** *improve* **do**
3:         **for** each pair $(c_i, c_j) \in C$ where $i \neq j$ **do**
4:             d_i and d_j are D2D pairs assigned with c_i and c_j receptively
5:             **if** $I_{c_i,d_j} + I_{c_j,d_i} < I_{c_i,d_i} + I_{c_j,d_j}$ and $S_{c_i,d_j} + S_{c_j,d_i} \geqslant R$ **then** ▷ Swapping
6:                 remove RBs of c_i from d_i and assign those RBs to d_j
7:                 remove RBs of c_j from d_j and assign those RBs to d_i
8:             **end if**
9:         **end for**
10:     **end while**
11:     **Return Current Allocation.**
12: **end procedure**

5.3.3.2 Improvement Phase (Phase-II)

The goal of Phase-II is to minimize the interference while keeping the sum rate above the target sum rate R. We consider any two cellular users, c_i and c_j, where c_i and c_j are sharing RB's with D2D pairs d_i and d_j respectively and try to swap these allocations whether it can minimize the interference (line 5). We also have to make sure that the target system sum rate is still maintained after this swapping. So if we can improve the solution with this swapping while maintaining the target sum rate, then we assign RBs of c_i to d_j and c_j to d_i and continue these steps until we find no such pair that can improve the solution.

5.3.4 Complexity Analysis

The running time of the Phase-I of FARA is dominated by the Hungarian algorithm which is $O(n^3)$ [20] (n is the total cellular UEs). If the total interference returned by the Phase-I of the algorithm is W, then the running time of the Phase-II of FARA is $O(n * m * W)$ (where m is the total D2D pairs). So, the overall running time of FARA is $O(\max(n^3, n * m * W))$ which is pseudo-polynomial in the worst case. However, we can get an $(1 - \epsilon)$ approximate solution for any local search algorithm (in our case phase-II) in time that is a polynomial in the input size and $\frac{1}{\epsilon}$.

5.4 Simulation Environment

We implemented the algorithms by extending NS3 (network simulator) [ns3] that supports D2D communication underlaying the LTE system. The simulation parameters are given in Table 4.2.5. Every simulation result is an average of 20 different runs for a particular scenario. The confidence interval of the mean of our experiments are quite narrow.

5.5 Performance Evaluation

We consider two existing algorithms, TAFIRA [22] and MIKIRA [21] to compare the performance of FARA. MIKIRA uses the 0-1 minimum knapsack algorithm to allocate D2D pairs to available cellular UEs and considers the interference of cellular UE (c_i) and a D2D pair (d_j) as an item (I_{c_i,d_j}) to be placed in the knapsack. If the solution of the minimum knapsack algorithm has the item I_{c_i,d_j}, then according to MIKIRA, c_i and d_j share RBs. MIKIRA does not prevent of having two items, I_{c_i,d_j} and I_{c_i,d_k} (where d_j and d_k are two D2D pairs and c_i is a cellular UE) in the final solution and same is true for I_{c_i,d_j} and I_{c_k,d_j} (where c_j and c_k are two cellular UEs and d_j is a D2D pair). Thus, MIKIRA fails to provide the guarantee of maintaining 5.11 and 5.10 of the optimization problem that we consider.

TAFIRA minimizes the interference while achieving the system sum rate demand by allocating all D2D pairs to the available cellular UEs. It is a two-phase auction based fair approach that satisfies sum rate demand while minimizing interference. In Phase-I, TAFIRA creates a bidding pool with all cellular UEs and a set of bidders with all D2D pairs. Each bidder has a greedy choice to bid for the cellular UE that produces minimum interference calculated from (5.4). Once all D2D pairs are allocated to cellular UEs, the algorithm calculates the total system sum rate according to the allocation. If the calculated system sum rate satisfies the sum rate demand according to (5.9), then TAFIRA terminates and reports the allocation as the final result. But if the demand is not satisfied in Phase-I, TAFIRA goes to Phase-II with the allocation formed in Phase-I where it releases a D2D pair and allocates it to any of the unallocated cellular UEs only if it improves the system sum rate. If TAFIRA fails to meet the sum rate demand in Phase-II, it reports that the allocation satisfying sum rate demand is not possible. Though TAFIRA can provide good solutions in average cases, the performance of the algorithm can be unbounded in the worst cases. Moreover, TAFIRA can return no solution even when it exists.

Though we prove that both TAFIRA and MIKIRA fail to provide solutions in several cases, we try to compare the results of our algorithm with TAFIRA through various simulations. We skip discussing the results of MIKIRA as we find that MIKIRA fails in most of the simulations. We consider a single cell network in our simulation. All the cellular UEs and D2D pairs are uniformly distributed in the cellular region and one eNB is placed in the center. The distance between transmitter and receiver of a D2D pair is confined within 15 meters to provide active D2D communication [22]. Other parameters of our simulation environment are the same as mentioned in [21, 22]. We consider various target sum rate. The lower bound of the target sum rate is the sum rate contributions of the channel users without sharing RBs with any D2D pairs. The upper bound of the target sum rate of a system can be found from [23].

Figure 5.4 represents the comparison of the total system interference due to sharing of RBs. RARA and FARA algorithm produces less amount of interference than TAFIRA. In RARA algorithm, we do not consider those D2D pairs which decreases system sum rate and RARA algorithm produces less amount of interference than FARA algorithm. We also find the optimal solution of the problem (implementing integer linear program in “Gurobi” [gur]) and find that RARA is either optimal or very close to the optimal. Figure 5.4 also depicts those cases where TAFIRA fails (shown as $\times$ in the graph) to produce a feasible solution even if such solutions exist. From the figure 5.5, it is clear that our algorithm outperforms TAFIRA in terms of system sum rate. Moreover, TAFIRA fails to achieve target sum rate in many cases, whereas our algorithm gives solutions in those cases too. The difference in the system sum rate gets higher with the increased number of D2D pairs for the fixed number of cellular UEs. Figure 5.6 indicates the total interference at D2D receivers. It shows that our proposed algorithms introduces significantly less interference at D2D receivers. From the results, we can conclude that our proposed algorithms (FARA & RARA) returns very close to the optimal interference by satisfying the sum rate demand. In addition, our algorithms return better system sum rate than TAFIRA while introducing less amount of total system interference. Unlike TAFIRA, our algorithms guarantee a solution if such solution exists. Moreover, our

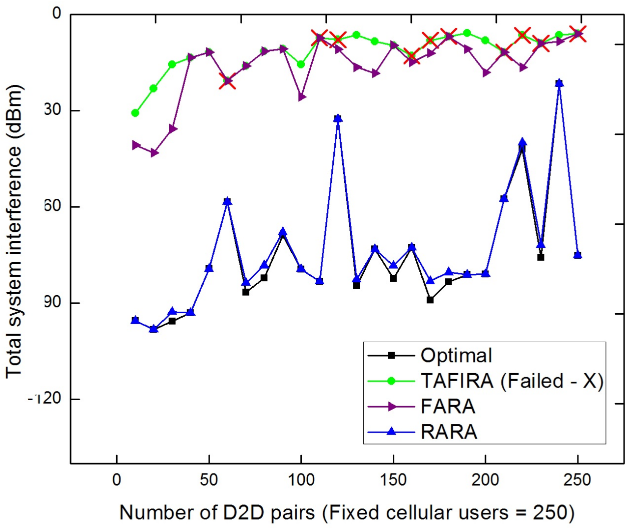

FIGURE 5.4: Comparison of total system interference

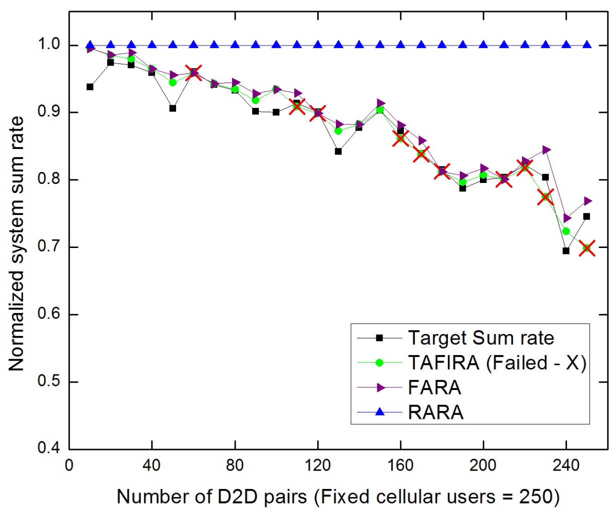

FIGURE 5.5: Comparison of normalized system sum rate

algorithms cause less interference than TAFIRA at D2D receivers. In all cases, RARA algorithm outperforms FARA algorithm because of the restriction of choosing D2D pairs (5.13). In summary, we can conclude that our proposed algorithms outperforms existing algorithms in terms of system interference while satisfying system sum rate demand.

5.6 Theorem

We can derive the following lemma and theorems from our both FARA and RARA algorithm.

Lemma 5.1: In case of RARA algorithm, a cellular UE c_i should not share RBs with a D2D pair, d_j if $S_{c_i,d_j} < S_{c_i,0}$. (equations (5.5) and (5.6))

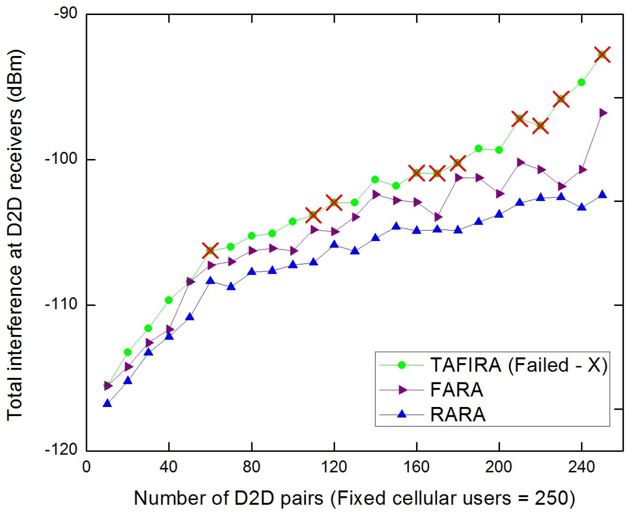

FIGURE 5.6: Interference at the D2D receivers

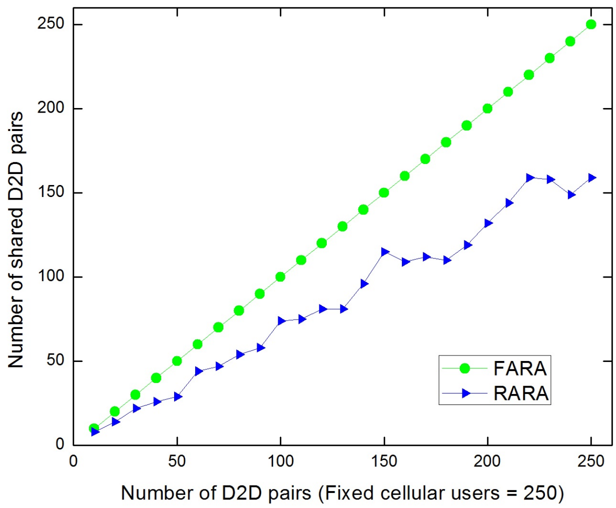

FIGURE 5.7: Number of shared D2D pairs

Lemma 5.1: The minimum bipartite matching (considering interference as edge weight) between cellular UEs and D2D pairs provides the lower bound of our minimization problem (equation 5.8).

Theorem 5.3: If the solution of the minimum bipartite matching satisfies the target sum rate then our algorithm is optimal.

Theorem 5.4: Total interference never increases in the phase-II (Local Search) while maintaining the target sum rate.

Theorem 5.5: Our algorithm always finds a solution if it exists.

Chapter 6

Conclusion

Sharing RBs of an existing cellular network with D2D pairs can increase the capacity of the system. For maximization of system capacity we propose an algorithm which removes nonviable D2D pairs and matches D2D pairs with cellular users that share RBs while maintaining QoS constraints. Our algorithm returns the optimal sum rate, introduces minimum interference in the network satisfying all constraints. Allowing multiple assignment increases the system sum rate. We shows two variants of multiple assignment, in one case access rate of D2D pair is totally ignored and in another keeping the access rate moderate maximization of sum rate is performed. For minimization of introduced interference, we propose two types of approach. In one we do not care about the access rate and in other case we give access to each D2D pair.

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