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Device-to-Device communication control in 5G networks

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Abstract

In the last decade, the number of mobile users has witnessed an unmatched growth leading to overloading the cellular network core. To keep up with this development of cellular networks, many technologies are being investigated to get to the next generation of cellular networks “the fifth generation” (5G). One of those technologies promises to offload the network core, to improve spectral and energy efficiency, to reduce delay and to maximize overall throughput. All those promises have been made by the Device-to-Device (D2D) communication technology. D2D communication is a direct communication among devices without involving the Base Station (BS).

Many challenges face D2D communication technology to fulfill its promises. Allocating resources and controlling power efficiently lead to minimize interferences and maximize overall throughput. In this thesis, we investigate the joint channel allocation and power control problem for D2D communication underlay 5G cellular networks.

In this dissertation, we propose the use of a bio-inspired method because of its efficient properties like self-organization, autonomy, scalability and adaptation. The Bee Life Algorithm (BLA) has achieved best results for many problems like job scheduling in cloud computing and packet routing in vehicular ad hoc networks. For those reasons, we have adopted BLA to solve the joint spectrum and power control problem for D2D communication underlay 5G cellular networks.

Afterward, we have proposed a new bio-inspired approach called an enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications (E-BLAD2D). The E-BLAD2D is considered as a population-based metaheuristic, suggesting an initial population generation in the basis of a simulated annealing algorithm. This non-random initialization increases the capability of obtaining promising solutions to reach optimal D2D communications in 5G cellular networks with best spectrum allocation and power control. E-BLAD2D is also based on reproduction and food foraging behaviors inspired by bees colony contributing to this optimization process. After that, we proposed another solution for the joint problem based on Matching Algorithm and BLA named Matching Bees Algorithm (MBA). This last proposition consists of using Matching algorithm (one-to-many with externalities) to generate the initial population by optimally allocating resources followed by the use of BLA to reach the best solution.

The three proposed algorithms achieve better networks throughput compared to Genetic algorithm (GA) and Particle Swarm Optimization (PSO) that are widely used to solve the joint channel allocation and power control.

Keywords

5G cellular networks, D2D communication, simulated annealing, BLA, PSO, GA.

Résumé

Au cours de la dernière décennie, le nombre d'utilisateurs mobiles a connu une croissance énorme, entraînant une surcharge sur le cœur du réseau cellulaire. Pour suivre ce développement des réseaux cellulaires, de nombreuses technologies sont examinées pour passer à la prochaine génération des réseaux cellulaires « la cinquième génération » (5G). L'une de ces technologies promet de décharger le cœur du réseau, d'améliorer l'efficacité spectrale et la consommation d'énergie, de réduire les délais et de maximiser le débit global. Toutes ces promesses ont été faites par la technologie de communication Device-to-Device (D2D). La communication D2D est une communication directe entre les appareils sans impliquer la station de base (BS).

La technologie de communication D2D doit relever de nombreux défis pour tenir ses promesses. L'allocation des ressources et le contrôle efficace de la puissance permettent de minimiser les interférences et de maximiser le débit global. Dans cette thèse, nous étudions le problème conjoint d'allocation des ressources et de contrôle d'énergie pour les communications D2D dans les réseaux cellulaires de la 5G.

Dans cette thèse, nous proposons l'utilisation d'une méthode bio-inspirée en raison de ses propriétés efficaces telles que l'auto-organisation, l'autonomie, l'évolutivité et l'adaptation. L'algorithme Bee Life (BLA) a obtenu les meilleurs résultats pour de nombreux problèmes tels que la planification des tâches dans le cloud computing et le routage de paquets dans les réseaux ad hoc et les réseaux véhiculaires. Pour ces raisons, nous avons adopté BLA pour résoudre le problème de contrôle conjoint du spectre et de la puissance pour les communications D2D dans les réseaux cellulaires 5G.

Par la suite, nous avons proposé une nouvelle approche bio-inspirée appelée « an enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications (E-BLAD2D) ». L'E-BLAD2D est considéré comme une méta-heuristique basée sur la population, suggérant une génération initiale de population sur la base d'un algorithme de recuit simulé. Cette initialisation non aléatoire augmente la capacité d'obtenir des solutions prometteuses pour atteindre des communications D2D optimales dans les réseaux cellulaires 5G avec la meilleure allocation de spectre et le meilleur contrôle de puissance. E-BLAD2D s'appuie également sur des comportements de reproduction et de recherche de nourriture inspirés des colonies d'abeilles contribuant à ce processus d'optimisation. Après cela, nous avons proposé une autre solution pour le problème conjoint basée sur le « Matching Algorithm » et BLA nommée « Matching Bees Algorithm (MBA) ». Cette dernière proposition consiste à utiliser l'algorithme de correspondance (un-à-plusieurs avec externalités) pour générer la population initiale en allouant de manière optimale les ressources et de l'utilisation de BLA pour atteindre la meilleure solution.

Les trois algorithmes proposés permettent d'obtenir un meilleur débit de réseaux par rapport à l'algorithme génétique (GA) et à l'optimisation de l'essaim de particules (PSO) qui sont largement utilisés pour résoudre l'allocation des spectres et le contrôle d’énergie.

Mots clés

Réseaux cellulaires 5G, communication D2D, recuit simulé, BLA, PSO, GA.

ملخص

في العقد الماضي ، شهد عدد مستخدمي الهواتف المحمولة نموًا لا مثيل له أدى إلى زيادة التحميل على قلب الشبكة الخلوية. لمواكبة هذا التطور في الشبكات الخلوية ، يتم التحقيق في العديد من التقنيات للوصول إلى الجيل التالي من الشبكات الخلوية "الجيل الخامس (5G)". تعد إحدى هذه التقنيات بإفراغ نواة الشبكة ، وتحسين استخدام الترددات والطاقة ، وتقليل التأخير وزيادة الإنتاجية الإجمالية. تم تقديم كل هذه الوعود من خلال تقنية الاتصال من جهاز إلى جهاز(D2D) . اتصال جهاز إلى جهاز هو اتصال مباشر بين الأجهزة دون إشراك المحطة الأساسية (BS).

تواجه تكنولوجيا الاتصال من جهاز إلى جهاز العديد من التحديات للوفاء بوعودها. يؤدي تحسين استخدام الترددات والتحكم في الطاقة بكفاءة إلى تقليل التداخلات وزيادة الإنتاجية الإجمالية. في هذه الأطروحة ندرس مشكلة تحسين استخدام الترددات والتحكم في الطاقة لشبكات الاتصال الخلوية من جهاز إلى جهاز داخل شبكات الجيل الخامس 5G.

في هذه الرسالة نقترح استخدام طريقة مستوحاة من الطبيعة نظرًا لخصائصها الفعالة مثل التنظيم الذاتي والاستقلالية وقابلية التوسع والتكيف. حققت الخوارزمية المستوحاة من حياة النحل Bee Life Algorithm (BLA) أفضل النتائج في العديد من المشكلات مثل جدولة الوظائف في الحوسبة السحابية وتوجيه الحزم في الشبكات المخصصة للمركبات. لهذه الأسباب ،

اقترحنا استخدام هذه الخوارزمية لحل مشكلة تحسين استخدام الترددات والتحكم في الطاقة لشبكات الاتصال الخلوية من جهاز إلى جهاز داخل شبكات الجيل الخامس 5G.

بعد ذلك ، اقترحنا خوارزمية جديدًا مستوحاة من حياة النحل و خوارزمية محاكاة التلدين (Simulated Annealing algorithm) لحل مشكلة تحسين استخدام الترددات والتحكم في الطاقة (E-BLAD2D) . تعمل هذه الخوارزمية على توليد الحلول الأولية علي أساس خوارزمية محاكاة التلدين. تزيد هذا التهيئة غير العشوائية من القدرة على الحصول على حلول واعدة للوصول إلى اتصالات من جهاز إلى جهاز مثلى في شبكات الجيل الخامس الخلوية مع أفضل استخدام للترددات والتحكم في القدرة. يعتمد E-BLAD2D أيضًا على سلوكيات التكاثر والبحث عن الطعام المستوحاة من خلايا النحل التي تساهم في عملية تحسين الحلول. بعد ذلك ، اقترحنا حلًا آخر للمشكلة بناءً على خوارزمية المطابقة و BLA المسمى Matching Bees Algorithm (MBA). يتكون هذا الاقتراح الأخير من استخدام خوارزمية المطابقة لتوليد الجيل الأول من خلال التخصيص الأمثل للموارد متبوعًا باستخدام BLA للوصول إلى أفضل حل.

تحقق الخوارزميات الثلاثة المقترحة إنتاجية أفضل للشبكات مقارنة بالخوارزمية الجينية (GA) و تحسين سرب الجسيمات (PSO) التي تستخدم على نطاق واسع لحل تخصيص القناة المشتركة والتحكم في الطاقة.

الكلمات المفتاحية

الاتصال من جهاز إلى جهاز(D2D) , الشبكات الخلوية للجيل الخامس (5G) , خوارزمية محاكاة التلدين , الخوارزمية المستوحاة من حياة النحل , الخوارزمية المستوحاة من الأسراب , الخوارزمية المستوحاة من الجينات الوراثية.

Thesis publications

Journal Paper

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Conference Paper

BENBRAIKA Mohamed Kamel, BITAM Salim and MELLOUK Abdelhamid, Joint resource allocation and power control based on Bee Life Algorithm for D2D Communication. In IEEE Wireless Communications and Networking Conference (WCNC) 2019, p. 1-6.

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PRAISE BE TO GOD FIRST AND FOREMOST

SALIM BITAM HAS BEEN AN IDEAL TEACHER, MENTOR, AND THESIS SUPERVISOR, OFFERING ADVICE AND ENCOURAGEMENT WITH A PERFECT BLEND OF INSIGHT AND HUMOR. I AM PROUD OF, AND GRATEFUL FOR, MY TIME WORKING WITH SALIM.

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Introduction

Introduction

Novel technologies modified the way people interchange information among themselves, mainly in wireless communication. Even though, cellular mobile networks are still relying on infrastructures. The cellular mobile customers communications are constrained by the coverage of base station (BS), and does not allow straight communication between mobile devices. Although the sender and the receiver are next to each other, the traffic routing goes over the core network. Based on this incapacity, the potential exchange of data between cellular mobile users is restricted, particularly seeing the change process of individual computing from desktop personnel computers (PCs) to portable PCs and lastly to mobile devices. Because of the leaning to shift to mobile equipment, the mobile data traffic increased over 30 Exabyte/month in 2020, assessed as eight times augmentation over 2015. Innovative connection technologies are talented in data exchanging on-demand through suitable network links, and can be capable of scaling the network capacity.

Device-to-device (D2D) communications are seen as promising approach, which permit cellular mobile equipment to interconnect among themselves directly without passing through the BSs or an access points. D2D approach targets the use of devices communicating range to improve the signal for cellular mobile equipment in a dispersed environment. To supplement each other, the D2D technology needs to cooperate with services of cellular networks. Many serious issues must be carefully investigated when scheming D2D, namely mode selection, device discovery, power and resource allocation, interference management and security.

The next generation of cellular networks, namely the fifth-generation (5G) and beyond 5G (B5G) promise to handle huge number of different kind of users, assure low latency and high data rat. D2D communication technology can help achieve those goals since it is conceived to offload network core, improve network throughput and expand cell radius. However, the low life of devices battery and the limited useful available spectrum are considered a handicap to D2D communication. To handle those issues, the researchers work on reducing energy consumption and increasing spectrum efficiency by solving the spectrum allocation and power control problem. The spectrum allocation and power control problem is a nonlinear and limited by several nonlinear constraints, which causes issues to solve it with traditional methods. Many solutions have been proposed to solve this problem and among those propositions, the bio-inspired algorithms which provided low complex and better solutions such as Genetics algorithms (GA) and Particle Swarm Optimization (PSO).

In this thesis, we propose the use of bio-inspired methods because of its efficient properties like self-organization, autonomy, scalability and adaptation. The bio-inspired algorithms help researchers thru providing pointers for systems and solution methods that compromise between the limited resources and the high demand. Among these bio-inspired approaches, the Bee-based methods achieved excellent results in many fields. As illustration, in the foraging process, the bees use their limited resources of individuals to optimize the behavior of the colony in order to discover food sources in a cost-effective way. Moreover, the Bee Life Algorithm (BLA) has achieved best results for many problems like for job scheduling in cloud computing and for packet routing in vehicular ad hoc networks. For those reasons, we have proposed a new improved algorithm based on BLA to solve the joint spectrum and power control problem for D2D communication underlay 5G cellular networks.

We used the BLA to solve the joint resource allocation and power control problem with improving the networks throughput as main objective. Moreover, in this thesis, a new bio-inspired approach called an enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications (E-BLAD2D) is used to solve the nonlinear joint problem of channel allocation and power control. Since BLA is based on random initialization, we tried to generate a non-random initial population before using BLA to solve the joint problem. E-BLAD2D is considered as a population-based metaheuristic, suggesting an initial population generation in the basis of a simulated annealing algorithm. This non-random initialization increases the capability of obtaining promising solutions to reach optimal D2D communications in 5G cellular networks with best spectrum allocation and power control. E-BLAD2D is also based on reproduction and food foraging behaviors inspired by bees colony contributing to this optimization process. Furthermore, we used another approach to improve population initialization, which is matching algorithm, leading to propose the Matching Bee Algorithm (MBA) to solve the joint spectrum allocation and power control problem. The MBA algorithm begins with allocating resources to users using Matching algorithm (one-to-many with externalities). After generating the initial population with matching algorithm, we use an improved version of the BLA to solve the tackled problematic.

This dissertation is structured into six parts, general introduction, four chapters and a general conclusion. The general introduction introduces this study by citing the motivation, the key contribution and the organization of the dissertation. Chapter 1 provides and overview of cellular networks and their generations. It presents their characteristics and key technologies used in each generation. In addition, this chapter mentions the fifth generation cellular networks (5G) and the main promising technologies of this generation and focuses on D2D communication technology, its characteristics, usage cases and main challenges in cellular networks. Chapter 2 presents the tackled problematic of joint channel allocation and power control for D2D communication. We introduce each problem separately followed by metrics of evaluation for proposed solution. Then we present a large number of related works on this subject and conclude the chapter with the problem formulation. Chapter 3 presents the first two solutions that we proposed to solve the joint problem of channel allocation and power control for D2D communications namely BLA and E-BLAD2D. For each proposed solution, numerical results are presented alongside other bio-inspired algorithms to prove the efficiency of our proposed schemes. Moreover, in chapter 4, we presented the third contribution, which is the MBA algorithm. Numerical results are presented and compared to those obtained by BLA, GA and PSO. Finally, we conclude this dissertation and point some future directions in the general conclusion.

Chapter 01

An Overview on 5G Cellular Networks and D2D Communications

Chapter 01: An Overview on 5G Cellular Networks and D2D Communications

1.1. Introduction

In this thesis, we are working on Device-to-Device communication under 5G cellular networks. In order to better understand the context of this work, some knowledge needs to be acquired first. Therefore, in this chapter, we are presenting an overview of cellular networks and its generations from 1G to 5G, and we are concentrating on the fifth generation of cellular networks and its promising key technologies. We also introduce the D2D communication for cellular networks, its classification, challenges and the promising benefits of these technology in future cellular networks. First, we are going to introduce the D2D communication in conventional cellular networks and its application. Then we discuss D2D technology in future cellular networks namely 5G.

1.2. Cellular mobile networks evolution (from 1G to 4G)

The wireless industry witnessed an astonishing growth in the past few years, in terms of number of subscribers and in the mobile technology [1]. Since the start of this century, there was a large shift from linear telephony to mobile cellular. Moreover, at the start of the last decade, statics have counted more than four times subscriptions in mobile cellular compared to fixed lines telephone systems. The operators of mobile network and the vendors gathered around the importance of designing and managing cellular networks efficiently [2].

The immediate development of cellular generation from 2G to 4G, along with all advances in technologies, the influence of services on efficiency of networks have become more dangerous [3]. Many scheming scenarios have evolved not only with 2G networks but as well with the development of 2.5G, 3G and 4G networks. Beside this, considering inter-operability among networks has yet to come [4]. Figure 1.1 shows the main differences between cellular generations, from the 1^{st} to the 5^{th} generation.

The first generation (1G) is the analog cellular technologies; it came to existence in the 1980s. Nippon Telegraph and Telephone (NTT) launched the first commercially cellular network (1G) in Japan in 1979, firstly in Tokyo metropolitan area. The second generation (2G) symbolizes primary digital systems with the introduction of the services of short message (SMS) and lower speed data [5]. The code-division multiple access (CDMA2000) and the global system for mobile communications (GSM) are the main 2G technologies, even though CDMA2000 is occasionally called a third generation (3G) technology since it meets the mobile throughput requirement of 144 kbps [6]. However, Enhanced Data rates for Global Evolution (EDGE) or Enhanced Data rates for GSM Evolution, also reaches the same requirement. In the 1990s, the 2G technologies were available. Requirements of the 3G were specified by the International Telecommunication Union (ITU), in which digital networks needed to provide a throughput of 144 Kbps for a mobile speed, and for pedestrian speeds 384 Kbps, while in indoor environments a throughput of 2 Mbps [7].

Universal Mobile Telecommunications System (UMTS), High Speed Packet Access (HSPA) and CDMA2000 EV-DO (Evolution-Data Optimized) are the principal 3G technologies, even if Wireless Interoperability for Microwave Access (WiMAX) was labelled as a 3G technology. In the 2000s, the deployment of 3G technologies have started [8].

Figure 1.1. Evolution of the mobile networks.

The fourth Generation (4G) of cellular networks was announced in the late 2000s and it was based on IP network system [9]. 4G main goal is to offer high speed, low cost, high capacity, high quality and security services for data and voice services, internet and multimedia over IP. The purpose behind the transition to IP system is to create a common ground for all heterogeneous technologies. Its throughput capability start from 100Mbps to 1Gbps [10]. To offer wireless services anywhere and anytime, the key feature of 4G is terminal mobility. Terminal mobility means automatic moving among diverse wireless networks. The 4G technology assimilate diverse existing and upcoming wireless technologies like Orthogonal

Frequency Division Multiplexing (OFDM), Multi-Carrier Code-Division Multiple Access (MC-CDMA), Large Area Synchronized Code Division Multiple Access (LAS-CDMA) and Local Multipoint Distribution Service (Network-LMDS) to provide liberty of movement and continuous roaming among heterogeneous technologies [11]. The evolution of 4G comes with Long Term Evolution (LTE) and WiMAX. In Japan, end of 2005, the first promising field experimental of 4G technologies was conducted [12].

1.3. Moving Towards fifth generation (5G)

In 2011, the 4G standards were finalized and currently networks are being installed. The communities of mobile researchers are now directing their attention towards new innovative technologies in wireless communication, which is referred to as the next generation of cellular networks technologies: The Fifth Generation (5G) technologies [13]. Based on historical, every generation last around 10 years and the next generation is born, it was predicted that 5G networks are going to be installed around 2020 [14]. The usage cases projected by IMT for 2020 5G networks and beyond mostly can be categorized as follows:

1.3.1. Mobile Broadband Enhancement: The enormous growth in every kind of data consuming devices, combined with the enhancement of multimedia applications, has caused great increase of mobile data traffic volume [15]. From 2020, mobile users expect, all the time, to be flawlessly connected, to any device and at any location. This poses severe pressures on 5G networks, which must arrange for users a seamless and a uniform connectivity experience without considering where they are or from what network/device they connect [16].

1.3.2. Massive Machine Communications: This use case discusses the great interest in Internet of Things (IoT) and the machine-to-machine communication (M2M) field [17]. Together, these denote billions of daily connected by wireless networks. One can imagine building a large number of applications by linking thousands of surrounding objects. For examples [18]:

a- Smart cities/homes, in which smart devices autonomously reduce energy cost and consumption.

b- Distant monitoring of medical and industrial equipment.

c- Distant sensing of ecological metrics like air pollution, water pressure …etc.

1.3.3. Low-latency and Ultra-reliable Communications: This use case talks about IoT applications, which are stricted with the necessities of low latency, reliability and network availability [19]. Examples include [20]:

a- Vehicle-to-Vehicle communications (V2V) in which the cars respond in real time to avoid accidents.

b- Body area networks in which vital signs are tracked and generate an emergency response if the life of a human being is at risk.

c- Wireless control of production processes or industrial manufacturing.

As showed by various use cases expected by 2020, the 5G networks will necessitate a large enhancement of performance beyond what 4G provides, which included latency, coverage, peak rate and spectral efficiency [21]. Table 1.1 summarizes the differences between 4G and what 5G networks performances is expected to be.

Key requirements	**Explanation of key requirements**	**4G**	**5G**
User experienced data rate	Minimum achievable data rate for a user in real network environment	10 Mbps	100 Mbps
Connection density	Total number of connected devices per unit area	10^5 Devices/Km^2	10^6 Devices/Km^2
Traffic volume density	Total data rate of all users per unit area	0.1 Mbps/m^2	10 Mbps/m^2
Mobility	Relative speed between receiver and transmitter under certain performance requirement	350 Km/h	500 Km/h
Peak data rate	Maximum achievable data rate per user	1 Gbps	20 Gbps
Latency	Delay from the time a packet is sent from transmitter until it is received at the receiver (several definitions exit)	10 ms	<1 ms

Table 1.1. Comparison between 4G and 5G networks [22].

1.4. 5G Networks technologies

We briefly describe the most promising key enabler technologies for 5G cellular networks in the following [23]:

1.4.1. Millimeter Wave (mmWave)

Also known as 5G new radio frequency (5G NR), it is one of the promising emerging key technology for 5G cellular networks due to its capacity of achieving the immense throughputs required for the fifth generation. The mmWave is an advanced technology for physical layer, which has lately arise to the front of research attention and might be capable of rising the challenge of achieving high-rate mobile broadband services, as well as to offer chances for reducing the wireless latency [24].

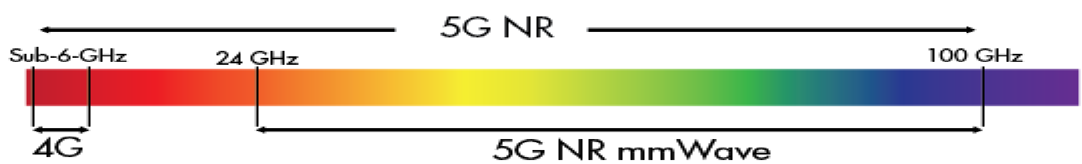


Figure 1.2. 5G New Radio frequency (5G NR): The mmWave.

MmWave uses the radio frequency spectrum between 30 and 300 GHz as illustrated in figure 1.2. However, the research experiments prolong to inferior frequencies (above 6 GHz). mmWave offer large bandwidths of spectrum in some of them can surpasses 1 GHz. The technology enabler of mmWave devices is the directional smart antennas since they can overcome the inferior propagation effects and reveal this high-frequency spectrum [25]. Nevertheless, in order to realize mmWave technology for 5G networks effectively, there are many challenges to be considered, and the most important are:

a- Adaptive beamforming and beam tracking.

b- Directional synchronization and broadcast channels.

Table 1.2. Show the mmWave radio frequency used nowadays by some country for 5G networks [26].

Country	**mmWave radio frequency**
USA	27.5 - 28.35 GHz and 37-40 GHz
Korea	26.5 - 29.5 GHz
Japan	27.5 - 28.28 GHz

China	24.25 – 27.5 GHz and 37 – 43.5 GHz
Sweden	26.5 – 27.5 GHz
EU	24.25 – 27.5 GHz

Table 1.2. mmWave radio frequency used in some country for 5G networks.

1.4.2. Massive Multiple Input Multiple Output (Massive MIMO or mMIMO)

Massive MIMO is commonly regarded as one of the key enabler of 5G technologies and is estimated to play a big part in achieving 5G goals. Massive MIMO, firstly introduced as "Large-Scale Antenna Systems" or "Full-Dimension MIMO", "Very Large MIMO", which makes a spotless break with the use of a huge number of antennas at the base station (BS) [27]. Originally, the name massive MIMO was identical to the number of antennas raises to infinity. However, like showed in figure 1.3, mMIMO is a great number of antennas at the BS with a configuration beyond the current LTE (which is 8x8). Firmly speaking, there is no big breakpoint between the massive MIMO and conventional MIMO. Compared to traditional MIMO, the additional antennas presented by massive MIMO aid to focus energy in smaller areas, by doing so, it achieves low interference stages, so that all user terminals (UTs) benefit from large enhancements in throughput. Other benefits of massive MIMO consist of cell coverage extension. Furthermore, massive MIMO becomes mainly attractive with mmWave bands. One of the greatest challenges is low-overhead attainment of channel state information (CSI) at the BS concerning the channels between the massive MIMO BS and the UTs it serves [28].

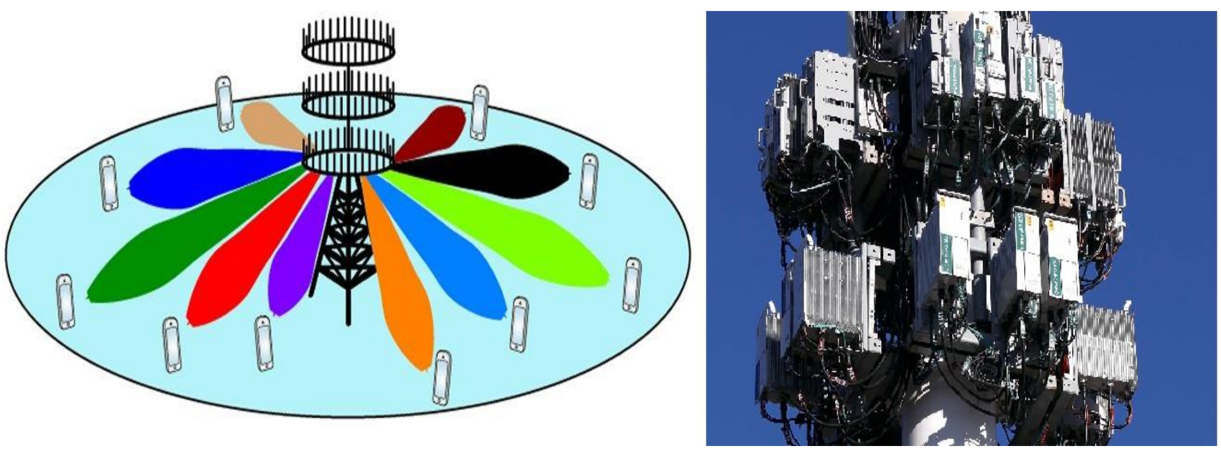


Figure 1.3. Massive MIMO for 5G networks

Beside the important performance improvements of massive MIMO, some properties are exclusive to massive MIMO. These properties that massive MIMO offer are the following:

a- Large spectral efficiencies.

b- Near-optimal performance with simple transceivers.

c- Much greener technology.

d- Substantially improved edge-user performance.

e- Flexible off-loading and load balancing.

1.4.3. Ultra Dense Network (UDN)

An UDN is a network that holds much greater density of radio resources compared to the current networks. That means the 4G macro cell will be divide to a large number of small cells each with its own base station as illustrated in figure 1.4.

The motives behind choosing the ultra-dense networks is that mmWave technology can not broadcast above 100m as coverage because of the propagation degradation in mmWave. Moreover, the BSs equipped with mMIMO antennas require a huge mass of energy to serve all users inside the macro cell. Driven by the previous reasons, small cells networks are the solution for 5G cellular networks. The density of 5G base stations is highly expected to rise up to 40 or 50 BS/Km^2. Consequently, the next generation of cellular networks (5G) is an ultra-dense cellular network [29].

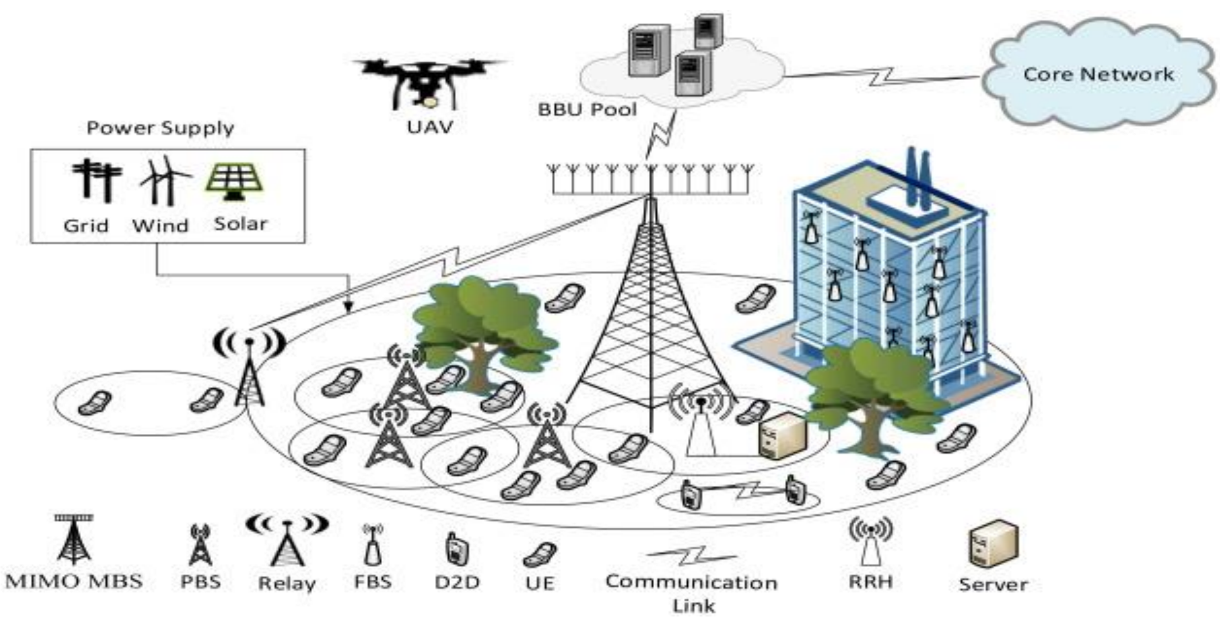


Figure 1.4. Ultra dense networks in 5G cellular networks.

1.4.4. D2D communication for 5G

Device-to-Device (D2D) communication is a promising technology for enhancing spectral efficiency in 5G cellular networks. D2D benefits from the short distance of communicating devices for improving data rates, efficient exploitation of available resources, increasing network capacity and reducing latency. The research community is permanently studying the D2D paradigm to achieve its integration in future cellular networks and to reach its full potential. D2D communication is direct communication among devices or UE (user equipment) without participation or with a restricted intervention of the base station [30]. Figure 1.5 illustrate the D2D communication under cellular networks.

In the following, we will focus on D2D communication and present its technology, classification, benefits and challenges.

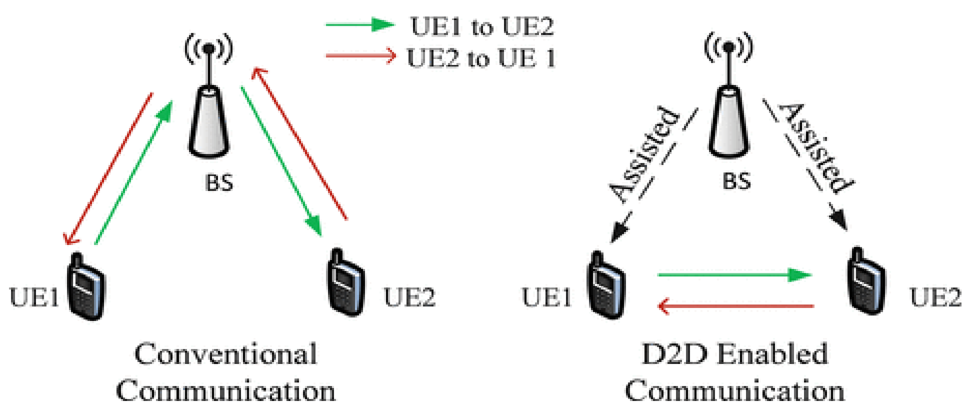


Figure 1.5. D2D communication and Conventional communication.

1.5. D2D Communications: an overview

A promising technology for spectrum efficiency in cellular networks is Device-to-Device (D2D) communication. D2D communication allows straight communication among near mobile devices without BS involvement. Due to the need for high data rate, low latency, and required quality of service (QoS) for specific communication, D2D is actuality considered as one of the key enabling of 5G cellular networks.

D2D communication continuously exists in the unlicensed spectrum, nonetheless, for three cellular generations (1G, 2G and 3G), it was not studied in the licensed spectrum. D2D was presented in the 4G, afterward LTE release 12 (in 2012) by the Third Generation Partnership Project (3GPP) [31].

5G is anticipated to be the greatest extensively used cellular network and will provide a better spectral efficiency, better energy efficiency, more than 1 Gbps for transfer data rates and resolve the restricted storage volume of devices. The outcome of direct communication among neighbor devices is lower latency and higher throughput compared to conventional communication (through the closest BS) of these devices. Furthermore, D2D technology can offer several more benefits such as QoS guarantees, congestion control and fairness. D2D communication is above all beneficial at increasing cell coverage and network throughput at the edge of each cell where the BS signals are most weaker. Even though, D2D communication comes with many benefits, many open challenges are still undergoing investigations to make use of this technology successfully. To be precise, D2D communication will necessitate a bright mode selection (cellular or D2D) algorithm, an efficient device discovery, an effective resource management and power control techniques, mobility management protocols and a strong security procedures.

1.6. Basics of D2D communications

D2D potential to enhance future generations of cellular networks has led to the assimilation of D2D in numerous areas counting vehicular networks [32], public safety services [33], multi hop relaying [34], cellular offloading [35] and proximity based services [36]. D2D communication supports local data services over all casting mechanisms (unicast, group cast and broadcast). Facebook, Waze and Tinder are appropriate examples of D2D communication applications. Streaming services similar to IPTV and Google Chromecast can be assisted by D2D communication by creating clusters. Data offloading is as a remarkable use case, where a device can turn to a hotspot. The BS can offload data in that device through peak hours and other users can take data from that device directly.

D2D communication can be categorized to two classes, In-band D2D (by using cellular spectrum) and Out-band D2D (using unlicensed spectrum) as illustrated in figure 1.6.

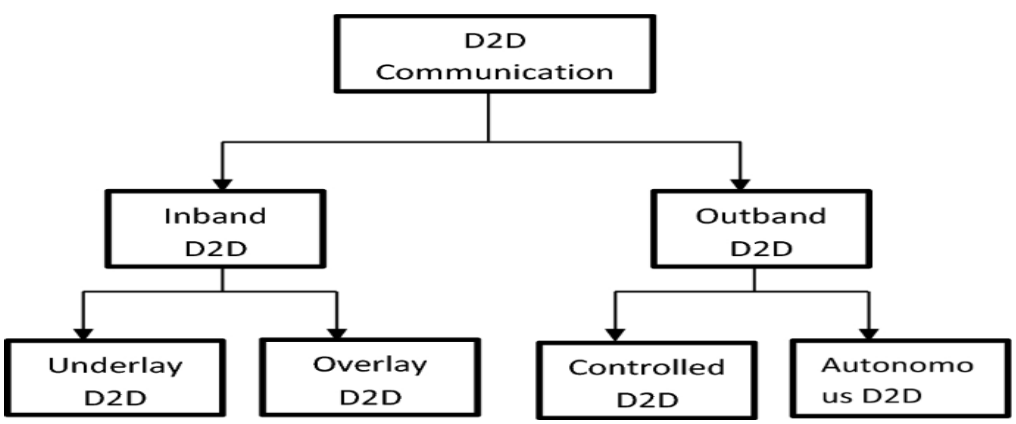


Figure 1.6. Classification of D2D communication.

1.6.1. In-band D2D communication: In this case, the cellular spectrum resources are shared by both cellular and D2D communications. In-band D2D communications are categorized into overlay and underlay.

A. In-band underlay communication

D2D and cellular users compete and share resources allocated to cellular users, causing improvement of spectral efficiency. The cellular users have dedicated resource blocks, and D2D senders reuses these resource blocks [37]. Underlay communication improve cellular networks performance by assuring better spectral efficiency, nonetheless it is the origin of interference on cellular communication by D2D communication (and cellular causes interferences on D2D communication). Although a complex resource allocation algorithm can answer this disadvantage, this algorithm will be the cause of higher computation overhead at BS.

B. In-band overlay communication

A portion of spectrum is dedicated to D2D communication. This decreases interference problem because both, cellular and D2D communications use their distinct spectral bands. The benefit of this class of D2D communication is its ability to improve scheduling and power control for D2D communication [38]. In addition it improve signal strength in relay assisted networks and spectral efficiency [39], [40].The main limitation of in-band overlay communication is that the portion of spectrum dedicated to D2D might be left unused efficiently which results to mediocre resource exploitation and decrease throughput.

1.6.2. Out-band D2D communication: In this mode, D2D communication uses unlicensed spectrum and cellular devices takes place over licensed spectrum. Because D2D and cellular communications use different spectrum bands, the spectrum interference problem is eliminated for cellular links produced by D2D devices and vice versa. Nevertheless, out-band D2D has problems in organizing communications on two distinct bands since D2D communication happens on a another radio interface. Out-band D2D is categorized to two subcategories: Autonomous D2D and Controlled D2D.

A. Out-band autonomous communication

In autonomous out-band, D2D communication is controlled by the communicating devices in D2D mode contrary to the cellular communication where the BS controlled the communications. This method considerably reduces the workload on the network and as no major alterations are needed during BS positioning, this is a mind-catching solution for mobile service providers and the operators. The devices using D2D mode are in charge of resource allocation to recent arriving devices which lessens the signaling overhead of the network [41]. This essential benefit makes the placement of BS easier since the devices can transfer diverse traffic requests within themselves [42]. This lessens the overhead on the network. An important challenge faces out-band D2D communication is how to coordinate communication on dissimilar bands.

B. Out-band controlled communication

In this category of communication, the matching among radio interfaces is the BS responsibility. Spectrum resources are allocated in advance to D2D users so they can equally compete and utilize the industrial, scientific and medical band (ISM) resources [43]. The BS can preferred a particular user to meet the QoS necessities. This increases networks performance (throughput and resource efficiency). Nonetheless, one obvious disadvantage of this type of communication is the augmented signaling overhead alongside the growth of network size. This causes long delays and deteriorates the network performance.

1.7. D2D communication : use cases, enabling technologies

1.7.1. D2D communications use cases

D2D communication did not get the attention of researchers only for its performance gains but due to practical exigence of new applications. Figure 1.7 illustrates some of the use cases and main applications of D2D communications.

a. **Traffic offloading:** D2D communication is in in-band underlay cellular communication. In this scenario, D2D communication is used to lessen the load of BS. For example, if the devices are mobile and the meeting QoS requirement is difficult, the solution is to proceed with tolerant delay services to offload the network. Nevertheless, if either or both communicating devices are immobile, then D2D links is considered for offloading services such as cooperative streaming and social gaming with enhanced results [44].

b. **Provision of emergency services:** If there is no coverage of the network, this application scenario is the solution. Emergencies is the perfect scenario for this use case, like when the cellular infrastructure is damaged, partially or completely (for example due to natural disaster). The neighbor devices can establish connection autonomously among themselves and organize a D2D communication even in the nonexistence of the BS. This use case is like Mobile Ad-hoc Networks (MANETs). Yet, the MANETs operate in unlicensed spectrum while D2D communications take place on licensed spectrum.

Figure 1.7. Use Cases of D2D Communication.

c. **Extension of cellular coverage:** At each cell edge, the cellular users experience bad or decreased signal strength and augmented channel fading. However, by using D2D links, devices can relay the transmission to the base station. This improves network throughput, which is affected by the users in the edge of cells.

d. **Reliable health monitoring:** For health monitoring, reliable communication is considered an essential obligation. Patients equipped with devices need at every moment to communicate with the sink node to observer the health of that patients. D2D links can afford enough reliability to reach a completely effective health monitoring system.

e. **Mobile tracking and positioning:** Object tracking and accurate positioning are an essential share of wireless communications since various location-based routing protocols greatly depend on those information [45], [46]. D2D communication can simplify obtaining that information by deploying outdoor devices. The location of these pre-installed devices is known, then several multi lateration [47] based positioning techniques are used to assess the position of indoor and outdoor mobile devices with worthy accuracy.

f. **Data dissemination:** Another evolving application is data dissemination, which use proximity based and direct data transmission features. Besides augmenting the probability of receiving data, the above-mentioned service can as well create new sources of income for the operators. For example, the people passing by a shopping mall can receive discount offers and promotion sent by the mall. Theaters can inform people entering the cinema about movies like show times and release dates. As well as advertising agencies, they can aim a group of people by means of social-aware D2D communications [48], [49].

1.7.2. Enabling technologies

The traditional cellular system is based on a BS and mobile terminals. An innovative architecture was introduced in [50] to enable direct communication of mobile devices with a short-range communication architecture. The authors suggested using the name "mobile devices" as a replacement for "mobile terminals" since, in reference to traditional cellular architecture; the services do not end at the device. The idea of merging ad-hoc and cellular architecture was also suggested in [51]. The system was designed for multi-player gaming, in which the cellular network were used for distribution of high scores and updating maps and ad-hoc links were formed for the game. Founded on pre-mentioned studies, a number of short-range ad-hoc communications technologies have been suggested like Ultra-Wide Band (UWB), Zigbee and Bluetooth Low Energy (BLE).

a. **UWB communications:** According to the Federal Communications Commission (FCC), UWB communications uses a bandwidth below 500 MHz in frequency range between 3.1 to 10.6 GHz. This sorts UWB as sensitive environment indoor communications. Wireless monitors and video players use the above-mentioned range for transmitting data up to 480 Mbps.

UWB is an ideal candidate for exact localization for indoor environment, which can accompany the Global Positioning System (GPS).

b. Zigbee: It is founded on the IEEE 802.15.4 standard and its objective is low-data rate use cases. The Zigbee association has been occupied with smart home and industrial automation solutions since they generally work with data rates between 20 and 250 kbps. Zigbee can employs three network topologies (star, cluster tree and mesh) and afford multi hop routing. Some fresh works proposed using Zigbee for wireless body area networks in indoor environments like hospitals or homes [52].

c. Bluetooth Low Energy technology: BLE is the enhanced version of Bluetooth Low End Extension (BLEE). Its first introduction was by Nokia in 2004 to afford connection among mobile terminals and small devices. BLE can improve data rates (get to 1 Mbps) with faster synchronization. We can divide BLE products in two categories, which are dual mode chips and standalone chips. The standalone chips communicate only with each other, meanwhile, the dual-mode chips communicate also with other devices.

1.8. D2D Communication in 5G technologies

Over the previous few years an exceptional development of D2D communication has been made, several issues need to be solved before D2D technology can be beneficial for 5G networks. As showed in figure 1.8, we now debate how D2D technology can be useful to future 5G cellular networks (applications and technologies).

1.8.1. Hyper dense networks

Future generation networks are estimated to change from the centralized networks to non-linear heterogeneous and random networks [65]. Private organizations are expected to install a combination of networks module (including Road Side Units, femto-cells and Wi-Fi access points) in an environment ultra-dense. A dense network setting consists of diverse types of opportunities and issues in contrast to conventional cellular networks [66]. The existence of huge number of UEs can be used to feat social networking. Further explicitly, trust based ultra-dense networks can be used to guarantee safe exchange of data among devices [67] while efficiently managing network resources. The UEs can also correct themselves in way users asking common data can be simplified. This can consequently assure efficient resources utilization while instantaneously decreasing the load on BS [68] by dropping the diffusion of redundant data to UEs. Even with these progresses, exceptional consideration should be given to design matters [69] affecting authentication and devices mobility in the network. Interference in heterogeneous networks is another upsetting issue. In this framework, interference from adjacent small networks and access points is estimated to rise exponentially, which will reduce D2D performance.

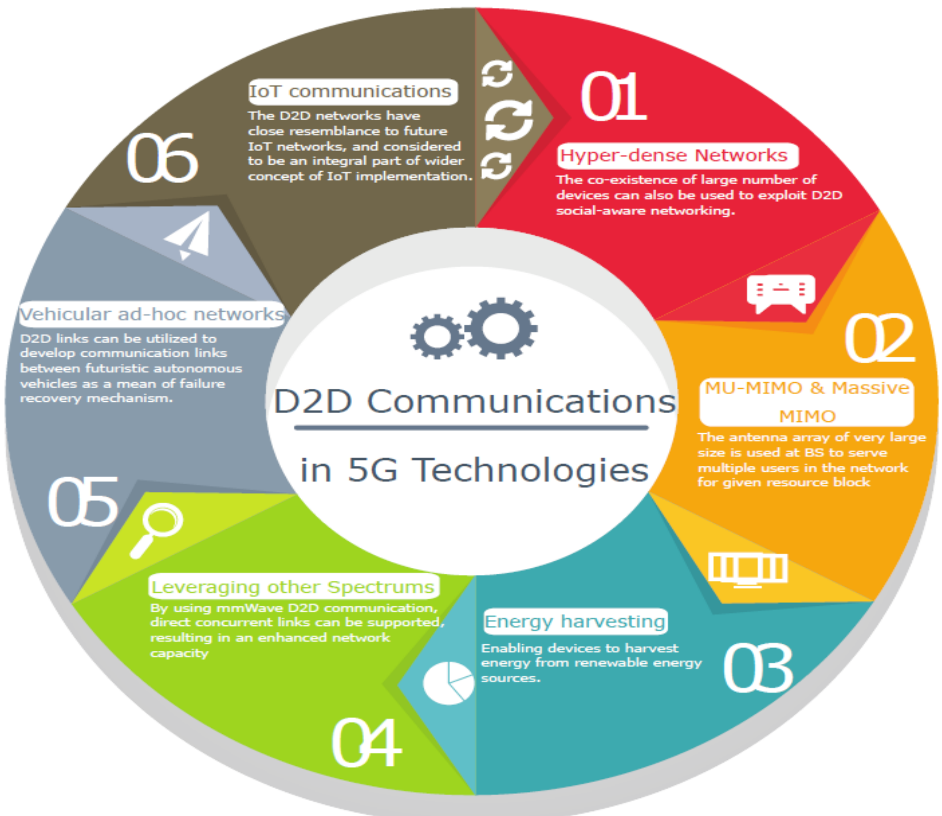


Figure 1.8. D2D applications and technologies.

Even though network interference elimination schemes can be beneficial, these techniques need a priori awareness of the channel. Moreover, the feasibility of power alteration approaches may also require to be checked since small intermission of logical time can disturb the transmissions adaptive power.

1.8.2. Multi user MIMO and massive MIMO

Multi user MIMO (MU-MIMO) is an important technology, which has been adopted to several systems counting LTE-A to achieve greater user mixture gain. The combination of MU-MIMO and D2D can increase spectral efficiency however it increases inter-cell and intra-cell interference. In addition to MU-MIMO, the massive MIMO systems can be engaging to increase the uplink dependability of D2D communication. The massive MIMO is an antenna array of enormous size used at the BS to attend to many users in the network [70]. It is confirmed that channels are almost orthogonal for all users. This permits simple reception or transmission signal processing systems while alleviating the effect of interference [71], [72]. This accordingly indicates that the use of massive MIMO alongside D2D for uplink communication can achieve nearly zero interference via energy efficient methods at the devices. Although this unique benefit of using massive MIMO for D2D communication, the outcome of interference for Cellular Users (CU) to D2D pairs still occur. Precisely, for a specific dimension of antenna array and growing number of devices, the D2D uplink can undergo significantly big interference.

1.8.3. Energy harvesting in D2D communication

The problematic impacts of exponential growth in mobile users on earth atmosphere have begun to become more obvious with passing day. The diagnosis delivered by [73], specifies that the carbon footprint of mobile communications will yearly rise, by 2020 it will reach up to 11 Mto CO2, which is the same to the carbon footprint produced by 2.5 million families in entire Europe. Thus, to lessen the energy consumption systems such as ambient and dedicated energy harvesting have been suggested. For this concern, radio frequency (RF) energy harvesting (storing energy by means of electromagnetic waves) has grown great research awareness. It is mostly due to double nature of RF signal, which are the aptitude to transfer power and information at the same time. That is why the energy harvesting has lately been explored in mobile networks [74], relay assisted networks [75] and cognitive networks [76]. Pre-charged batteries usually power D2D devices. Due to the repeated transmission of data, greatest part of their energy is degenerate while processing RF signal and transmitting. These devices come to be futile once their batteries are worn out. One encouraging solution to solve this challenge is to permit these devices to gather energy from renewable energy sources. The harvested energy can considerably expand the lifetime of devices.

1.8.4. Exploiting new spectrum bands

A favorable key technology for the future 5G cellular network is mmWave bands [77]. mmWave comprises a wide variety of carrier frequencies functioning on the frequency band of 30-300 GHz. It offers short range, high bandwidth connectivity for cellular devices. The mmWave band has numerous wanted features, which contain high bandwidth, reasonable isolation, compatibility with directional broadcasts and dense deployment. In mmWave networks and using D2D communication, direct simultaneous links can be maintained, resulting in an improved network capacity [78]. The authors in [79] debated about challenges of employment of mmWave technology for 5G cellular networks and highlighted the effect of users' mobility on the performance worsening. Nonetheless, to address this issues, the authors in [80] showed that directional antennas would be necessary for successful incorporation of D2D communication underlying mmWave schemes. It is obvious that mmWave alongside D2D communication can produce important income for mobile service providers and network operators [81], however the high absorption rate and extend exposure to mmWave can be harmful for humans.

1.9. D2D Communication Challenges

D2D communications mainly faces five challenges namely, mode selection, device discovery, resource allocation and power control, mobility management and security, as illustrated in Figure 1.9. Mode selection is essential for D2D communications to be efficient, nevertheless, many schemes were proposed, but even with these improved solutions, challenges like stable mode selection and mode alteration overhead still exist.

Device discovery for D2D communications is also important. Many studies proposed schemes like quick and asynchronous device discovery. Yet these proposed schemes needs to be energy efficient. Nonetheless, the key challenges of device discovery are synchronization and the frequency of discovery. Resource and power management along with decreasing interference are under massive investigation, numerous approaches like linear optimization, game theoretic optimization, graph theoretic optimizations and admission control have already been proposed. However, issues like role of interference in D2D and device densification are still under investigation. Mobility and handover criteria are main challenges that need further research. Security is also an important issue for D2D communications. Application and physical layer authentication systems have been suggested. Nonetheless, they did not take in consideration the tradeoff between security and energy issue.

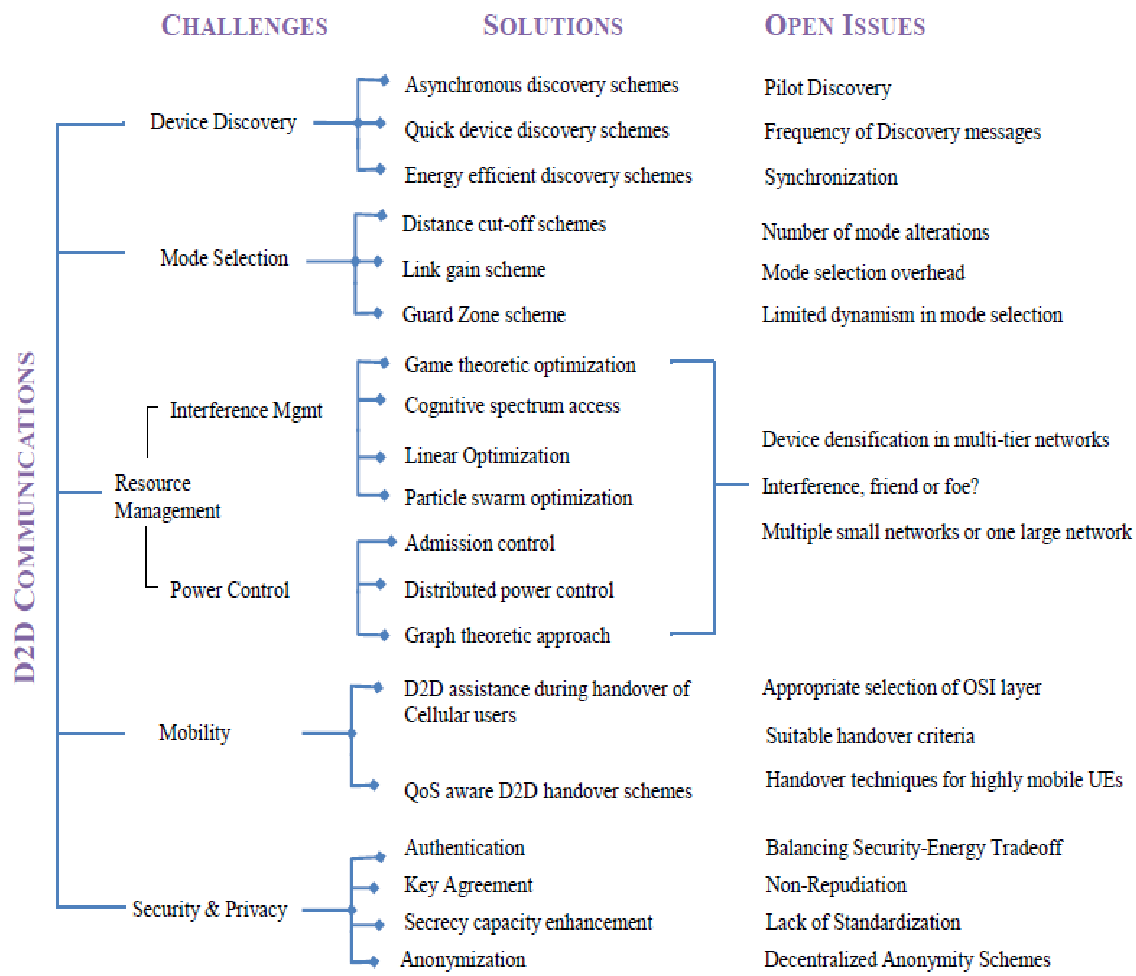


Figure 1.9. Challenges of D2D Communication, Solution and Open Issues.

1.9.1. Device Discovery

A very important part for D2D communications is device discovery, which allows devices to find possible candidates in the neighborhood and launch a direct connection among them. To achieve this task, devices broadcast a beacon signals between themselves to collect information like device distance, location, device ID and channel state etc. The devices use the collected information to assess the feasibility of forming into pairs. A posteriori discovery is when the discovery and communication occur simultaneously, however the priori discovery is when the device discovery is a requirement for D2D communication. In general, device discovery for D2D networks is categorized in two types: Centralized and Distributed Discovery.

a. Centralized discovery: in this type of discovery, the devices discover the neighborhood devices with assistance from a centralized unit or usually the BS. The device notifies the BS about its intent of communicating with close devices. The BS initiates the conversation among devices to acquire vital information like channel conditions, power control policies and interference based on network conditions. The contribution of the BS thru the device discovery can be partial or complete based on the protocols pre-configuration [53]. The devices can not be permitted to initiate the discovery process in the case of complete involvement of the BS. The BS organizes every message between devices. The devices merely pay attention to the messages transmitted from the BS and send messages to the BS to initiate the discovery process. In case of partially involvement of the BS, the devices exchange messages among themselves for device discovery without having prior authorization from the BS. Nevertheless, the devices implicate the BS to notify the Signal to Interference and Noise Ratio (SINR) level and the path gains of each device. This aids the BS to decide the possibility of communication among those devices. In the end, the BS demands from the devices to begin the communication. Figure 1.10 illustrates the discovery process of the partial and complete involvement of BS.

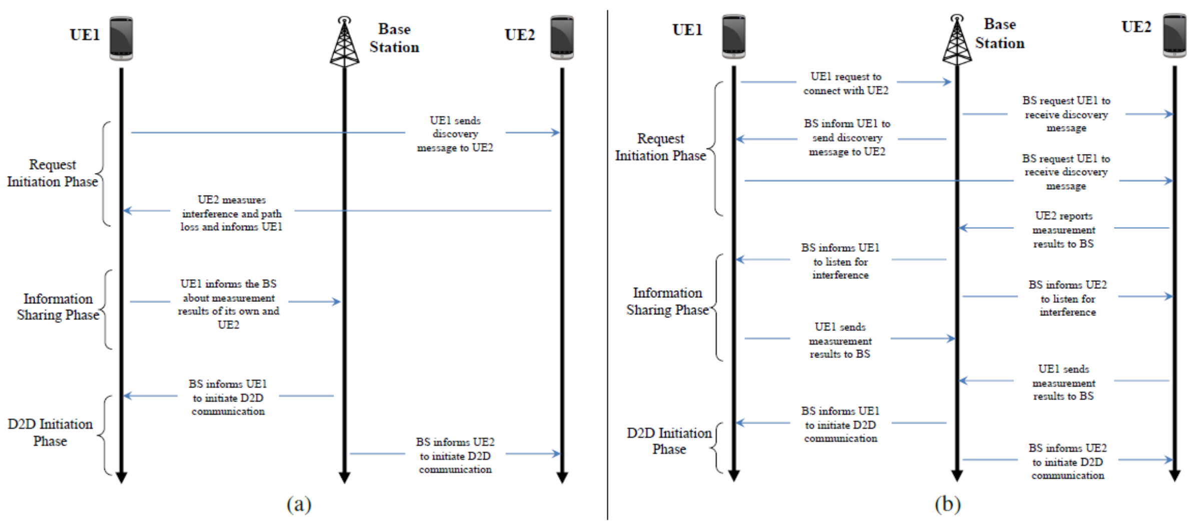


Figure 1.10. Centralized device discovery (a) Partial involvement of BS, (b) Complete involvement of BS.

b. Distributed discovery: This approach lets the devices to detect each other by themselves without the participation of the BS. The devices communicate messages of control periodically to find the adjacent devices. Nonetheless, issues rise in the distributed mode like synchronization and interference.

1.9.2. Mode selection

In D2D communications, UEs communicate directly among themselves and/or with the BS. This ability meaningfully increases the performance of the network in terms of delays and throughput. Nonetheless, it leads to new design issues such as resource management and network overloading. Moreover, the communicating devices can operate in the same or different mode (or even in a hybrid mode), which complicates network management. Naturally, devices can pick one mode of communication of the four following modes as shown in Figure 1.11:

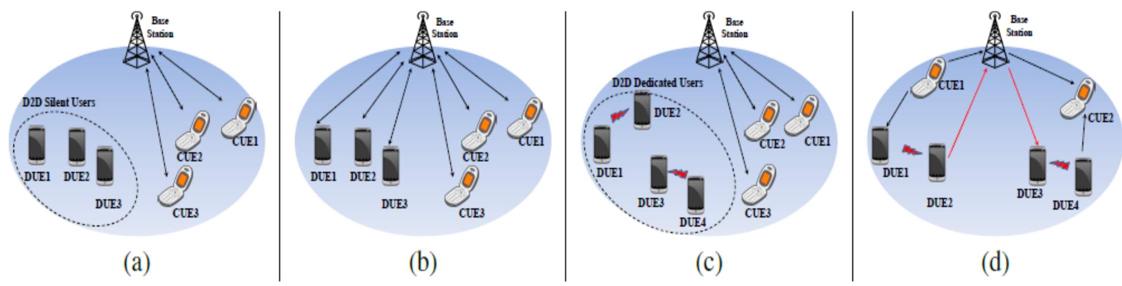


Figure 1.11. Modes of communication in D2D networks (a) Pure cellular mode (b) Partial cellular mode (c) Dedicated mode (d) Underlay mode.

A. **Pure cellular mode:** In case where the availability of resources is short and the interference is high which leads to stopping all D2D communication, only pure cellular mode is adopted by devices. In this mode, there is no D2D communication.

B. **Partial cellular mode:** In this mode, two devices are able to interconnect through the BS without sharing spectrum.

C. **Dedicated mode:** This mode means that devices communicate among themselves over dedicated spectrum channels.

D. **Underlay mode:** This mode allows D2D users to share the cellular Uplink and Downlink resources.

1.9.3. Mobility Management

Since most users are moving while communicating, D2D communication needs an efficient mobility manager to avoid disturbing the connectivity of the mobile users. Consequently, it is a requirement to have a mechanism that tack care of the communication while the User Equipment (UE) is mobile. Assessing movement patterns of UE and their effect on reliability of the communication is a main challenge [58].

Mobility management involves two operations namely, handoff management and location management [59], [60]. Location management allows the network to find out the connection points of UE amid successive communications as they wander everywhere in the networks. Handover (or handoff) management allows the network to preserve the connectivity of users while they changes from one connection point to another as illustrated in figure 1.12. Horizontal handover rises among homogeneous networks when the serving BS signal strength declines lower than a defined threshold. Vertical handover rises amongst heterogeneous networks and can be initiated by either users or network. The vertical handover choice depend on multiple aspects such as category of application (conversational, streaming), delay preferences, minimum bandwidth, estimated data rates, observed network load, power requirements and so on. Such relative information is used to generate profiles and predict a trajectory, which is used to assist in coming up with an optimized handoff decisions.

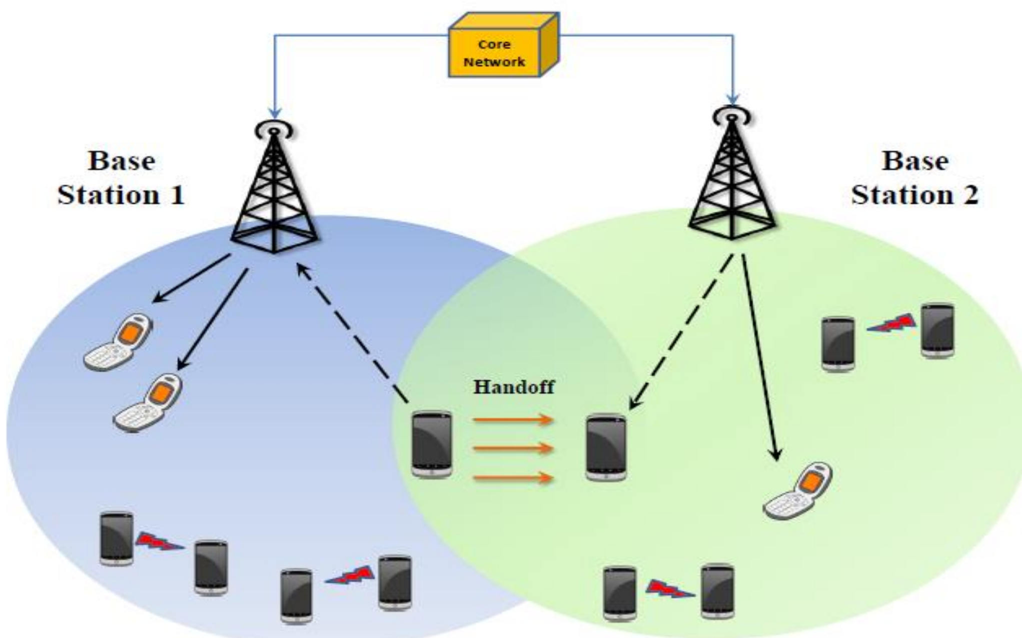


Figure 1.12. Typical handover scenario in D2D Communication.

1.9.4. Privacy and Security in D2D Communications

Security issues for D2D communications have been mostly overlooked by both industry and academia. D2D communications consist of a hybrid design where both centralized and distributed approaches are attached together. It is consequently defenseless against the same privacy and security threats facing both ad-hoc and cellular networks [61]. D2D communication is threaten by numerous security issues that can touch authentication, integrity, confidentiality and availability. Therefore, D2D communications necessitate an effective security solution to guarantee a private, secure and trusted exchange of data among cellular network and devices; and a direct communication of neighbor devices without any support from cellular network [62].

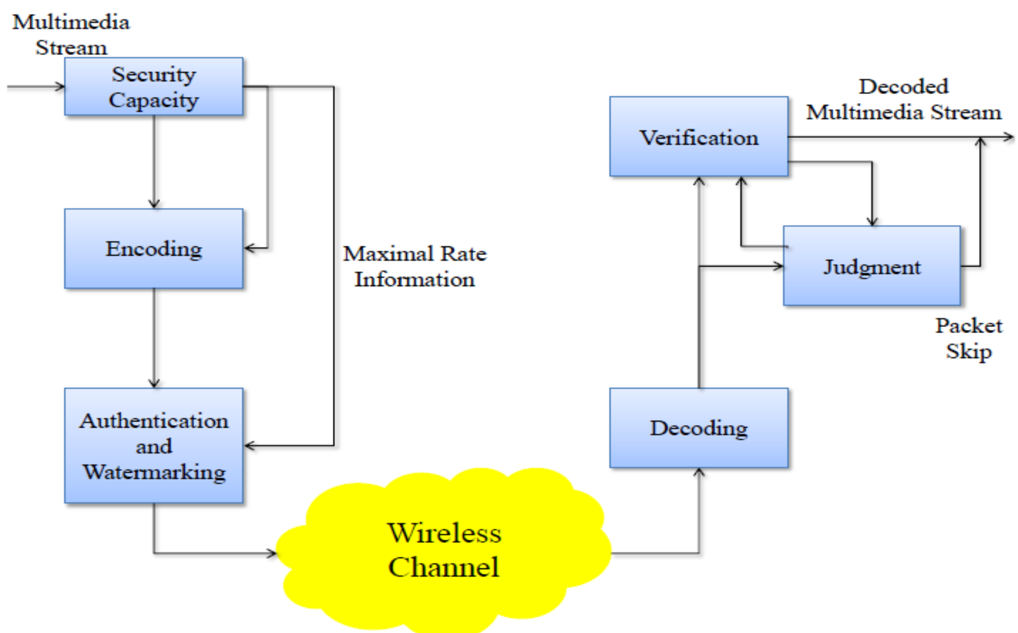


Figure 1.13. Combined Physical-Application Layer Security Scheme

In cases where the network is in charge of coordinating the communication of devices, it is mandatory to protect connections amid user and BS. Current cryptographic tools that encrypt messages can be used to ensure radio channels against well-known safety threats like eavesdropping, message modification, replay attacks and node impersonation. Existing cryptographic tools encode messages by means of a shared secret, which requires the assistance of a Trusted Third Party (TTP) or simply the BS. In this scenario, Public Key Infrastructure (PKI) accomplishes security purposes. This security tool is not achievable for direct D2D communications since there is no cellular infrastructure. Moreover, because of the great numbers of mobile devices, the diversity of manufacturers and variances in standards, a predefined secret key in devices is not an applied solution. A cross layer security framework could increase reliability of D2D communications [63]. In the cross layer security framework, the physical layer offers wireless connection security, while, the application layer guarantees authentication over watermarking. Both layers have the power to guarantee integrity and confidentiality of data as it travels over the wireless channel. Figure 1.13 illustrate this security model.

Privacy is an extra obstructing challenge for D2D communications, since D2D presents a dynamic setting where connections among diverse devices have a different level of sensitivity depending on the context. It is essential to build access control schemes, which permit users to identify the transmitted data and to whom. A considerably essential personal information is being indirectly shared while communicating in D2D mode. Any opponent eavesdropping on these connections might not be capable of understanding the encoded content but withdrawal apparently innocent looking data for a long period permits the opponent to expose useful information concerning users' connection patterns. Cellular devices are entirely related to a lone person and consequently, connection patterns like time, location, length of connection, device type and so on, produced from innocent looking information can help an opponent to recognize a specific user of a device. Anonymity maintaining methods are working to separate personal information from identity of users to reserve privacy [64]. D2D communications necessitates decentralized privacy conserving structures. These structures also require reflecting on how privacy can be sustained while exchanging information. D2D communications rises numerous privacy problems like device specific privacy and location privacy. These simple security necessities embrace securely storing information by means of a device particular key, guaranteeing software function individually and that each exterior device is capable to approve an accommodating platform version.

1.9.5. Resource Management

It takes place at the same time with mode selection. Effective management of resources means mitigate interference considerably, preserve power and increase throughput. Power consumption and interference mitigation are associated to the topic of resource management. We briefly present these issues in this section.

a. Interference management

Adequate allocation of spectrum is very important to maintain the necessary level of QoS. With the introduction of D2D communication in cellular networks, the challenge of interference grow into a more complex issue. Cellular networks in the future will assimilate many heterogeneous devices and an ultra-dense deployment of small and/or macro cell networks, thus making interference management challenging and more critical [54]. With the assimilation of D2D communication, the architecture of cellular networks has developed to a two-tier system. A cellular network with two-tier consists of a device tier and a macro cell tier. A device tier consist of D2D communications and a macro cell tier involves cellular communications from cellular users to base station. Two sorts of interference can happen in the two-tier setting: a co-tier interference and a cross-tier interference. Co-tier interference happens in case a resource block is assigned to more than one D2D user in the same network tier. Meanwhile, cross tier interference happens between D2D users and cellular users. Cross-tier interference occurs in case D2D user (one or multiple) shares a resource block allocated to CU. Diverse interference mitigation methods can be found in the literature, these proposed approaches can be classified into centralized, semi-distributed and distributed.

In the centralized methods, the BS (a central controller) is in charge for assigning resources to D2D and cellular users while observing the cell information about channel state information, SNR and interference level of users [55]. Yet, the complexity of centralized methods increases with the increasing of users' number since a single entity necessities to gather and process huge volumes of information. Consequently, a centralized method is more appropriate for networks with a small size.

The distributed method does not require a central entity and the users' shares the channel assigned to cellular users. This method necessitates frequent trading of information among neighbor D2D users. The method also obliges the D2D users to overhear current cellular communications to gather information concerning free resource blocks and channel quality, which leads to a huge power consumption by the devices [56]. The distributed method suits the bigger networks but involves complex interference prevention algorithms to guarantee high quality communications for cellular users alongside a reliable communications for D2D users.

The semi-distributed method consists of a hybrid approach where the management of interference is completed at diverse levels of network. These methods focus on decreasing computational complexity and signaling overhead at the BS. Inter cell D2D interference is an additional important problem that requires to be solved.

b. Power control

The procedure of regulating power in BS through DL communications and for users during UL communications is identified as power control. Rising transmission power of users is favored since it improve the link capacity nonetheless it will increase interference among devices allocated to the same resources. Power control approaches help preserve energy resources [57]. Joint optimization of channel allocation and power control are essential to improve networks capacity and throughput.

1.10. Conclusion

In this chapter, we have presented an overview of cellular networks and its generation from 1G to 4G and 5G. We detailed a little more the fifth generation since our work in this thesis is under 5G cellular networks. We presented the most promising enabler technologies for 5G starting with the mmWave, followed by Massive MIMO antenna technology and the densification of networks for the fifth generation, and we presented the D2D communication technology for the conventional cellular networks and the vision of D2D communication for the future 5G networks. Many challenges face the employment of D2D technology in different levels, yet the promising benefits of D2D communication drive researchers to address these challenges and integrate D2D communication in every technology developed for future cellular networks. Among them, we cited device discovery, mobility management, security and the problem we are addressing in this dissertation the joint channel allocation and power control problem.

Chapter 02

Related Work

Chapter 02: Related Works

2.1. Introduction

In this chapter, we start with the resource allocation and power control problem for D2D communication in cellular networks. After that, we are going to present the existing similar works for this problem and discuss their limitations. Lastly, with the objective of improving network throughput, we formulate the joint problem of resource allocation and power control for D2D communications underlay 5G cellular networks.

2.2. Resource Management for D2D communication

Orthogonal spectrums are assigned to users while working in D2D mode or in cellular mode, which can conduct to ineffective use of existing spectrum resources. To increase spectrum efficiency, D2D communication can operate by reusing the same physical resource blocks (PRBs) with cellular users. Nonetheless, co-channel interference originated from spectrum sharing must be synchronized wisely to guarantee the necessary QoS for those involved users. In the co-channel sharing mode, scenarios of interference are diverse when D2D communications reuse downlink or uplink cellular channel resources [93].

When D2D links reuse downlink resources, the Cellular User Equipment (CUEs) and the D2D receivers sharing the same PRB would interfere. For Device Users Equipment (DUEs) sharing the downlink spectrum, interference arises from the BS and other co-channel DUEs. Since the D2D pair is generally formed amid neighbor UEs, the power required for D2D communications is inferior compared to traditional cellular communications. Meanwhile, for CUEs using downlink resources, the interference emanates from co-channel DUEs. Even D2D receivers and the BS are as well victims of interference when DUEs reuse the uplink cellular resources. For this scenario, DUEs have to maintain themselves off CUEs co-channel to evade suffering unbearable interferences. In the uplink, since the BS is the receiver unite, it must control the interference and synchronize the DUEs to mitigate interferences of all co-channel DUEs [94].

The spectrum allocating approaches for D2D communications can be classified as follows.

2.2.1. Overlay D2D communications: in this approach, the available cellular spectrums are allocated to the D2D users for communication. This method can totally eradicate cross-tier interference by slicing the licensed channels into two slices. The cellular users will be allocated with one fraction of spectrum. while the D2D pairs would be using the other fraction of spectrum. Even though it is ideal from a cross-tier interference point of view, this method does not achieve an efficient spectrum reutilization [95].

2.2.2. Underlay D2D communications: In this scheme for spectrum sharing, several D2D users are permitted to act as an underlay along with the cellular users, and therefore increase the spectrum efficiency. Assignment of co-channel to D2D and cellular users will be more effective and beneficial for operators, even though this is more complicated than the overlay approach in term of technical point of view [96].

The overlay approach is simple to realize, but cannot be spectrally efficient. However the underlay scheme sustains a rather larger signaling overhead, it can accomplish a better overall network performance. To enhance the performance of the system over spectrum allocation of both modes (D2D and cellular), resource management is very significant. Managing radio resources can be completed in both cooperative and non-cooperative mode. For the non-cooperative approach, every D2D user can handle its spectrum to improve quality of service (QoS) and to increase the network throughput. On the contrary, in a cooperative method, the D2D users can collect fractional information about state of spectrum and complete channel allocation considering the impact on its co-channel users [97].

2.3. Power Control for D2D communication

Power control is applied in cellular networks to allocate/to regulate transmission powers of users, and thanks to that, a desired data rate is maintained. In 3G of cellular communication, controlling power was an essential module, mainly for transmission in uplink channels to solve the far/near problem. This problem was originated because simultaneous transmission to the BS were not orthogonal, therefor, when the transmissions power of users near the BS are high, they can overpower the transmissions of users at the cell edge since their signal power arrive at the BS weak. In 4G cellular networks, intra-cell interference was not a problem since the uplink communications are orthogonal signals. Consequently, the power control module mostly compensates for shadowing and path loss [98]. However, considering D2D communication for 5G cellular networks, sharing cellular spectrum, will restore the meaning of power control module. Since it can lessen power consumption and handle the interferences in these new scenarios [99]. In D2D networks, the CU are mostly given highest priority to whom an assured quality of communication must be guaranteed. The most natural means to mitigate the interference originated from D2D users on cellular communications is by controlling the transmission power of D2D communications [100].

2.4. Evaluation Metrics for Resource Allocation and Power Control (RA&PC)

Countless metrics exist to evaluate the performance of resource allocation and power control in mobile cellular networks. We present the most used in the recent published works of researchers.

2.4.1. Energy efficiency: is the slice of total energy goes to a system or a machine that is spent usefully at a job and not lost as futile heat or something else. It measures the amount of energy employed by any equipment or system to achieve the wanted performance. These days, energy efficiency is measured worldwide as source of energy since it can produce energy and claim savings, which can be relocated to generation of electricity from principal energy resources.

2.4.2. Spectral efficiency: bandwidth efficiency or spectrum efficiency states the information rate, which can be communicated over a certain bandwidth in a precise communication network. It is a degree of how effectively a restricted frequency spectrum is exploited by the protocol of physical layer or in some cases by the medium access control.

2.4.3. Network throughput: denotes the amount of data that can be transported from a transmitter to a receiver within a specified interval of time. Throughput quantifies the number of packets reach their destinations effectively. Mostly, the measure unit of networks throughput is in bits per second, yet sometimes it can as well be quantified with data per second.

2.4.4. Sum rate: data rate is the sum of all users rates of all actual communications in a network. It represents the times users equipment can transfer data; the more times they communicate, the more data is transferred.

2.4.5. Ergodic capacity: is the superior limit of the capacity of a statistics spectrum. It can be estimated by calculating the average capacity achieved at a precise time instance over a limitless time interval on a fading channel.

2.4.6. Interference: is an event in which waves (two or more) superpose to produce a wave of lower, greater or the identical amplitude. Interference originated by interaction of radio waves that are coherent or correlated among themselves, either since they originated by the same source or they have identical or almost a similar frequency.

2.5. Related Work of Resource Allocation and Power Control for D2D Communication

In the literature, there are many schemes proposed for spectrum sharing and power controlling for D2D communication. Many of these studies have target improving network throughput alongside other metrics as their main objective.

The authors of [101] proposed a random model for a D2D networks based on stochastic geometry. This model allows to see how the different network parameters influence the performance and quality of links. A novel distributed power control system has been presented to effectively control interference relying on distance based path-loss parameters. The same authors proposed in [102] to add to a resource allocation module to the previous proposition. The proposed channel allocation allows D2D users to share resources with more than one cellular user to decrease interference on one cellular user while the other cellular users are interference free.

In [103] Salem et al. proposed a joint resource allocation system for D2D Non-Orthogonal Multiple Access (NOMA) systems. Based on the interference among D2D users and CU, the proposed algorithm uses the Kuhn-Munkres (KM) technique to allocate channels. The proposed scheme is aiming to increase energy efficiency while assuring the QoS of all users.

Mudassar et al. in [104] formulated the problem as a mixed integer nonlinear programming (MINLP). To solve the MINLP problem, a solution founded on Outer Approximation Algorithm (OAA) was proposed. The presented solution achieves optimal results and converges linearly.

The authors of [105] inspected the exploitation of the cooperative D2D in cognitive radio (CR) network in order to mitigate interferences. They proposed a clustering relay selection scheme to permit simultaneous transmission. Then, an interference management method is proposed to increase the performance of the system. The proposed system is based on cooperative beamforming (CBF) technique for each cluster of D2D users.

In [106] Koushik et al. proposed a method for mode selection, resource allocation and interference mitigation in licensed spectrum D2D communication for ubiquitous and public safety networks. The authors proposed a power control and orthogonal precoding based system to reduce interference. Meanwhile, Abdulkadir et al. in [107] inspected the resource allocation and interference management problems for D2D communications underlying Heterogeneous Networks (HetNet). They proposed a novel centralized concatenated bi-partite matching approach to allocate resources and mitigate interferences.

The authors of [108] split the original joint problem of power control and channel assignment into two sub-problems. The power control was solved with monotonic optimization theory; they presented a new polyblock-based algorithm. Hussein et al. formulated the channel assignment problem as a matching problem and used Khun-Munkers algorithm to solve it.

Yanpeng et al. in [109] investigated the mode selection and channel allocation problem for D2D non-orthogonal multiple access (NOMA) networks. With maximizing system sum rate as objective, the authors formulated the joint mode selection and spectrum allocation as a combinatorial optimization problem. To solve this combinatorial problem, they proposed a graph-based scheme by using the branch-and-bound algorithm to achieve an optimal solution.

In [110], the authors considered two-hop downlink D2D relaying. They have used a hierarchical control framework to solve the problem of network management (channel allocation). Junquan et al. have proposed a distributed interference coordination to synchronize relaying communications. Xianbang et al. in [111] considered power and channel allocations for Mobile Edge Computing NOMA based system assisted by D2D networks. They divided the joint problem to two sub-problems. Firstly, they proposed a Particle Swarm Optimization (PSO) based algorithm to optimize the power. Then, used a one-to-one matching algorithm, which it was prolonged to a many-to-one matching approach to solve the channel allocation problem.

The authors of [112] formulated the joint problem of resource and power allocation as a Stackelberg game and proposed a distributed learning algorithm. The proposed system consists of defining prices by the BS and the D2D users uses the stochastic learning algorithm to find RB indices. Dominic et al in [113] proposed a distributed joint channel and power allocation algorithm to improve energy efficient. The joint problem is formulated as a satisfaction game by defining an Efficient Satisfaction Equilibrium (ESE). Then a many-to-one matching algorithm was used to solve the joint problem. Meanwhile in [114], the authors formulated the joint problem as MINLP. A Fractional Frequency Reuse design is used to formulate the problem aiming to maximize the sum rate of the uplink channels. Therefore, a based decomposition approach was used to formulate the problem into three sub problems, which was solved with Kuhn-Munkres algorithm.

Feng et al. in [115] investigated the issues of D2D multicast (D2MD) for content distribution in social-aware cellular networks, and present our D2MD content sharing scheme. In the proposed scheme, both social and physical domain factors are used to create valuable clusters. The authors used geometry programming to formulate the RA and PC problem. Then, employed a bipartite matching approach to accomplish optimal spectrum allocation and power control for distributed content transfer. Meanwhile, the authors of [116] studied RA and PC problem in downlink channels. As a main objective to maximize throughput of the network, Hongyuan et al. proposed an optimization algorithm based on quantum coral reefs. Gengtian et al. in [117] investigated the power control problem in a single cell scenario. They proposed a reinforcement learning method and Deep Q Network to adaptively control power to guarantee QoS of CUs, improving network throughput and reducing interference.

In [118], the authors presented an energy efficient channel and power allocation scheme for D2D networks underlying Cloud radio access network (C-RAN). Jinsong et al. modeled the joint problem as two non-cooperative games. In the first game, each D2D user and cellular user improves its energy efficiency individually with help of remote radio heads (RRHs) by using the Dinkelbach algorithm and Lagrangian theory. While in the second game, each cellular user optimizes its spectrum efficiency by using D2D users as relays.

Yeakub et al. in [119] addressed the interference minimization for D2D networks in cellular network. They presented a two-stage channel allocation approach. The first is for fair assignment in which all D2D pairs have the flexibility to share only one RB used by a cellular UE and the second one is a constrained allocation where D2D pairs are obstructed if their sharing of a RB decreases the sum rate of a cellular user. For the first stage, the problem was formulated as a weighted bipartite matching problem and solved with the Hungarian algorithm. In the second stage, the authors proposed a local search algorithm that begins with achievable solutions found in stage one and attempts to decrease the total system interference.

In [120], Gang et al. proposed a resource allocation scheme based on D2D communication mode selection. Based on their location and priority order, D2D users are allocated modes (cellular mode, orthogonal mode and multiplex mode), and the channel allocation is enhanced by comparing the SNIR. Meanwhile, Jinming et al. in [121], proposed a novel Overlapping Coalition Formation Games algorithm (OCFG). This approach, to efficiently assign resources and mitigate interference, let UEs to collaborate to mold an overlapping coalitional structure. In the OCFG, each D2D communication can separately choose whether to leave or to join a coalition to achieve higher system efficiency based on sum rate of all D2D communications.

Sharing resources between cellular users and D2D pairs can improve the system capacity. Faisal et al. in [122] proposed an algorithm that eliminates the realizable D2D pairs and matches celluar users with D2D pairs that share RBs without neglecting the QoS constraints. The proposed algorithm was based on weighted bipartite matching to optimally allocate resources and improve system sum rate while guaranteeing the QoS of all communications. Meanwhile, Ishan et al. [123] formulated the spectrum allocation problem as mixed integer nonlinear programming and then split it to two sub-problems. First, groups of D2D users were formed to decrease intra user interference. Second, a resource allocation scheme was proposed using many-to-many mapping scheme. Finally, based on a successive convex approximation, the difference of two convex functions programming approach was proposed to optimize power control.

The authors of [124] studied the power allocation problem for D2D communications in company of simultaneous wireless information and power transfer (SWIPT). The problem was formulated by using a new game theoretic model based on Stackelberg game. To improve energy efficiency of networks, each D2D pair can update its transmit power to obtain the Nash equilibrium based on the game model and pay a certain fee to the BS based on pricing strategies. In the meantime, Junghoon et al. in [125] proposed a new optimization algorithm to maximize energy efficiency for resource allocation with MIMO signal design. The authors proposed a greedy approach to allocate spectrum and an interference coordination techniques to regulate the transmission power and the transmit beam-former. The authors of [126] studied the power and resource allocation problem to enhance energy efficiency in the downlink channel. The problem was formulated as a MINLP optimization problem with constraints and the target is to maximize the energy efficiency. In order to solve this problem, an algorithm based on the Dinkelbach and Lagrangian scheme was proposed.

Nandish et al. in [127] investigated interference for D2D communications in uplink channels. They proposed an interference aware power allocation that does not restrict D2D pairs to guarantee CU QoS. Yet, the CUEs with unsatisfied SINR (lesser than the SINR threshold) because of interference from D2D users will be improved with suitable power to exceed the interference. Meanwhile, the authors of [128] proposed a pure D2D scheme to assure flexibility for channel allocation, which lets some resource blocks to be allocated only to D2D users. Lai et al. grouped users with vertex coloring and changed each group with the Branch and Bound (BnB) algorithm in order to increases transmission power to enhanced SINRs.

Xiaoshuai et al. in [129] worked on improving throughput and fairness of the system. They have formulated channel assignment problem with proportional fairness and solved it by adopting the maximum carrier to interference ratio algorithm to improve overall system throughput. Meanwhile, Jun et al. in [130] discussed mode selection for D2D users and proposed a spectrum allocation algorithm. The authors used the Hungarian matching algorithm to reduce interference and increase the system throughput by optimally allocating resources. In the meantime, the authors of [131] considered the power and channel allocation problem for high data rate in D2D communications. They formulated the PC and RA problem a MINLP optimization problem, then proposed a two layer algorithm based on carrier aggregation and outage probability constraints to improve energy efficiency while guaranteeing a minimum QoS for all users (CU and D2D users).

Xiaoshuai et al. in [132] aimed at maximizing the sum ergodic capacity of users with non-complete channel state information (CSI). The authors formulated the power control problem based on Jensen’s inequality and solved it using the lower bound based algorithm. After regulating transmission power, the channel allocation was assured by using an improved Gale–Shapley algorithm.

As shown in Table 2.1, some works namely [104], [105], [109] [110], [114], [116], [119], [120], [122], [122], [123], [125], [126], [127], [129], [130], [131] and [132] consider only one pair of D2D users to share an RB with a cellular user, limiting the number of served D2D users. On the other side, there are some distributed approaches like [101], [102], [112], [113], and [124] consider D2D pairs responsible for performing a part of tasks, which reduces the workload compared to centralized approaches that use only the BS for the computational processing. However, those distributed solutions need a valid and accurate channel prediction algorithm to foresee the current channel state information (CSI). Most of the related works divide the joint power control and resource allocation to two separate problems and solve each problem independently of the other, leading to a sub-optimal solution and not to the overall one.

Reference	**Year of Publication**	**RA**	**PC**	**D/C**	**D2D Nbr**	**Objective (improving)**
101	2017	X	√	D	Many	Spectral efficiency
102	2018	√	√	C/D	Many	Spectral and energy efficiency
103	2019	√	√	C	Many	Energy efficiency and throughput
104	2020	√	√	C	One	System sum rate
105	2020	X	√	C	One	Interference mitigate
106	2020	√	√	C	Many	Interference mitigate
107	2017	√	√	C	Many	Interference mitigate
108	2019	√	√	C	Many	Throughput and energy efficiency
109	2019	√	X	C	One	System sum rate
110	2017	√	√	C	One	Interference mitigate
111	2019	√	√	C	Many	Energy efficiency
112	2017	√	√	D	Many	Spectral efficiency
113	2020	√	√	D	Many	Spectral and energy efficiency
114	2020	√	√	C	One	System sum rate
115	2018	√	√	C	Many	Throughput
116	2019	√	√	C	One	Throughput
117	2020	X	√	C	Many	Interference mitigate
118	2018	√	√	C	Many	Energy efficiency
119	2017	√	X	C	One	Interference mitigate
120	2020	√	X	C	One	Throughput
121	2018	√	X	C	Many	Throughput
122	2017	√	X	C	One	System sum rate + interference mitigate
123	2020	√	√	C	One	System sum rate
124	2020	X	√	D	Many	Energy efficiency
125	2020	√	√	C	One	Energy efficiency
126	2018	√	√	C	One	Energy efficiency

127	2019	√	√	C	One	Throughput + energy efficiency
128	2020	√	√	C	Many	Spectral efficiency
129	2018	√	√	C	One	Throughput
130	2019	√	X	C	One	Throughput
131	2020	√	√	C	One	Energy efficiency
132	2020	√	√	C	One	Sum ergodic capacity

Table 2.1. A summary of resource allocation and power control studies for D2D communication, we compare if the two problems are solved or just one of them, if the solution is centralized or distributed and if the cellular users share their RB with just one or with many D2D pairs. (RA: resource allocation, PC: power control, C/D: centralized/ distributed, D2D Nbr: D2D pairs number sharing RB with a CU, √: satisfied, X: not satisfied).

2.6. System model for joint RA&PC in D2D communication underlay 5G

To generalize a proposed solution, we firstly studied the model of one cell, therefore, we consider that the system is an Urban Micro System (UMi), presenting a small cell with a large user density and high traffic loads in a dense urban area. As illustrated by figure 2.1, this system has one BS, nbC cellular user equipment and several D2D pairs (nbD D2D pairs). The D2D

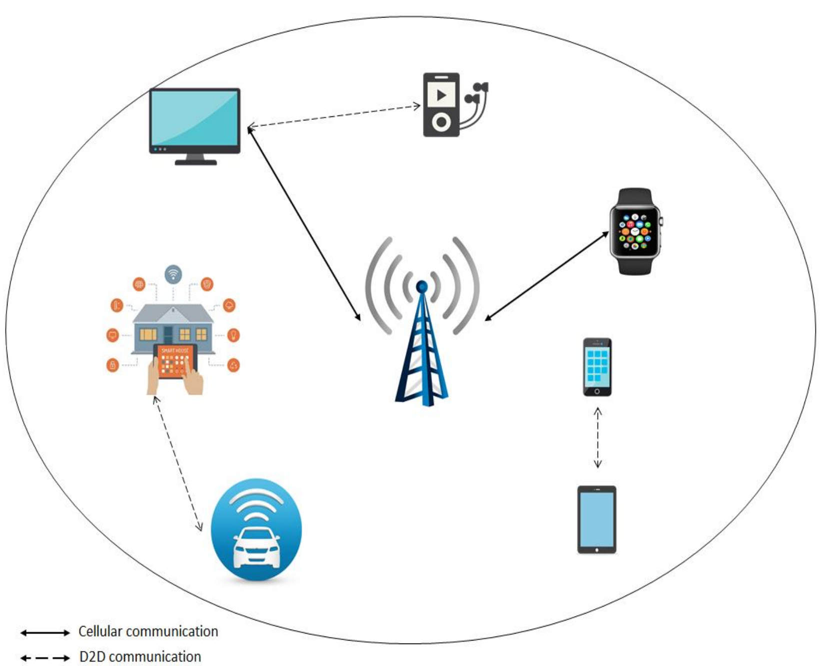


Figure 2.1. Network structure illustration.

pairs are sharing uplink resources with cellular users. More interferences will be created from sharing uplink channels between CUs and D2D pairs. In our system, D2D pairs have direct communication but the BS has the responsibility of allocating resources and establishing connection between different devices. Table 2.2 contains all notation used to formulate the joint RA&PC problem.

Notations	**Explanation**
S	The set of users
nbC/nbD	CU and D2D pairs number, respectively.
RB	Resource blocks set
M	Resource blocks number
L	Matrix of Allocation
T, C_T, D_T	Network throughput, cellular throughput, D2D throughput, respectively
SINRm	CUs minimum SINR
Gij	Gain between UEi and UEj
PLM	Path Loss model
B	Bandwidth
Pcm	CUs maximum power
Pdm	D2D pairs maximum power
WGN	White Gaussian Noise
F	Carrier frequency

Table 2.2. Notation used to formulate the joint RA&PC problem for D2D communications underlay 5G cellular networks.

We denote the set of cellular communications and D2D pairs as follows:

$$S = \{S_1, S_2, \dots S_{nbC}, S_{nbC+1}, \dots, S_{nbC+nbD}\}$$

Where, S_i is the i-th communication of the set of CUs and D2D pairs. The frequency resource is divided into M resource blocks (RB). The set of RBs is defined as:

$$RB = \{rb_1, rb_2, \dots., rb_M\}$$

We denote $L \in \{0,1\}\, nbC + nbD, M$ the matrix of allocation where $Li, r = 0$ means that the r-th RB is not assigned to the i-th communication; and $Li, r = 1$ indicates that the r-th RB is assigned to the i-th communication.

We formulate the joint RA&PC problem with improving network throughput as our objective. Hence, according to Shannon's equation [133], the equation of throughput of the i-th communication on r-th resource block is expressed as:

$$T\,(i - th) \;=\; B\; log2\,(1 \;+\; SINR\; i, r)$$

Where B is the available bandwidth and SINR i,r is the signal to-interference-plus-noise ratio of i-th communication in r-th RB. The SINR i,r equation is given as follows:

$$\mathrm{SINR\ i,r} \;=\; \frac{\mathrm{Gii\ Pi\ Lir}}{\mathrm{WGN} + \sum_{\mathrm{j \in S, j \neq i}} \mathrm{Gji\ Pj\ Ljr}}$$

Where, Lir indicates if a UE is assigned to a RB, it is equal to 1 if the i-th user is allocated to the r-th RB and 0 otherwise, WGN is the white Gaussian Noise and Pi presents transmission power of the i-th communication, and Gj,i presents the channel gain of i-th and j-th communication.

We adopt the Urban Micro System (UMi), the same system model used in [119] where the UMi presents a small cell with great user density and high traffic loads in a dense urban area [134], and follows the Rayleigh fading path loss model [135]. Path loss is the weakening of power density while the wave spreads through space [136]. The path loss model equation is given as follows:

$$PLM = 36.7 \log_{10}(d) \; + 22.7 + 26 \log_{10}(F)$$

Where d means the distance (measured in meter) between sender and receiver and, F is the communication medium frequency (measured in GHz). Thus, the channel gain between two UEs is expressed as [119]:

$$Gi, j = \; 10^{-PLM/10}$$

The throughput of CUs is the sum of the throughput of all CUs and it is expressed as follows:

$$C\_T \ = \ \sum_{i=1}^{nbC} \sum_{r=1}^{M} \mathrm{B} \log 2\,(1 + \mathrm{SINR\ i, r})$$

The throughput of D2D pairs is the sum of throughput of all D2D pairs, it is written as follows:

$$D\_T \ = \ \sum_{i=nbC+1}^{nbC+nbD} \sum_{r=1}^{M} \mathrm{B} \log 2\,(1 + \mathrm{SINR\ i, r})$$

The network throughput is the sum of CUs throughput and D2D throughput, which is:

$$T \ = \ C\_T \ + \ D\_T$$

If we replace the C_T and D_T in the network throughput equation and simplify the equation, the expression of network throughput becomes:

$$T \ = \ \sum_{i=1}^{nbC+nbD} \sum_{r=1}^{M} \mathrm{B} \log 2\,(1 + \mathrm{SINR\ i, r})$$

The formulated joint RA&PC problem is bind by some condition in order to operate in the best way possible and enhance spectral and energy efficiency. Thus, the maximization problem of joint spectrum allocation and power control with conditions is formally modeled as follows:

$$T \ = \sum_{i=1}^{nbC+nbD} \sum_{r=1}^{M} \mathrm{B} \log 2\,(1 + \mathrm{SINR\ i, r})$$

Subject to the following constraints:

$$Pi \ \le \ Pcm \ \forall \ \ i = 1 \dots nbC$$

$$Pi \ \le \ Pdm \ \forall \, i = nbC + 1 \ \dots nbC + nbD$$

$$Li, r \ \le \ 1 \, \forall \, i = 1 \dots nbC, \forall \, r = 1 . . . K$$

$$SINRir \ \ge \ SINRm \, \forall \, i = 1 \dots nbC, \forall \, r = 1 \dots K$$

The first and second constraints specify that the transmission powers of CUs and D2D pairs cannot exceed upper limits Pcm and Pdm, respectively. The third constraint indicates that for CUs, the Li,r value can only be 0 or 1 which signifies that each RB cannot be allocated to no more than one CU at a time because the base station is the receiver of CUs, and if two CUs are allocated to the same RB, the BS cannot differentiate between their signals. However, it is possible for more than one D2D pairs to be assigned to the same RB since the receiver is not the same. To guarantee a minimum quality of service for cellular users, the fourth constraint indicates that for each CUs, there is a minimum SINR (SINRm) to be achieved even if we have to block some D2D users since the first priority is for cellular users.

To be able to serve the maximum number of D2D pairs and efficiently exploit the spectrum resources, we do not limit to the number of D2D pairs that share one RB with a cellular user if the fourth condition is satisfied.

2.7. Conclusion

In this chapter, we presented the resource allocation and power control problem for D2D communication underlaying cellular networks. First, we defined each problem, and then we presented the evaluation metrics used to show the efficiency of the proposed schemes. After that, we presented a large number of related works newly published and discussed their advantages and disadvantages. Lastly, we formulated the resource allocation and power control problem for D2D communications underlay 5G cellular networks with objective of maximizing the network throughput.

Chapter 03

Bees Life Algorithm for Spectrum Allocation and Power Control in D2D Communications

Chapter 03: Bees Life Algorithm for Spectrum Allocation and Power Control in D2D Communications

3.1. Introduction

In this chapter, we present the work done for solving the joint resource allocation and power control problem in D2D communication underlay 5G cellular network. The first proposition consists of using the bee life algorithm, which is inspired by two main behaviors of bees. The second proposition improves the first by adding simulated annealing algorithm in the initialization step to generate a better initial population, which will be improved with the BLA. The results of those two propositions were compared to the performance of two bio-inspired algorithms namely, Genetic algorithm (GA) and Particle Swarm Optimization (PSO).

3.2. Motivation

The spectrum allocation and power control problem is a nonlinear and limited by several nonlinear constraints, which causes problems to solve it with traditional methods. Many solutions have been proposed to solve this problem and among those propositions, the bio-inspired algorithms provided low complex and better solutions such as Genetics algorithms (GA) and Particle Swarm Optimization (PSO). We use a bio-inspired method because of its efficient properties like self-organization, autonomy, scalability and adaptation. The bio-inspired algorithms help researchers thru providing pointers for systems and solution methods that compromise between the limited resources and the high demand. As illustration, in the foraging process, the bees use their limited resources of individuals to optimize the behavior of the colony in order to discover food sources in a cost-effective way. Moreover, the Bee Life Algorithm (BLA) has achieved best results for many problems like for job scheduling in cloud computing [137] and for packet routing in vehicular ad hoc networks [138]. For those reasons, we have proposed to use the BLA to solve the joint spectrum and power control problem for D2D communication underlay 5G cellular networks [144].

3.3. The Bee Life Algorithm (BLA)

The bio-inspired algorithms are an effective optimization approaches. The bio-inspired algorithms can solve any problems in the most efficient and optimized way. Bio-inspired optimization algorithm is an emerging method, which is based on the basics and inspiration of the biological evolution of nature to improve or to create new and strong optimization techniques. One of those algorithms is the Bee Life Algorithm, which is inspired by food foraging and reproduction in bees colony.

3.3.1. Bees in nature

Bees perform an imperative, yet slightly recognized part in most ecosystems of earth. In forests, various kinds of animals and plants will not stay alive if bees are lost. This is because the production of fruits, berries, nuts and seeds are highly dependent to insect pollination, and bees are the foremost pollinators. Bees colony is composed of a queen, which is a breeding female, thousands of sterile females named Workers, Drones which are males, their number can reach several thou-sands and there are several Broods; they are young bee larvae.

The bees communicate among themselves with an extremely precise language, which is founded on two types of dances performed when bees search for food; the round dance, used when food source is nearby, and the infinity symbol (∞) dance, when food source is far away. The bees reproduction is assured by the queen. She mates with quite a lot of males while flying, until filling her spermatheca. Unfertilized egg will become drones and the fertilized egg produce a new queen or a worker based on food quality [139].

3.3.2. Bee life algorithm inspiration

The Bee Life Algorithm originated from two primary behaviors of bees in their lives, which are food foraging and reproduction. In the first behavior, the workers recruit bees in their area to discover new food source and assess each bee with the quantity and the quality of the food source. Meanwhile in the second behavior, the queen mates with drones and engender broods. Those broods will become workers, drones and even a new queen can appear among them [137].

The BLA begins with population initialization by picking X bees (random solutions). After assessment, those bees can be classified into one (1) queen (the finest bee in the colony), D drones (following D best bees) and W workers (the rest of bees). Then, we first employ the reproduction behavior in which the queen begins mating with drones generating Y broods. We can keep the number of broods small in order to reduce the complexity of the bee life algorithm. This mating behavior can be formulated with crossover and mutation as optimization operators of BLA.

Afterward, in the second phase of BLA, the W workers start looking in their local areas for best flowers (food sources), then they notify and employee their nest mates to harvest the discovered source. As technical projection, we propose a greedy local search method to employ the workers' jobs finding the nearest best flower region. We consider that the worker bee that finds the best source food is perceived as the best solution in this area.

After execution of this life cycle (i.e. a BLA iteration), we assess all the new solutions (i.e. new workers and new broods). Hence, we pick among all bees (i.e. previous and current generation, the queen, drones, workers, new broods and new workers) only the finest X bees having the top fitness to form the new population. We go back to the mating step until ending criteria is gotten, either we have a limited number of repetitions or we notice that there is no progress in the population fitness (the stagnation state). In the following, we present the fitness function then we explain each optimization operators in the two parts of the Bee Life Algorithm.

A. Fitness function: also identified as the Evaluation Function, it assesses how close a specified solution is to the ideal solution of the chosen problem. It defines how appropriate a solution is. For the RA&PC problem with improving network throughput as objective, the fitness function was presented in the previous chapter and it is expressed as follow:

$$Fitness\ (bees) = \sum_{i=1}^{nbC+nbD} \sum_{r=1}^{M} \mathrm{B}\log2\,(1+\mathrm{SINR}\ \mathrm{i,r})$$

Subject to the following constraints:

$$Pi\ \leq\ Pcm\ \ \forall\ \ i = 1 \ldots nbC$$

$$Pi\ \leq\ Pdm\ \ \forall\, i = nbC + 1\ \ \ldots nbC + nbD$$

$$Li,r\ \leq\ 1\ \forall\, i = 1 \ldots nbC, \forall\, r = 1 \ldots K$$

$$SINRir\ \geq\ SINRm\,\forall\, i = 1 \ldots nbC, \forall\, r = 1 \ldots K$$

B. Crossover Operation

Crossover operation associates a Queen chromosome on behalf of a solution coding with chromosome of any Drones to generate a broods. As an outcome, some gens from the drone and some from the queen form the chromosomes of a new brood. This process is probably completed with a probability of crossover defined as Crossover Threshold (Cr_Th). In the proposed solution for the joint RA&PC problem we use one-point crossover. A random number is chosen from the interval [1, nbC+nbD]; it is the number of communications (gens) used from the Queen and the drone provides the rest of gens to get the first brood, after that we perform the opposite to construct the second brood as illustrated in figure 3.1.

Queen = $\{U_1, U_2, U_3, U_4, U_5, U_6, \ldots, U_{nbC+nbD}\}$

Drone i = $\{ \mathbf{U'_1, U'_2, U'_3, U'_4, U'_5, U'_6, \ldots, U'_{nbC+nbD}} \}$

If the random number equals three then the broods will be the following:

Brood 1 = $\{ U_1, U_2, U_3, \mathbf{U'_4, U'_5, U'_6, \ldots, U'_{nbC+nbD}} \}$

Brood 2 = $\{ \mathbf{U'_1, U'_2, U'_3}, U_4, U_5, U_6, \ldots, U_{nbC+nbD} \}$

Figure 3.1. One-point crossover in BLA for joint RA&PC problem.

C. Mutation Operation

In the reproduction process, several broods, and with a probability mostly low, experience a minor modification in their gens, that is the mutation. In this proposed solution and as shown in figure 3.2 the mutation process is happening with a probability equal to Mutation Threshold (Mu_Th). Therefore, we pick randomly a communication (one gen) from the brood and we choose randomly a solution, then we swap the chosen communication (gen) among those two individual. It is obviously to switch the same type of communications (gens) in order to respect the conditions of the formulated joint RA&PC problem (presented in the previous chapter). Thus, if the selected communication is a D2D, then the other one must be a D2D communication and if it is the opposite, we do the same (if the picked communication is cellular, the second must be a cellular communication).

D. Food Foraging

In this phase of BLA, the workers discover their local area to search for good flowers signifying good source of food. Precisely, for each solution amid workers solutions, we employ a greedy local search scheme to discover the best solutions in each region leading to the optimal solutions in that neighbor replacing the ancient ones. To accomplish this, we pick a number in the interval [nbC+1, nbC+nbD] randomly, and that will be the identity of the D2D pair that we will change its transmission power and its resource block (RB). If an improvement of fitness is gotten, then the new solution is preserved; otherwise, it will be overlooked as shown in figure 3.3.

Brood = $\{U_1, U_2, U_3, U_4, U_5, U_6, \ldots, U_{nbC+nbD}\}$

Random-bee = $\{U'_1, \mathbf{U'_2, U'_3, U'_4, U'_5, U'_6, \ldots, U'_{nbC+nbD}}\}$

If the random communication equals five then the brood will be the following:

Brood = $\{U1, U_2, U_3, U_4, \mathbf{U'_5}, U_6, \ldots, U_{nbC+nbD}\}$

Figure 3.2. Mutation in BLA for joint RA&PC problem.

$$
A= \begin{array}{c}
\begin{array}{ccccccc} U1 & U2 & U3 & U4 & U5 & \ldots\ldots\ldots & U_{nbC+nbD} \end{array} \\
\left(\begin{array}{ccccccc}
0 & 1 & 0 & 0 & 0 & \ldots & 0 \\
1 & 0 & 0 & 0 & \mathbf{1} \rightarrow \mathbf{0} & \ldots & 1 \\
0 & 0 & 1 & 0 & \mathbf{0} \rightarrow \mathbf{1} & \ldots & 0 \\
0 & 0 & 0 & 1 & 0 & \ldots & 0 \\
0 & 0 & 0 & 0 & 0 & \ldots & 1
\end{array}\right)
\end{array}
\begin{array}{l} \\ Rb1 \\ Rb2 \\ Rb3 \\ \ldots \\ Rb_M \end{array}
$$

Figure 3.3. Food foraging: For example, if U5 is the picked D2D communication, we swap from Rb2 to Rb3 and improve its transmission power.

In algorithm 1, we present the pseudo-code of the Bee Life Algorithm with its optimization operators for joint RA&PC in D2D communication underlaying 5G cellular networks.

```
BLA for channel allocation and power control
1. Initialization: random X bees
2. Evaluation: calculate_fitness (X bees)
3. Arranging: one Queen, D drones, W workers      // First phase: Reproduction
4. while (not (stopping_criteria)) do
5.   for (i ← 1 to D) do
6.       Crossover(drone[i], Queen) // With a crossover probability: Cr_Th
7.   end for
8.   for i ← 1 to Y     // Y: broods number
9.        Mutate (broode[i])  // With a mutation probability: Mu_Th
10.   end for
    //   Second phase: Food Foraging
11.   for  i ← 1 to W
12.      random_selection (D2Dpair)
13.      random_selection (RB)
14.      allocate (D2Dpair, newRB)
15.      improve_power (D2Dpair)
16.   end for
17.   Evaluation: calculate_fitness (broods, new workers)
18.   Selection (best X bees amid all bees)
19. end while
20. output (Queen)
End Bee Life Algorithm
```

Algorithm 1. Pseudo code of the BLA for resource allocation and power control.

E. BLA Computational Complexity

We present the computational complexity of the BLA for joint RA&PC in D2D communication underlaying 5G cellular networks.

For picking and assessing X bees (population individual):

$$O(X) + O(X) \approx O(X) \text{ time units.}$$

In each repetition, we have: Crossover with Cr_Th, amid them there is Mutation with Mu_Th :

$$O((X * Cr\_Th) * Mu\_Th) \text{ time units.}$$

Food foraging completed by W worker in Z areas by means of a greedy local search:

$$O(W * Z) \text{ time units.}$$

Therefore, for one repetition of BLA, the complexity is expressed as:

$$C\,(BLA) \approx O(I*(X+((X*Cr\_Th)*Mu\_Th)+(W*Z))) \text{ time units}$$

$$O(X)+O((X*Cr\_Th)*Mu\_Th)+O(W*Z) \approx O(X+((X*Cr\_Th)*Mu\_Th) +(W*Z)) \text{ time units}$$

Thus, the BLA complexity with I iteration is:

$$C(BLA) \approx O(It*(X+((X*Cr\_Th)*Mu\_Th)+(W*Z))) \text{ time units}$$

The BLA complexity is linear and that is the smallest possible computational complexity

3.4. Simulation and results

We assess the performance of BLA with a set of simulations. The cell radius of the considered network is 500 m; there is one BS in the center of the cell. The users equipment are arbitrarily dispersed inside the cell. The extreme distance functional between D2D users is 50 m [140]. The radio frequency used is 2.4 GHz and the maximum power of transmission for both users (CU or D2D users) is 23 dBm. The parameter settings used in the simulations are illustrated in table 3.1.

CUs have orthogonal channels assigned sequentially while for D2D users the channels firstly allocated are integers, arbitrarily picked from the interval [1, M]. To form the initial population, we begin with the initialization phase (a set of CUs and D2D pairs). In this phase, we assign resources and define transmission power for users randomly; the D2D pairs and CUs get a random number from 1 to 8; this number define the resource bloc identification they will use. After that, we assess the fitness of the population and order them from the finest to the worse bees (solutions) using the evaluation function. After that, we employ the BLA operators on the joint RA&PC problem to improve the overall network throughput.

Parameters	values
Cell radius	500 m
D2D users coverage	50 m
Carrier frequency	2.4 GHz
Channel bandwidth	1 MHz
Number of cellular users	8
Maximum transmission power CU/D2Dusers	23 dBm
Transmit/Receive antenna gain Gt/Gr	1
White Gaussian noise	-174 dBm
Population account (number of bees)	20
Number of drones	7
Number of workers	12
Number of broods	14

Table 3.1. Simulation parameter settings.

To evaluate the BLA algorithm, we firstly compare the convergence of our algorithm with the PSO and GA algorithms. The convergence is considered as a metrics of evaluation for iterative algorithms. Note that an algorithm converges when it reaches the optimal solution and do not improve this solution for the next iterations. Therefore, the best algorithm is the one that quickly reaches a state of convergence.

Then, we investigate the effect of D2D number on network performance by increasing the number of D2D users while observing the network throughput. Furthermore, we studied two scenarios; in the first one, we did not set a minimum required rate for D2D users. Meanwhile, in the second scenario, we have imposed a minimum rate requirement for all users (cellular users or D2D users). A discussion of simulation results come along with every evaluation of the three algorithms.

3.4.1. BLA Convergence and quality performances evaluation

We used two scenarios to assess the convergence performance of the BLA alongside with two other bio-inspired algorithms which are Genetic Algorithm (GA) and the Particle Swarm Optimization algorithm (PSO). First, we set cellular users to 8 users and D2D pairs to 10 and run the three algorithms with the same initial population. In the second scenario, we set the cellular users to 8 and the D2D pairs to 20.

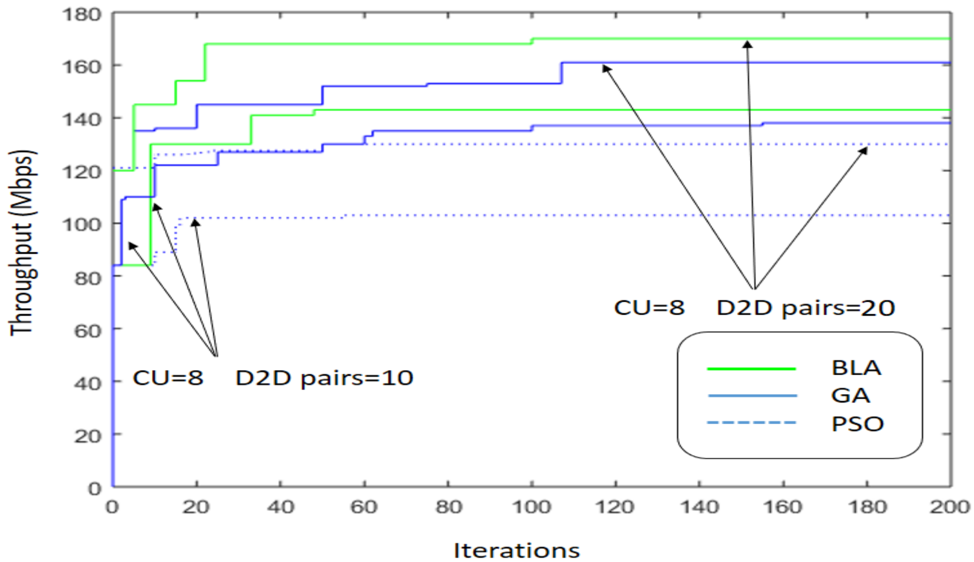


Figure 3.4. Convergence performance of BLA, PSO and GA.

Figure 3.4 shows that our proposed algorithm, the Bee Life Algorithm, provides better results compared to GA and PSO in terms of convergence and the quality of the optimal solution. Indeed, BLA converges to an optimal solution in early iterations, BLA stabilizes around the first 50 iterations. Moreover, the optimal solution that BLA converges to it is better than those obtained by GA and PSO even after 200 iterations.

3.4.2. Number of D2D pairs

In this subsection, we study and discuss the impact of increasing the number of D2D pairs on the overall throughput and the cellular throughput. In figure 3.5, we notice that with the growth of D2D pairs, the overall throughput and D2D throughput increases. However, the cellular throughput decreases because with the augmentation of D2D pairs, there is more interferences on cellular users. Meanwhile, the BLA still gets a better throughput then the other two algorithms.

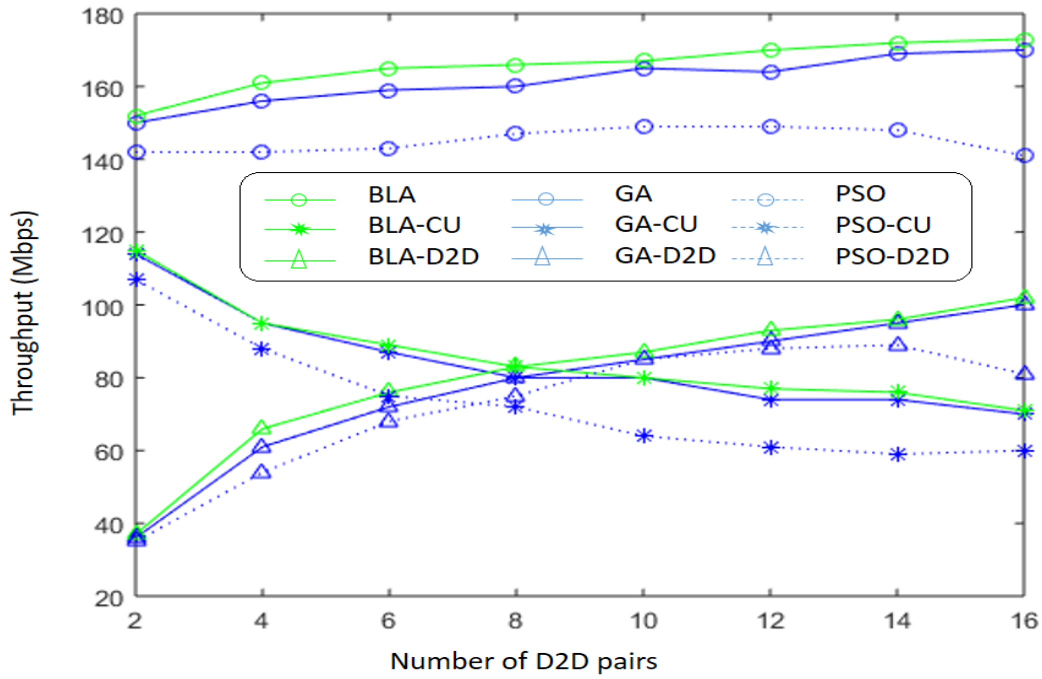


Figure 3.5. Impact of increasing D2D pairs on network throughput.

3.4.3. Effect of D2D pairs on network performance

D2D communication has great potential for improving the network throughput by increasing the ratio of the number of D2D pairs to the number of CUs.

The ratio goes from 1 to 5 which mean the number of D2D pairs start from 8 and increase till 40. Meanwhile, the number of CUs is 8. However, in this scenario, we define a minimum rate requirement for each user to be 250kbps. Figure 3.6 shows the effect of increasing the ratio of D2D pair number to CUs number with minimum rate requirement of 250kbps for each user.

BLA starts with a global search by performing crossover and mutation operations to guarantee a diversified solution search without blocking on a local optimum. Additionally, BLA applies a greedy local search to improve the quality of the talked solution. Simulation results showed that BLA outperformed Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in terms of quality of solution and speed of convergence. BLA converges much earlier than GA and PSO and gets a better solution in terms of throughput.

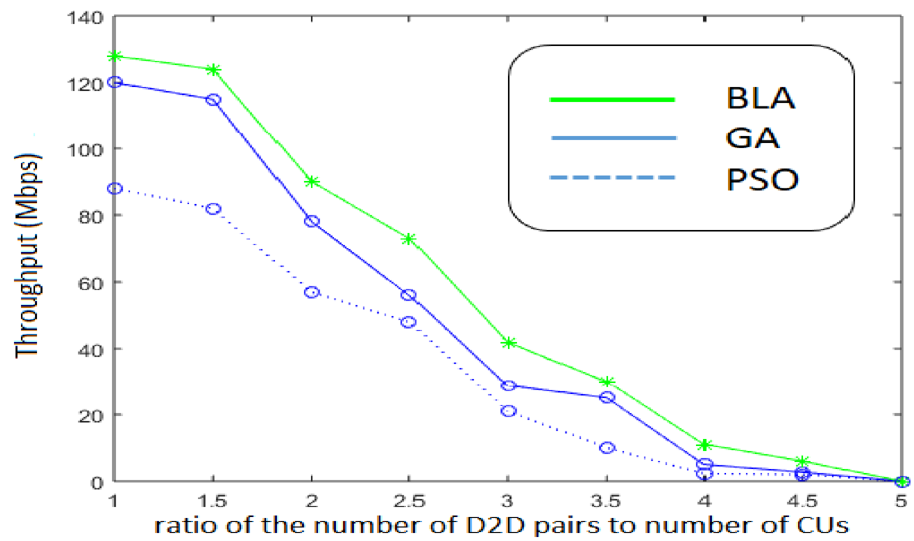


Figure 3.6. Impact of increasing ratio of D2D pairs number to CUs number with rate requirement of 250kbps for each user.

3.5. An enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications (E-BLAD2D)

The proposed E-BLAD2D algorithm suggests the use of a Simulated Annealing to generate a diversified initial population and then improves this population with the Bee Life Algorithm (BLA). Therefore, at first we present the Simulated Annealing algorithm. Afterward, we describe the used BLA and its optimization operators. At last, we present the E-BLAD2D algorithm that we have proposed to solve the spectrum allocation and power control for D2D communication underlay 5G cellular network.

3.5.1. Simulated Annealing Algorithm

The simulated annealing algorithm is inspired by an analogy between the simulations of the problem of solving large combinatorial optimization problems and the annealing of solids. From this motivation, the algorithm is named "simulated annealing". The Simulated Annealing consists of heating followed by slow cooling [141]. Often used in metallurgy, heating of the metal with very high temperature and the outcome is detachment of the bonds between atoms, which signifies the original structure destruction [142]. It is then followed by a slow cooling (lowering slowly temperature), which allows the formation of new bonds of atoms in a more regular way than the original structure; so, a softer metal, more flexible with less energy is then obtained [143].

In our proposed E-BLAD2D, the simulated annealing is performed to generate an initial population on N individuals (i.e. bees or solutions). To do that, the simulated annealing starts with a single solution generated randomly which is considered to be the metal that will be altered. Then, the energy (E0) of this solution is calculated; the energy represents the fitness of the initial solution. After that, we choose a very high initial temperature Temp0, which will follow decreasing law, expressed as:

$$Temp = Temp_0 \times K_B$$

Here, K_B is the Boltzmann constant which value is less than 1 to decrease the temperature.

The metal is heated with Temp0 and we obtain a new structure of that metal with either lower energy than E0 or higher than E0. If the new energy E is lower (i.e. better) than E0 we save that metal (solution) and replace the metal with the new one. Otherwise, we preserve the new metal with a probability known as the Metropolis criterion which is expressed as:

$$Prob = e^{-\frac{\Delta E}{\mathrm{KB} * Temp0}}$$

Where, ΔE is the difference between the new energy E and the old one E0 as follows:

$$\Delta E = E - E0$$

We repeat this process until no improvement is reached after a number of iteration and the result is an individual of the initial population. The simulated annealing algorithm is executed N time to generate N individuals forming the optimized initial population.

3.5.2. Bee Life Algorithm

BLA algorithm is an optimization process that has given significant results when applied in various research areas like packet routing and job scheduling optimization. BLA contains two sections which are inspired by the two important bees behaviors. In next subsections, initial BLA optimization algorithm applied for spectrum allocation and power control in D2D communications is explained in detail.

A. Encoding and evaluation of an Individual: In our study, an individual (i.e. a bee or a solution) of a population is encoded and represented by a set of allocated spectrum and controlled transmission power representing a solution as showed in figure 3.7. This individual is evaluated according to a fitness function (objective function) specified as an equation.

RB1	S7	S2	
	P7	P2	
RB2	S1	S4	S6
	P1	P4	P6
RB3	S5	S3	S8
	P5	P3	P8

Figure 3.7. Representation of population individual: number of RB is M=3 and CU and D2D pairs number is nbC+nbD=8 with nbC equals 3 and nbD equal 5. RB1 is allocated to S7 and S2 with transmission power P7 and P2. RB2 is allocated to S1, S4 and S6 with transmission power P1, P4 and P6, respectively. RB3 is allocated to S5, S3 and U8 with transmission power P5, P3 and P8, respectively.

B. Objective function (fitness): to estimate the D2D communication throughput given by this individual; it is subjected to some constraints and calculated as follows:

$$Fitness\ (bees) = \sum_{i=1}^{nbC+nbD} \sum_{r=1}^{M} \mathrm{B}\log 2(1+\mathrm{SINR}\ \mathrm{i},\mathrm{r})$$

Subject to the following constraints:

$$Pi\ \leq\ Pcm\ \forall\ i = 1 \ldots nbC$$

$$Pi\ \leq\ Pdm\ \forall\, i = nbC + 1\ \ldots nbC + nbD$$

$$Li,r\ \leq\ 1\, \forall\, i = 1 \ldots nbC, \forall\, r = 1 \ldots K$$

$$SINRir\ \geq\ SINRm\, \forall\, i = 1 \ldots nbC, \forall\, r = 1 \ldots K$$

C. Crossover operator: this operation is used to represent the mating behavior of bees reproduction and to guarantee the variety of solutions. To form an offspring, the crossover operator combines a part of queen genes with a part of a drone genes who mates with the queen, hence a new brood is engendered. This crossover operator is submitted to a fixed probability called the crossover threshold (noted Cr_Th). Specifically, in our proposed algorithm, we use a one-point crossover to achieve this operation. To do that, a random number is chosen from$[1, nbC + nbD]$; this number represents the slicing point of queen and drone chromosomes. Any time the queen and a drone mate produce two new broods as clarified in figure 3.8.

$$Queen = \{S_1, S_2, S_3, S_4, S_5, S_6, \dots, S_{nbC+nbD}\}$$

$$Drone\ i = \{\boldsymbol{S'_1}, \boldsymbol{S'_2}, \boldsymbol{S'_3}, \boldsymbol{S'_4}, \boldsymbol{S'_5}, \boldsymbol{S'_6}, \dots, \boldsymbol{S'_{nbC+nbD}}\}$$

If the random number is equal to three (3) then the next broods will be assembled from two components. The queen and the drone divided into two parts.

$$Brood\ 1 = \{S_1, S_2, S_3, \boldsymbol{S'_4}, \boldsymbol{S'_5}, \boldsymbol{S'_6}, \dots, \boldsymbol{S'_{nbC+nbD}}\}$$

$$Brood\ 2 = \{\boldsymbol{S'_1}, \boldsymbol{S'_2}, \boldsymbol{S'_3}, S_4, S_5, S_6, \dots, S_{nbC+nbD}\}$$

Figure 3.8. One-point Crossover of BLA

D. Mutation operator: in rare cases, brood genes mutate. This mutation occurs with a fixe probability and it is called Mutation threshold (Mu_Th). In BLA, mutation is modeled as follows; we choose randomly two communications (two genes of the brood chromosome) and swap the RB allocated to each communication. It is reasonable to assure that the two communications are from the same type. In other words, if the first communication is a cellular communication, then the second one must be a cellular communication. Moreover, when we choose a D2D communication, then the communication that will switch RB with the first communication is a D2D communication.

E. Food foraging process: The workers bees explore the neighborhood for food source searching. In BLA, for a worker bee (a solution), we use a greedy local search algorithm to discover the existence of a better solution (another worker with a better food source) in local area which leads to a local optimal solution. We apply a local search to guarantee that we end up with the best solution in the explored area as shown in figure 3.9 (a). By projection, we select a D2D communication randomly, and we improve the transmission power of that communication to its optimal value by choosing two values; one superior and the second less than the power of the selected communication, and by comparing the throughput produced by those two value we explore above or under the original value. The improved solutions are preserved and the rest are ignored as illustrated by figure 3.9 (b).

(a)

A worker	CU_1	CU_2	....	$D2D_1$	....	$D2D_i$ with **P=17** dBm	....	$D2D_N$

Neighbor1	CU_1	CU_2	....	$D2D_1$	....	$D2D_i$ with **P=12** dBm		$D2D_N$
Neighbor1	CU_1	CU_2	....	$D2D_1$	....	$D2D_i$ with **P=8** dBm	....	$D2D_N$
.				.				.
.				.				.
.				.				.
Neighbor1	CU_1	CU_2	....	$D2D_1$	....	$D2D_i$ with **P=20** dBm	....	$D2D_N$
Neighbor1	CU_1	CU_2	....	$D2D_1$	....	$D2D_i$ with **P=19** dBm	....	$D2D_N$

(b)

Figure 3.9. Food foraging in real life (a) and in BLA (b).

3.6. An enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications: our proposal

In this subsection, we present our proposal named An enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications (E-BLAD2D) algorithm [149]; it is a combination between the simulated annealing algorithm and the BLA.

We suggest a simulated annealing scheme to generate a promising initial population that improves the transmission power of D2D communications. Then, we optimize that population with BLA algorithm [137], [144], that improves spectrum allocation and power control.

Algorithm 2 presents the pseudo code of E-BLAD2D algorithm to solve spectrum allocation and power control for D2D communication underlay 5G cellular networks.

E-BLAD2D algorithm for spectrum allocation and power control

```
for (i ← 1 to N) do
    Sol ← random (solution)
    E0 ← fitness (Sol)
    while (not (stopping_criteria)) do
        NewSol ← Neighbor (Sol)
        E ← fitness (NewSol)
        if (E0 < E ) then
            Sol ← NewSol
            E0 ← E
        else
            Prob = e^{-ΔE/(KB*Tempo)}
            if (Prob > random()) then
                Sol ← NewSol
                E0 ← E
            end if
        end if
    end while
end for   // end of initialization of N bees with Simulated Annealing
while (not (stopping_criteria)) do
    Evaluation: calculate_fitness (N bees)
    Sorting: select one Queen, D drones, W workers
    Reproduction
        Crossover
        Mutation
    Food Foraging
        Optimize_transmission_power_D2D_pair
    Evaluation: fitness(broods, new workers)
    Selection (best N bees)
end while
```

30. output (Queen)
End E-BLAD2D Algorithm

Algorithm 2. Pseudo code of E-BLAD2D for joint spectrum allocation and power control problem.

A. Computational Complexity of E-BLAD2D: in this section, we discuss E-BLAD2D computational complexity, it I calculated as follows:
First, generating N bees with simulated annealing (population individual):

$$O(N) + O((Pm_{c/d} - 1) \times (nbC + nbD) \times N)$$

With O(N) is for generating N individual randomly. For each individual, $(Pm_{c/d} - 1)$ is the possible values of transmission power for cellular users (Pmc) and D2D pairs (Pmd) multiplied with the number of communications $(nbC + nbD)$. We do that for N individuals.

Second, for reproduction in BLA, there is T_C (crossover probability) crossover. Among the broods, there are those who mutated with probability T_M (mutation probability):
We have a $O\ ((N \times C\_T) \times M\_T)$ time units.

Additionally, for food foraging assured by W worker in NR regions with a greedy local search:

There is $O\ (W \times NR)$ time units.

As a result, each iteration of E-BLAD2D has a computational complexity equivalent to:

$$O(N) + O\left(\left(Pm_{c/d} - 1\right) \times (nbC + nbD) \times N\right) + O\big((N \times T\_C) \times T\_M\big) + O(W \times NR)$$

$$\approx O(N \times (1 + (Pm_{(c/d)} - 1) \times (nbC + nbD)) + ((N \times T\_C) \times T\_M) + (W \times NR))$$

BLA can run I iterations before reaching the optimal solution, which is considered as a stopping criterion in the worst case, hence, the E-BLAD2D computational complexity is then:

$$CC\ (E - BLAD2D) \approx O(N \times (1 + (Pm_{(c/d)} - 1) \times (nbC + nbD))) + O(I \times (N + ((N \times T\_C) \times T\_M) + (W \times NR)))$$

E-BLAD2D computational complexity is confirmed to be linear and it is the lowest computational complexity possible.

3.7. Simulation and Numerical Results

The validation of E-BLAD2D algorithm is done with a set of simulations. We compared E-BLAD2D algorithm with two other bio-inspired algorithms which are: Practical Swarm Optimization (PSO) [145] and Genetics Algorithm (GA) [146]. We consider one cell network as shown in figure 3.10. Generally, the radius of a macro cell starts from 1000 meters [140], so we consider the radius of a cell to be 1000 meters. The distance between two devices for D2D communication is restricted to a supreme bound of 50 meters which is used as the standard in various studies [147]. The BS is located in the center of the cell and users are randomly dispersed around the BS inside the cell. The radio frequency used in our simulation is 2.4 GHz and the maximum transmission power is fixed to 23 dBm for both CU and D2D pairs [148]. In this paper, E-BLAD2D algorithm is a centralized approach, which means that collecting Channel State Information (CSI) falls on the BS. We summarized the system parameters in our simulations in Table 3.2.

Parameter	Value
Cell radius	1000 m
D2D coverage	50 m
F	2.4 GHz
B	1 MHz
Pcm/Pdm	23 dBm
WGN	-174 dBm
N	20
D	7
W	12
Y	42

Table 3.2. Simulation Parameters.

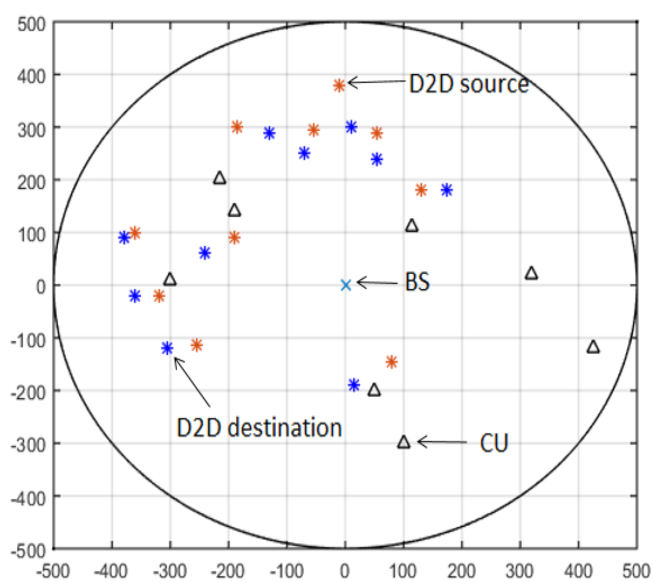


Figure 3.10. Snapshot of system simulation.

In the conducted simulations, we consider that the number of bees in a population is 20 with a single Queen, 7 Drones and the 12 Workers. The Crossover operation is a one point-crossover. Consequently, after coupling the queen and one of drones the number of generated broods is two, which means that each generation of broods is composed of 14 broods.

A. Convergence of the E-BLAD2D algorithm

Convergence in iterative algorithms is very important, it is the case of E-BLAD2D, GA, and PSO. Therefore, we assess the convergence of E-BLAD2D algorithm compared to PSO and GA Algorithms. The first scenario consists of fixing the number of CUs and D2D pairs to 08 and 10, respectively. And then, we set the D2D pair number to be 20, while keeping the number of CUs as it was (i.e. 08 CUs). All user have rate requirement fixed at 250 kbps.

From figure 3.11, the network throughputs of the second scenario is higher compared to the first scenario. This indicates that with the increasing of D2D pair number, the network throughput will improve.

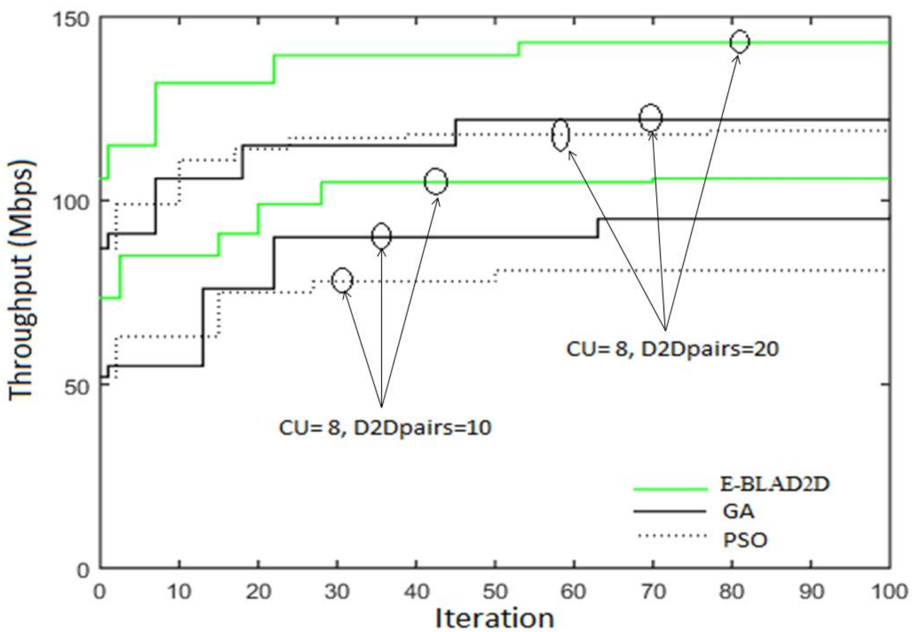


Figure 4.11. Evaluation of Convergence of E-BLAD2D, GA and PSO

The E-BLAD2D algorithm reaches a higher value of throughputs compared to those obtained by PSO and GA algorithms in the first and the second scenarios. PSO and GA algorithms converge in an acceptable time, yet to an optimal local, while the E-BLAD2D algorithm escapes the local optima and reaches a higher throughput compared to PSO and GA.

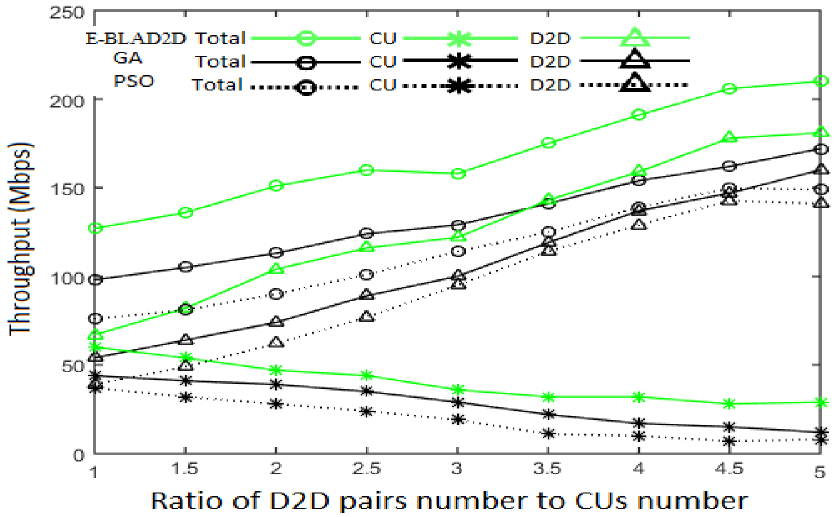
In this simulation, the E-BLAD2D algorithm reaches a higher value of network throughput equal to 106 Mbps in the first scenario and 143 Mbps in the second one; compared to those obtained by PSO and GA algorithms; 81 Mbps and 96 Mbps, respectively, in the first scenario. Meanwhile, in the second scenario PSO and GA algorithms reached 119 Mbps and 122 Mbps, respectively. In both scenarios, the E-BLAD2D converges to a higher throughput quicker than PSO and GA algorithms.

B. Impact of the D2D pairs on network performance

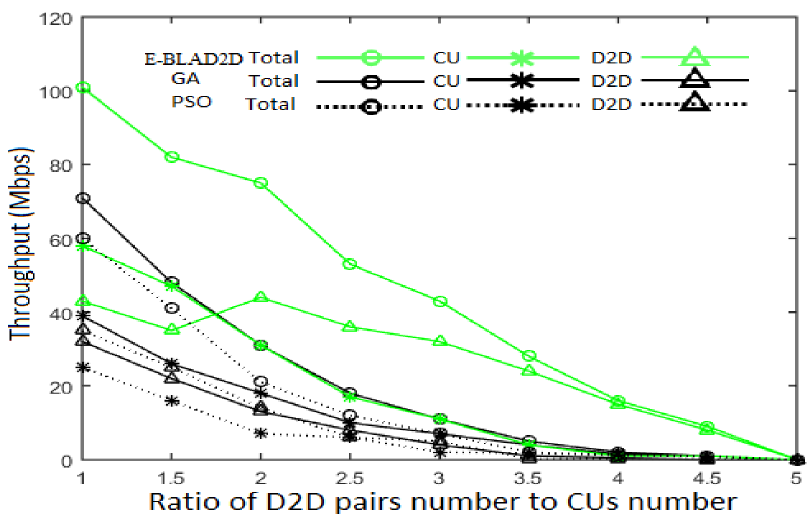
To study the influence of increasing the number of D2D compared to the number of CUs and its impact on network throughputs, we observe network throughput while we increase the ratio of D2D pairs to CUs. The number of CUs is 8, and we increase the number of D2D pairs in a way that the ratio of D2D pairs to CUs varies from 1 to 5 with an increment equal to 0.5. Therefore, the D2D pairs sharing channels with CUs are from 8 to 40 D2D pairs. We execute the simulations 50 times with each parameter setting. The total throughputs, D2D pairs throughput and CUs throughput reached by the E-BLAD2D, PSO and GA algorithms are depicted in figure 3.12 (a) and (b). In figure 3.12 (a), all users do not have any rate requirements. Meanwhile in figure 3.12 (b), the users have a minimum rate requirement equivalent to 250 kbps.

Figure 3.12 (a) shows that there is a decreasing in network throughput and D2D throughput while the number of D2D pairs increases. However, the CUs throughput decreases opposing to the D2D pairs number. The decreasing of CUs throughput is caused by the increasing number of D2D pairs, which leads to higher interferences on CUs. By comparing the reached throughputs of the three algorithms E-BLAD2D, PSO and GA, we can see clearly that E-BLAD2D algorithm achieves higher throughput of D2D, CUs and network throughput compared to PSO and GA.

The overall network throughput, CUs throughput and D2D pairs throughput (presented in figure 3.12 (b)) are reducing with the increase of D2D to CU ratio from 1 to 5. The reason generating this phenomenon is the condition of minimum rate requirement on users. This condition confines the three algorithms to improve the throughputs. Even when all throughputs, total, CU and D2D are lessening, E-BLAD2D algorithm performs better than PSO and GA.



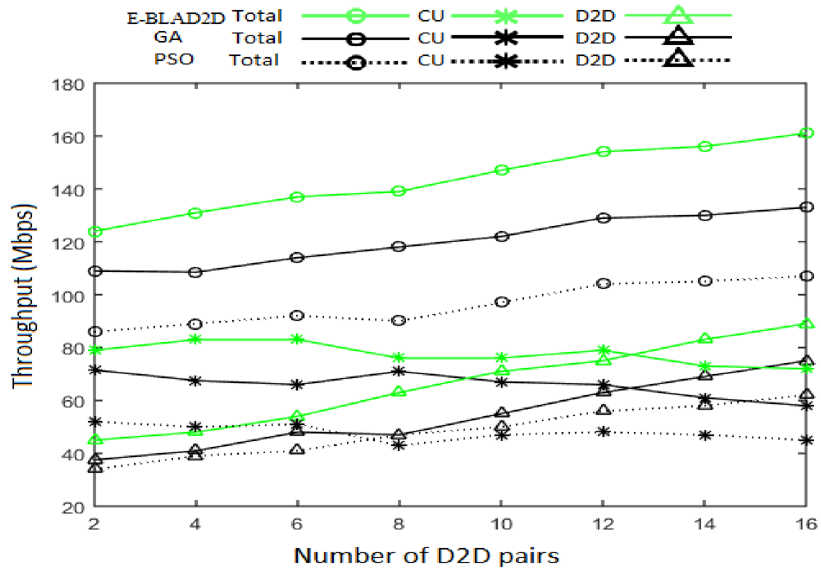
(a) : No rate requirement for each user.



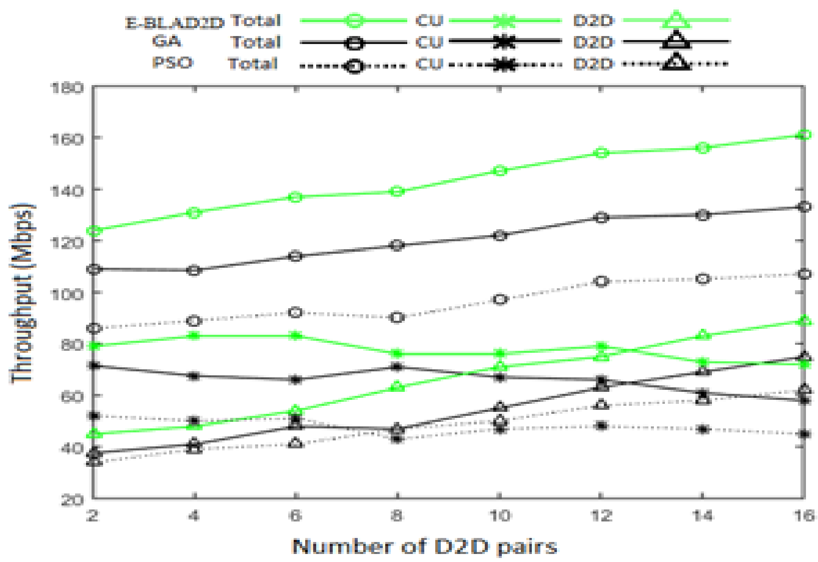
(b) : Rate requirement for each user is 250 Kbps.

Figure 3.12. Vary the ratio of the D2D pairs to the CUs, average results of many runs.

After studying the relationship between the number of D2D pairs and CUs and its impact on throughputs, we investigate in the next scenario the effect of increasing the number of D2D pairs on the network throughput. Many previous works found in the literature allow mostly two D2D communications to share a RB with a CU, we set D2D pairs at most two times CUs number. We fixed the number of cellular users to 8, and we increment D2D pair number starting with 2 until reached 16 by adding 2 D2D pairs each time. The results of this scenario, with and without rate requirement on one user only, are illustrated in figure 3.13 (a) and (b), respectively.



(a) : No rate requirement for each user.



(b) : Rate requirement for one user is 250 Kbps.

Figure 3.13. Vary D2D pairs number for E-BLAD2D, PSO and GA.

Figure 3.13 (a) shows that network throughputs and D2D throughputs for all algorithms increase alongside the number of D2D pairs. Still, CUs throughputs reached with all algorithms decrease opposing the increase of D2D pairs. The reason lays in the increase of interferences originated from the increasing number of D2D pairs. The performance of E-BLAD2D algorithm is obviously better, it is proved by the achieved throughput compared to those of PSO and GA algorithms.

In figure 3.13 (b), network throughput realized by E-BLAD2D algorithm increases while the CUs number is bigger than the D2D number, and D2D throughput augments when the number of D2D is less than almost twice the number of CUs. By comparing the achieved throughput of E-BLAD2D with and without rate constraint when the number of D2D is 16, we can see that the throughput is equal to 94 Mbps with rate constraint, and it is lower than 161 Mbps reached in without rate constraint. Both figures 3.13 (a) and (b) show that E-BLAD2D algorithm outperforms PSO and GA algorithms by achieving higher total throughput.

3.8. Conclusion

In this chapter, two bio-inspired spectrum allocation and power control schemes for D2D communication underlay 5G cellular networks were presented. Not only one D2D pairs can share a resource block with a cellular user, but as many as we can serve. Maximizing network throughput was the objective of these proposed algorithms without neglecting a minimum rate requirement for CUs. The first proposed scheme is the Bee Life Algorithm (BLA), meanwhile the second proposed system is a combination of simulated annealing and BLA, named an enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications (E-BLAD2D). We start with an initial population, which is generated using a simulated annealing algorithm to optimize transmission power for all users. Secondly, we used the iterative BLA which is composed of two main parts; the first one is the bees behavior of reproduction modeled with one-point crossover and mutation, where the second part is based on the food foraging behavior modeled with a greedy local search, applied to optimize the transmission power of D2D communications. After summarizing the related works and seeing the results of the E-BLAD2D, we are convinced that there is a better solution that can be achieved by using the Matching algorithm and BLA and that will be the subject of the next chapter.

Chapter 04

Matching Bees Algorithm for Spectrum Allocation and Power Control in D2D Communications

Chapter 04: Matching Bees Algorithm for Spectrum Allocation and Power Control in D2D Communications

4.1. Introduction

In this chapter, we present another work done to solve the joint spectrum allocation and power control problem in D2D communication underlay 5G cellular network. This proposition consists of using Matching Algorithms combined with a modified BLA to improve the results obtained by BLA and E-BLAD2D in the past chapter. The results obtained were compared to those reached with three bio-inspired algorithms namely, Bee Life Algorithm (BLA), Genetic algorithm (GA) and Particle Swarm Optimization (PSO).

4.2. Matching Bees Algorithm

This algorithm is based on modified BLA by enhancing its optimization operators. We use Matching theory techniques to improve BLA performance [150], [151]. We start improving individuals of the initial population by using one-to-many matching with externalities for resources allocation in order to serve D2D pairs. We allocate a RB to a D2D user only if that D2D user can achieve the highest throughput compared to the other throughput achieved on the other RBs.

After enhancing the initial population, we launch the iterative BLA after improving reproduction and food foraging. As depicted in the second algorithm (the MBA algorithm), improving initial population with matching theory is done by choosing a RB that increases the throughput more than the other RBs. For each pair of D2D users, we calculate the throughput of the pairs on each RB. After that, we sort the calculated throughputs and the duo (D2D pair and RB) that achieves the highest throughput is the chosen one. We repeat this process for every D2D pair. And if there are two (or more) duos that achieve the same highest throughput, we choose the RB that has less number of D2D pairs sharing it, and if the two (or more) duos have the same number of D2D pairs, then we choose one of theme randomly. Figure 4.1 and Algorithm 4.1 present the flowchart and the pseudo code with detailed optimization operators of the Matching Bees Algorithms, respectively.

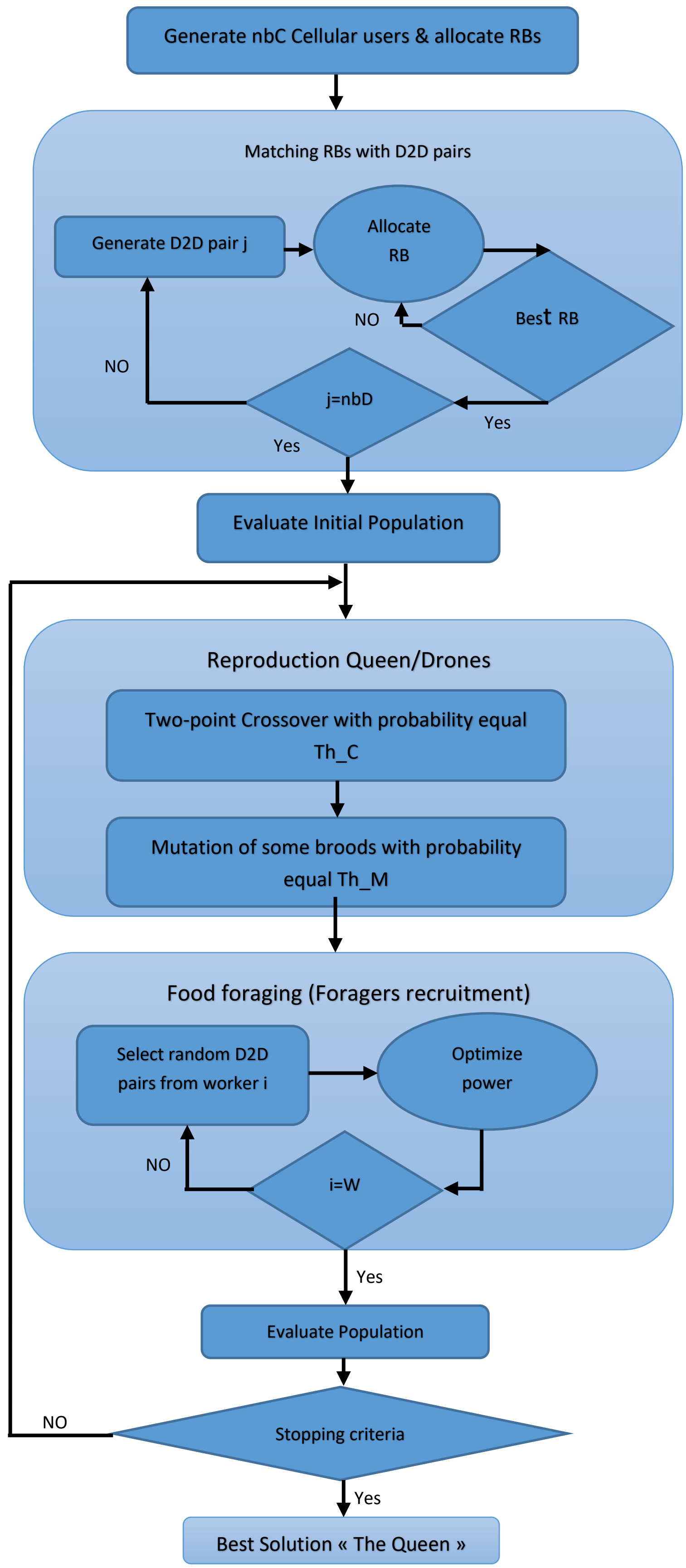


Figure 4.1. Flowchart of the MBA algorithm.

4.2.1. Initialization with Matching Algorithm

In this work, we used matching algorithm one-to-many with externalities which mean that if an individual change it implicate the change of the system (network throughput in our case). We start the initialization by allocating channels to cellular and D2D users. Each user is allocated to a channel only if that user achieve its highest throughput possible. The transmission power is randomly allocated to users. Figure 4.1 shows the principal function of the matching part and the rest of the MBA algorithm.

4.2.2. The Bee Life Algorithm

It was presented in the previous chapter in details; we will discuss briefly the modified optimization operators of the BLA.

A. Individual representation and fitness: as defined in the optimization domain, Individual Fitness is an equation used to evaluate each individual of the population. In our case, an individual is a solution which is a set of allocated resources and controlled transmission power as illustrated in figure 4.2.

```
MBA  pseudo code for resource and power allocation
1. for (i ← 1 to X) do
2.     for (r ← RB1 to RBK) do
3.           if ( Best_fitness < fitness (i-th, r-th) ) then
4.                 Best_fitness ← fitness(i-th, r-th)
5.           end if
6.     end for
7. end for   // end of initialization of X bees with matching theory
8. while (not (stopping_criteria)) do
9.      Evaluation: calculate_fitness (X bees)
10.     Categorization: One Queen,  W workers, D drones
11.     Reproduction
12.        Crossover
13.        Mutation
```

```
Food Foraging
    Optimize_transmission_power_D2D_pair
Calculate_Fitness (broods, new workers): Evaluation
Keep X  best bees: Selection
end while
Best Solution (Queen)
End MBA
```

Algorithm 4.1. MBA pseudo code for joint resource and power allocation problem.

RB1	U4	U2	U5
	P4	P2	P5
RB2	U1	U6	
	P1	P6	
RB3	U7	U3	U8
	P7	P3	P8

Figure 4.2. Individual representation: The RB number is K=3 and users number is nbC+nbD=8 with nbC and 5 respectively. RB1 is shared between U4, U2 and U5 with transmission power P4, P2 and P5, respectively. RB2 is shared between U1 and U6 with transmission power P1 and P6, respectively. RB3 is shared between U7, U3 and U8 with transmission power P7, P3 and P8, respectively.

Thus, the fitness of each individual is his throughput and it is calculated as follows:

$$Fitness(Bees) = \sum_{i=1}^{nbC+nbD} \sum_{r=1}^{K} B \log_2(1 + SINR_{i,r})$$

B. Crossover operation: the operation of Crossover merges the Queen gene signifying a part of solution with a percentage of chromosome from the Drone that the queen is mating with, in order to create new broods. Crossover operation is completed with a fixed probability (Th_C: crossover threshold). The MBA algorithm uses two-point crossover. Two random numbers are chosen from the interval $[1, nbC + nbD]$; those two numbers represent the slicing point of the Queen and the drone chromosome. Each time the Queen mates with a Drone, it produces new broods as illustrated in figure 4.3.

C. Mutation operation: in some cases, some of the brood genes mutate. This mutation happens with a probability (Mutation threshold Th_M). We randomly choose two communications in the brood chromosome and swap their RB allocated to each of them. It is naturally to assume that the two chosen communication have the same type of communication. In other word, if D2D pair is chosen, then the user that will swap RB with is a D2D pair and vice versa.

D. Food foraging: the workers discover the neighborhood to find food sources. For every worker bee (solution),a greedy local search approach is used to discover if there is a better solution in the local area of that worker leading to local optimal solutions.

$$Queen\ = \{U_1, U_2, U_3, U_4, U_5, U_6, \dots, U_{nbC+nbD}\}$$
$$Drone\ i\ = \{\boldsymbol{U_1}, \boldsymbol{U_2}, \boldsymbol{U_3}, \boldsymbol{U_4}, \boldsymbol{U_5}, \boldsymbol{U_6}, \dots, \boldsymbol{U_{nbC+nbD}}\}$$

If the two random numbers equal three (3) and five (5) then the broods will be built from three components. The parents, divided into three parts, giving to the new brood either a part or two to be born. Combining parts from the parents gives birth to the brood and changing part source lead us to a new brood as depicted in the following

$$\text{Brood 1} = \{\mathrm{U}_1, \mathrm{U}_2, \mathrm{U}_3, \mathbf{U_4}, \mathbf{U_5}, \mathbf{U_6}, \dots, \mathbf{U_{nbC+nbD}}\}$$
$$\text{Brood 2} = \{\mathrm{U}_1, \mathrm{U}_2, \mathrm{U}_3, \mathbf{U_4}, \mathbf{U_5}, \mathrm{U}_6, \dots, \mathrm{U}_{nbC+nbD}\}$$
$$\text{Brood 3} = \{\mathrm{U}_1, \mathrm{U}_2, \mathrm{U}_3, \mathrm{U}_4, \mathrm{U}_5, \mathbf{U_6}, \dots, \mathbf{U_{nbC+nbD}}\}$$
$$\text{Brood 4} = \{\mathbf{U_1}, \mathbf{U_2}, \mathbf{U_3}, \mathrm{U}_4, \mathrm{U}_5, \mathrm{U}_6, \dots, \mathrm{U}_{nbC+nbD}\}$$
$$\text{Brood 5} = \{\mathbf{U_1}, \mathbf{U_2}, \mathbf{U_3}, \mathrm{U}_4, \mathrm{U}_5, \mathbf{U_6}, \dots, \mathbf{U_{nbC+nbD}}\}$$
$$\text{Brood 6} = \{\mathbf{U_1}, \mathbf{U_2}, \mathbf{U_3}, \mathbf{U_4}, \mathbf{U_5}, \mathrm{U}_6, \dots, \mathrm{U}_{nbC+nbD}\}$$

Figure 4.3. Two-point Crossover for MBA

We use local search to assure that we get the best solution in that area in order to avoid missing the all best solution because we did not exploit the neighborhood of only a good solution. To accomplish this, we choose a random D2D communication, and we improve its transmit power to an optimal value. The new improved solutions are conserved; otherwise, they will be ignored.

4.2.3. Computational Complexity of MBA

The complexity of the MBA algorithm is the same as the complexity of the improved BLA in addition to the complexity of the matching part. Thus, the complexity of MBA is calculated as follows:

Creating and calculating fitness for X bees (population individual):

$$O(X) + O(X) \approx O(X)$$

The complexity of matching each D2D pair with all RBs and multiplied by the population individuals number, and in our case the number of individuals in a population is X:

$$O((nbD \times K) \times X)$$

One iteration has: Crossover with probability Th_C, inside those crossovers, we find Mutation with probability Th_M:

$$O((X \times Th\_C) \times Th\_M)$$

W worker search in R regions by doing a greedy local search to complete food foraging :

$$O(W \times R)$$

Therefore, for each iteration of MBA, the computational complexity is given as:

$$O(X) + O\big((nbD \times K) \times K\big) + O\big((X \times Th\_C) \times Th\_M\big) + O(W \times R)$$
$$\approx O\big((nbD \times K) \times X\big) + O(X + ((X \times Th\_C) \times Th\_M) + (W \times R))$$

The BLA computational complexity for S iterations is expressed as follows:

$$CC(MBA) \approx O\big((nbD \times K) \times X\big) + O(S \times (X + ((X \times Th\_C) \times Th\_M) + (W \times R)))$$

The computational complexity of MBA is verified to be linear, which is the lowest computational complexity.

4.3. Simulation and numerical results

The validation of our proposed algorithm, through simulation, is presented in this section. We compared The MBA algorithm with other bio-inspired algorithms, namely: Bee Life Algorithm (BLA), Genetics Algorithm (GA) and Practical Swarm Optimization (PSO). In our simulations, we study a network with a solo cell as illustrated in figure 4.4.

Typically, the radius of the macro cell starts from 1 Kilometers [140], so we choose the cell radius to be 1000 meters. 50 meters is the maximum distance separating the transmitter and the receiver of a pair of D2D users, which is the standard used in many papers [147]. The cell center is the location of our base station with cellular and D2D users arbitrarily scattered around the BS inside the cell. We used 2.4 GHz as radio frequency and the transmission power for both type of users is configured not to surpass 23 dBm. Since the proposed algorithm is centralized, the BS provides the Channel State Information (CSI) of the network. We summarized the parameters of the system used throughout our simulations in Table 4.1. The digit number of bees in a population is chosen to be 20 with One Queen, 7 Drones and 12 Workers. The Crossover operation is a two point-crossover. Thus, the number of broods each time the queen mates with a drone is three, so the total number of broods in each generation is 42.

4.3.1. Convergence of the MBA algorithm

MBA, BLA, GA, and PSO algorithms are iterative algorithms; converging as quickly as possible is very important. Therefore, we evaluate the convergence of MBA algorithm compared to BLA, GA and PSO through two scenarios. First scenario consists of eight (08) CUs and ten (10) pairs of D2D users. Meanwhile for the second scenario, we used twenty (20) pairs of D2D users and left eight (08) CUs. Each user has a minimum rate requirement equals 250 kbps.

Parameters	values
Cell radius	1 Km
D2D users coverage	50 m
WGN	-174 dBm
Pcmax/Pdmax	23 dBm
F	2.4 GHz
B	1 MHz
nbC	8
X	20
W	12
D	7
Y	42

Table 4.1. Simulation Parameters.

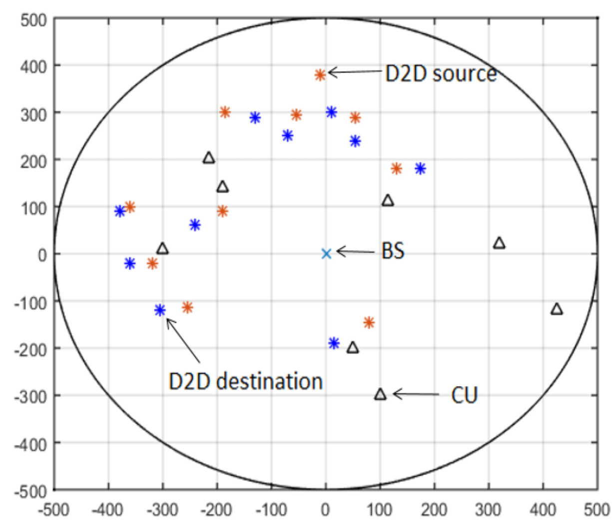


Figure 4.4. Snapshot of system simulation.

The total network throughputs, from figure 4.5, in the second scenario are higher compared to those in the first scenario, which suggests that increasing D2D pair number will ameliorate the network throughput. The MBA algorithm attains greater throughputs if it is compared to the BLA, PSO or GA in the two scenarios. BLA, GA and PSO algorithms converge within an acceptable time but to local optima, while the MBA algorithm has the potential to escape local optima and obtains a solution with a better throughput.

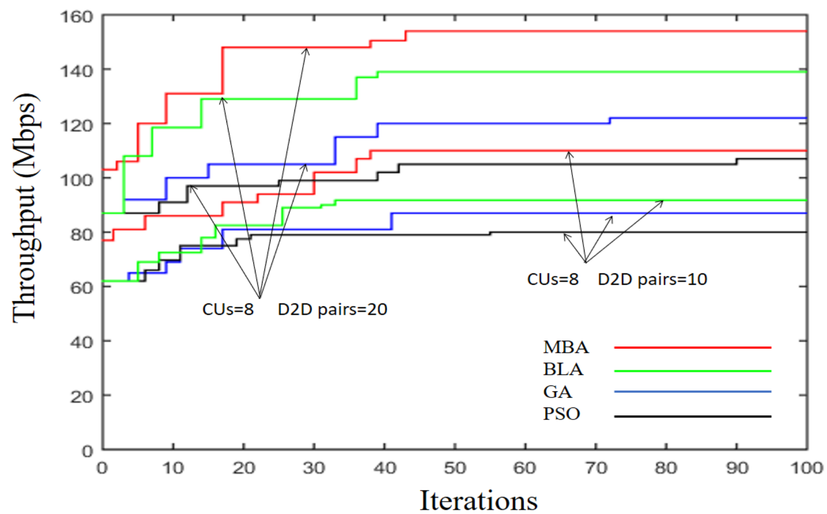
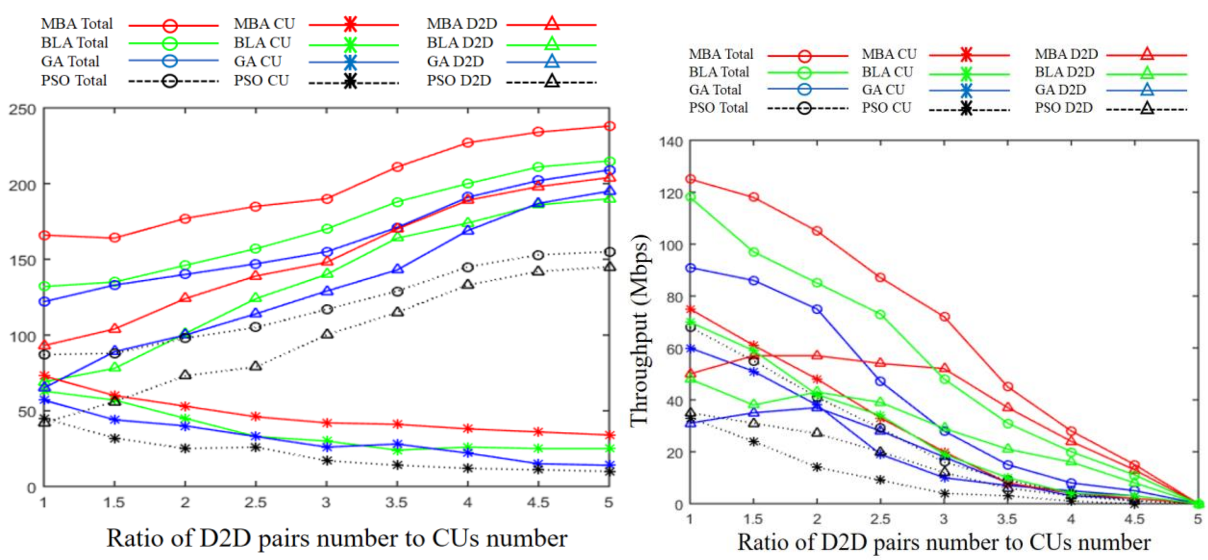


Figure 4.5. Evaluation of Convergence of MBA, BLA, PSO and GA for joint power and resource allocation

4.3.2. Effect of D2D pairs number on network performance

To reveal the effect of D2D communications on network throughput, we monitor the network throughput while rising the D2D pair to the CU ratio. We fixed the CUs (eight CU), and vary the ratio starting from 1 to 5 with an 0.5 augmentation. Consequently, for each CU there is eight (08) to forty (40) D2D pairs spliting the same RB. We run the simulations 50 times for each setting. The network, D2D and cellular throughput achieved by the MBA, BLA, GA and PSO



(a) : no rate requirement.

(b) : rate requirement of 250 Kbps.

Figure 4.6. Effect of the ratio of D2D to the CU, average results on 50 runs.

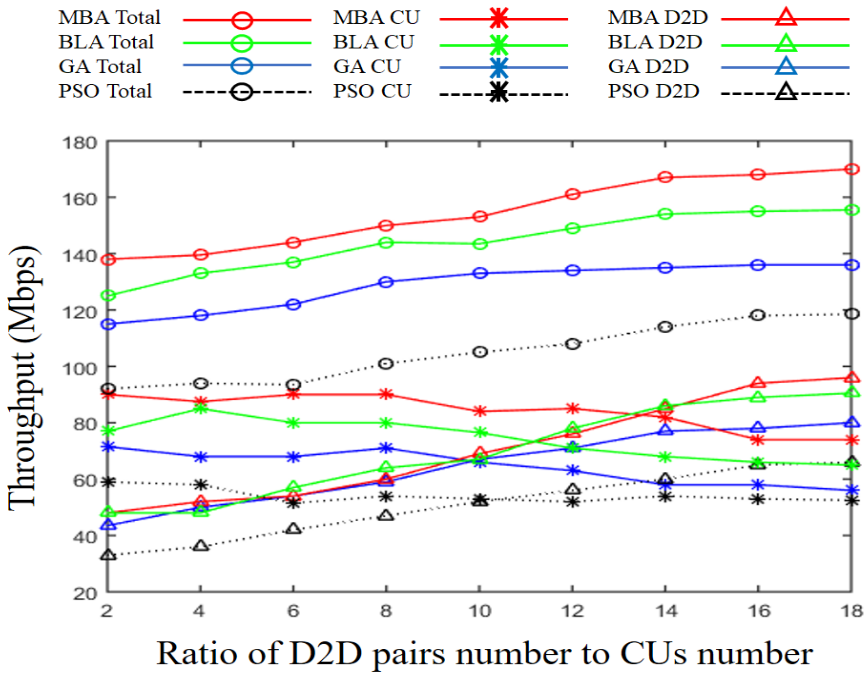
are displayed in figure 4.6 (a and b). For figure 4.6 (a) and for each user, we do not set any rate requirements. Meanwhile In figure 4.6 (b), each user has a minimum rate requirement equal to 250 kbps.

Figure 4.6 (a) displays that D2D and network throughput escalate alongside the D2D pairs number. In the meantime, the cellular users throughput drops contrary to the number of D2D pairs. The reason is that the interference on CUs will get higher if the number of D2D pair increases. Consequently, the outcome is a decrease in CUs throughput. If we compare the achieved throughputs by the MBA algorithm with BLA, GA and PSO algorithm, we recognize that the MBA algorithm achieves a greater cellular throughput and attains greater network throughput compared to the other bio-inspired algorithms, namely the BLA, GA and PSO algorithm.

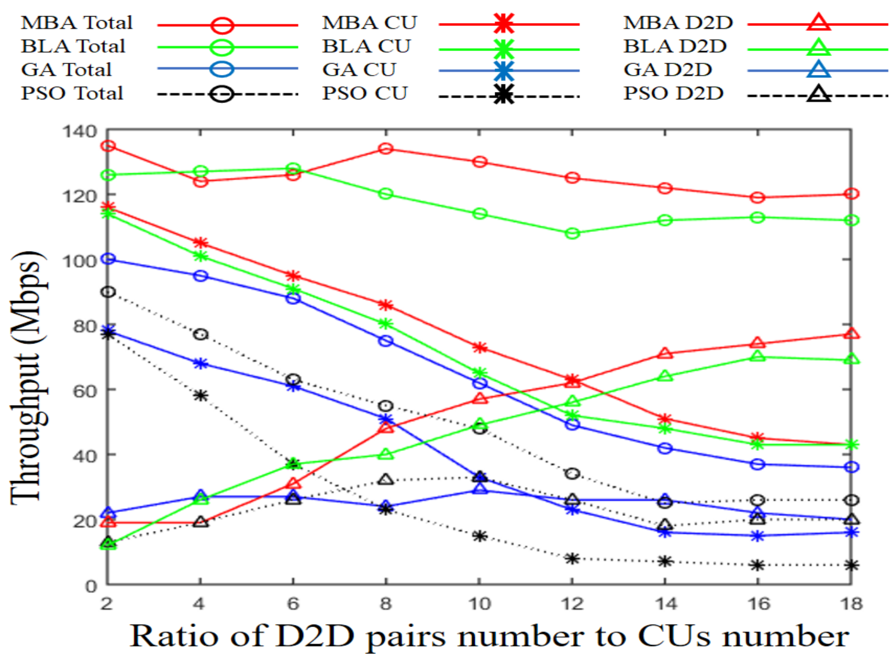
The network throughput in figure 4.6 (b), the throughput of D2D and cellular users are all diminishing as soon as the ratio of the D2D pair number to the CUs number escalates from 1.5 to 5. The essential cause triggering this is that the minimum rate requirement of every user bounds all algorithms from increasing the throughputs. Although all throughputs (D2D, cellular and network) are diminishing, the throughputs accomplished by the MBA algorithm outclass those realized by the BLA, GA and PSO algorithms.

Observing that many previous studies in the literature tolerate mostly two pairs of D2D users to share a RB with one cellular user, we setup a configuration where the pairs of D2D users reaches double CUs number. In our simulation, the cellular users number is fixed at eight (08), and we augment the D2D pair number starting with two (02) and adding two (02) each time until we reach sixteen (16). The outcomes of this scenario, with and without the requirement of a minimum rate on only one user, are displayed in figure 4.7 (a and b), respectively.

The network and D2D throughputs, as presented in figure 4.7 (a) and for the four algorithms, increase when the D2D pairs number increases. Nevertheless, the CUs throughputs obtained from the three algorithms decrease when the D2D pairs number increases, and that is because the augmentation in D2D pairs number leads to more interferences on cellular users. The benefit of MBA is evident due to the upper achieved throughput of cellular users compared to the BLA, GA and PSO algorithms even though the D2D pairs throughput is kept nearly the same if matched to that obtained by the BLA, GA and PSO algorithms.



(a) : No rate requirement for each user.



(b) : Each user has a rate requirement of 250 Kbps.

Figure 4.7. Vary D2D pairs number for MBA, BLA, GA and PSO.

In figure 4.7 (b), the throughput realized with the MBA is steady while the pairs of D2D users number is fewer than the number of cellular users, and when the D2D pairs number is less than 12, the D2D pairs throughput augments. It means that to increase the network throughput we must satisfy, for each user, the requirement of minimum rate. While trying, for each user, to satisfy the requirement of minimum rate, the interference inflicted by users must be kept under a specific level, and that binds the transmission power of users to a rather low level. Therefore, this leads to an inferior network throughput if matched to the second scenario where there is no minimum rate restriction on a sole user.

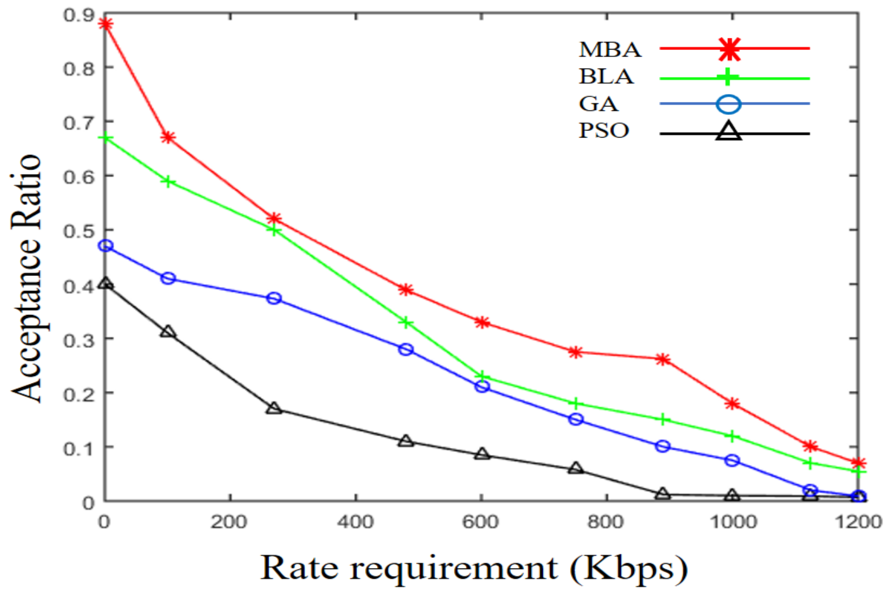
As an illustration, if we compare the network throughput reached with MBA algorithm in both scenarios (with rate constraint and without). Once the number of D2D pairs is sixteen (16), we can tell that it reaches 119 Mbps in the first scenario (rate constraint is activated), and that is under 165 Mbps is realized in the second scenario (no rate constraint). In the two figures, the MBA algorithm outperforms the BLA, GA and PSO algorithms by attaining higher network throughputs than those of the BLA, GA and PSO algorithms.

4.3.3. Rate constraint impact on acceptance ratio

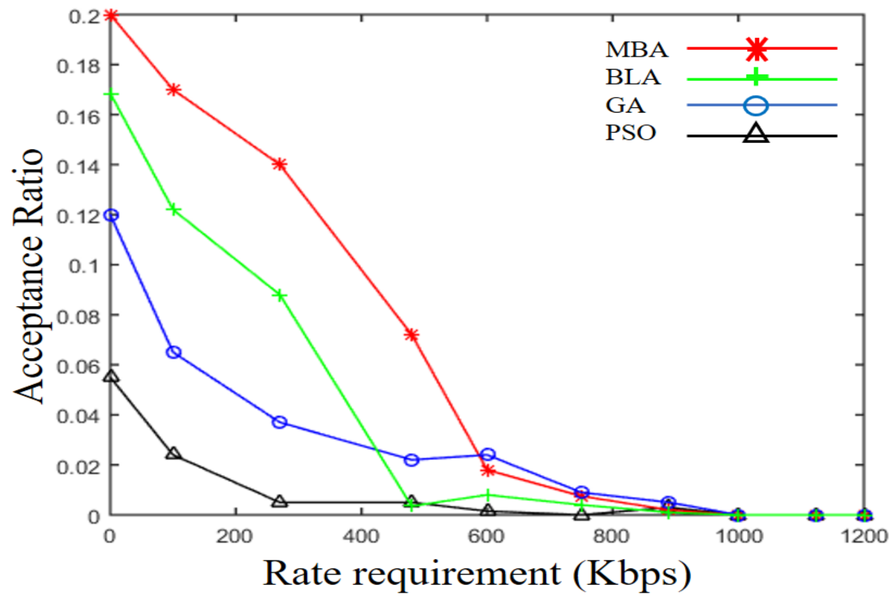
We study the rate requirement impact on acceptance ratio of the MBA, BLA, GA and PSO algorithms. If the simulation has been running for T times, while the approach converges to an achievable solution P times, then we calculate the acceptance ratio of an algorithm as follows:

$$Acceptance\ ratio\ = \frac{P}{T}$$

In our simulation, we fixed the CUs number to be 8. The D2D pairs numbers are fixed at ten (10) and twenty (20) in figure 4.8 (a and b), respectively. We run each algorithm fifty (50) times and estimate the acceptance ratio. Using an increment of 125 kbps, the required rate is augmented from 250 kbps to 1250 kbps. Figure 4.8 (a) and (b) show that the MBA, BLA, GA and PSO algorithms acceptance ratios decrease when we increase the rate requirement. This indicates that each user must meet its rate requirement, particularly if the required rate is large. If we compare figure 4.8 (a) and figure 4.8 (b), we find that the acceptance ratios of the first figure are higher than those of the second figure, and the reason of that lays in the users number since a greater users number leads to an extra mutual interference. In the two figures (figure 4.8 a and b), the MBA reaches superior acceptance ratios than BLA, GA and PSO algorithms. After that, we investigate the effect of rate condition on acceptance ratio when there is a total minimum CUs rate constraint; we setup the number of cellular users to eight (08) and the pairs of D2D users number is twenty (20). MBA, BLA, GA and PSO algorithms acceptance ratios are shown in figure 4.9.



(a) : Cellular users equal 8 and 10 D2D pairs.



(b) : Cellular users equal 8 and 20 D2D pairs.

Figure 4.8. MBA, BLA, GA and PSO for joint resource and power allocation.

In this scenario, we configure the required total rate minimum of cellular users to start with ten (10) Mbps and add ten (10) Mbps until it reaches 100 Mbps. We run the simulations 50 times and we calculate the acceptance ratios. The acceptance ratios attained by the MBA algorithm are better than those of the BLA, GA and the PSO algorithms. The simulation outcomes reveal the superiority of MBA. Moreover, this simulation indicates that the cellular

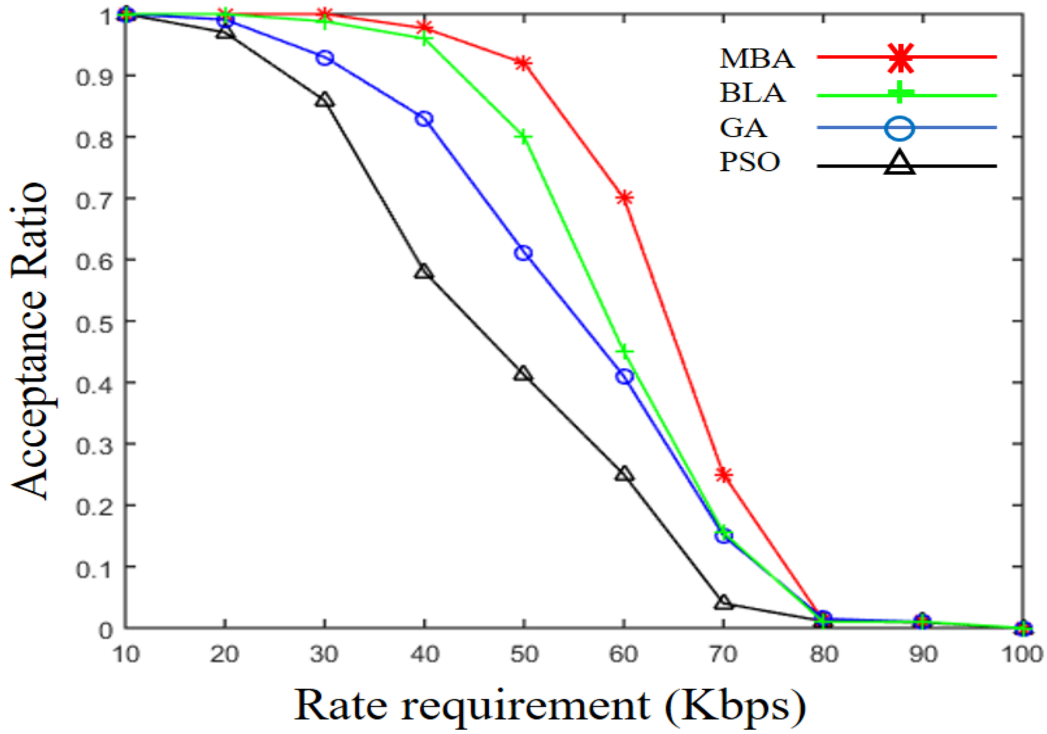


Figure 4.9. Acceptance Ratio of MBA, BLA, GA and PSO with total rate requirement for CUs

throughput is limited. In figure 4.9, all of the algorithms, MBA, BLA, GA and PSO have an acceptance ratio near zero once the rate requirement surpasses 80 Mbps.

4.4. Conclusion

In this chapter, maximizing network throughput was the objective of the proposed algorithm without neglecting the minimum rate requirement for CUs. The proposed scheme is a combination of Matching algorithms and BLA, named Matching Bees Algorithm for spectrum allocation and power control in D2D communications (MBA). We start with improving initial population by improving spectrum allocation with matching algorithm. Afterward, we used an improved BLA. We compared the results with three bio-inspired algorithms, namely BLA, GA and PSO. The results obtained are better then those achieved by the other bio-inspired algorithms, namely, BLA, PSO and GA.

Conclusion

Conclusion

D2D communication is a key technology for 5G cellular networks and beyond (B5G). It promises to offload network core, improve network throughput and expand cell radius. One of the most important challenges facing D2D communication is channel allocation and power control. In this dissertation, we focused on solving this joint problem for D2D communication in 5G cellular networks. First, we provide the reader with the essential background on this subject starting with a little overview on cellular networks from the 1st generation to the current 4th generation and an introduction of the next 5th generation and its key technologies.

After that, we presented detailed information about D2D communication like use cases, characteristics and challenges, in which we introduced the joint problem of resource allocation and power control. Afterward, we presented the resource allocation and power control problems alongside with a large number of related works and explained the problem formulation. Consequently, we perceived that the joint spectrum allocation and power control problem is a nonlinear and limited by several nonlinear constraints, which is not easy to solve with traditional methods. After that, we presented our first proposition, in which we use the Bee Life Algorithm (BLA) to solve the joint problem for D2D communication in 5G networks. The BLA is a bio-inspired algorithm based on the reproduction and food foraging behavior of bees in nature. We investigated the performance of our proposition compared to two most used bio-inspired algorithm for this joint problem, namely Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

To enhance the previous solution, we proposed a second system called an enhanced Bee Life Algorithm for spectrum allocation and power control in D2D communications (E-BLAD2D). In this second proposition, we ameliorate the initial population with Simulated Annealing optimization algorithm (SA) and after that, we use the BLA to find the all optimal solution for the joint channel allocation and power control problem for D2D communication in 5G cellular networks. We compared the E-BLAD2D with GA and PSO and the results was better compared to those obtained by BLA only. A third algorithm were proposed to improve results achieved by the previous algorithms.

This last proposition consists of using Matching Algorithm to generate the initial population by optimally allocate channels to users then uses the BLA algorithm to improve transmission power and reallocate resources to improve the network throughput. The results obtained by the MBA algorithm were better compared to BLA, PSO and GA.

As future direction of this work and because minimization of interferences is an important aspect for D2D communication in 5G cellular networks, we propose the investigation of inter-cell interference in which adjacent cells congest at the edges which results in deteriorating D2D and cellular communication at the same time.

Interference can be mitigated through mode selection, optimal resource allocation and efficient power control. Therefore, we are thinking of studying the possibility of adding mode selection problem to the considered joint channel allocation and power control problem since that can greatly enhance D2D performance by choosing the best way to communicate with, either cellular mode or D2D mode, since selecting the right mode of communication can improve spectral and energy efficiency and increase network throughput.

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