Resource Allocation Strategies in Cognitive Radio D2D Communication Networks

by

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Abstract

Device-to-device (D2D) communication is developed as a new paradigm to enhance net-work performance according to LTE and WiMAX advanced standards. On the other hand, cognitive radio (CR) approach provides efficient spectral usage using intelligent wireless nodes. In this thesis, a number of optimal resource allocation strategies for D2D communication networks are investigated using the CR approach.

As a first step, the CR approach in radio access networks is introduced. In the second step, the taxonomy of the RA process in CRNs is provided. For radio resource allocation (RRA), the most crucial task is to associate a user with a particular serving base station, to assign the channel and to allocate the power efficiently. In this thesis, a subcarrier assignment scheme and a power allocation algorithm using geometric water-filling (GWF) is presented for orthogonal frequency division multiplexing (OFDM) based CRNs. This algorithm is proved to maximize the sum rate of secondary users by allocating power more efficiently. Then, the RA problem is studied to jointly employ CR technology and D2D communication

in cellular networks in terms of spectral efficiency (SE) and energy efficiency (EE). In the first case, in terms of SE, a two-stage approach is considered to allocate the radio resource efficiently where a new adaptive subcarrier allocation (ASA) scheme is designed first and then a novel power allocation (PA) scheme is developed utilizing proven GWF approach that can compute exact solution with less computation. In the second case, in terms of EE, the power allocation problem of cellular networks that co-exist with D2D communication considering both underlay and overlay CR approaches are investigated. A proven power allocation algorithm based on GWF approach is utilized to solve the EE maximization problem which results in an "*exact*" and "*low complexity*" solution.

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Chapter 1

Introduction

The use of cognition in radio access and networking is expected to enable number of significant enhancements in wireless communications. In addition to better spectrum utilization, other areas such as autonomous network configuration, interference reduction, energy efficiency, interoperability and coexistence among different wireless communications systems and devices can also benefit from a cognitive approach. The cognitive and adaptive capabilities of radio access will be of fundamental importance in fifth generation (5G) and beyond networking contexts especially with heterogeneous networking and massive multiple input, multiple output (MIMO) scenarios. Cognitive networking will enable future networks to become more adaptive, self- configuring, self-organizing, self-healing, and self recovering. It will enable networks to cope with environmental changes, network dynamics, and malicious attacks, etc [1].

1.1 Cognitive Radio System

Ever increasing demand for myriad of wireless services poses two major challenges in the wireless network paradigm. One is the spectrum scarcity and the other is the demand of high data rates, up to tens of Gbps. While there is continuous effort to allocate more spectrum for wireless usage, it is observed that currently licensed spectrum is significantly underutilized [2,3] due to sporadic transmission nature of most communication devices.

Cognitive radio (CR) concept was first coined by Joseph Mitola [4], who proposed it as a solution for efficiently utilizing the radio resources. Since a CR transceiver shall have the ability to tune to different frequency bands, the CR is typically built using software-defined radio technology. Therefore, the transmitter operating parameters, such as the carrier frequency, modulation type and transmission power can be dynamically adjusted by software [1,5]. CRs, with its ability to smartly interact with the surrounding environment, are amenable to allow the coexistence licensed users or primary users (PUs) and unlicensed users or secondary users (SUs) sharing the same bandwidth opportunistically without causing

harmful interference to each other.

In fact, the coexistence of PUs and SUs in a CR environment are generally categorized into three paradigms:

Underlay: The SU determines the interference caused by their transmission to the PU and transmits only if interference below (under) a given threshold. The interference constraint may be met by using wideband techniques such as spread spectrum or ultra wide band (UWB) or by directional radiation.

Interweave: Interweave systems completely avoid interference by not transmitting in a band that is occupied by the PU.

Overlay: In overlay systems, simultaneous transmission is allowed. Here, the cognitive user has the knowledge of PUs message and/or encoding strategy. Simultaneous communication is achieved via various encoding and interference mitigation schemes.

CRNs have distinctive characteristics from a traditional wireless network where it intelligently recognizes the status of the radio environment and adjusts its functional parameters accordingly [5,6]. Most critical part of CRN is allowing CR users to share the licensed spectrum with PUs without degrading their performance [7]. This imposes new challenges and open research issues.

The basic elements for the operation of CR systems are depicted in Fig. 1.1 and the main functions of those elements to support intelligent and efficient utilization of frequency spectrum are envisioned in Fig. 1.2.

From Figures. 1.1 and 1.2, it can be seen that the proper functionality of a CRN depends on optimally sensing, accessing and sharing operations of the spectrum. Capacity of CR depends on what white spaces are available and how accurately they are detected. In addition to fading and shadowing, random interference can also cause false detection. Furthermore, SU transmitter and receiver must coordinate to find common holes for successful transmission. Therefore, the cognitive network throughput is usually difficult to guarantee. Ergodic
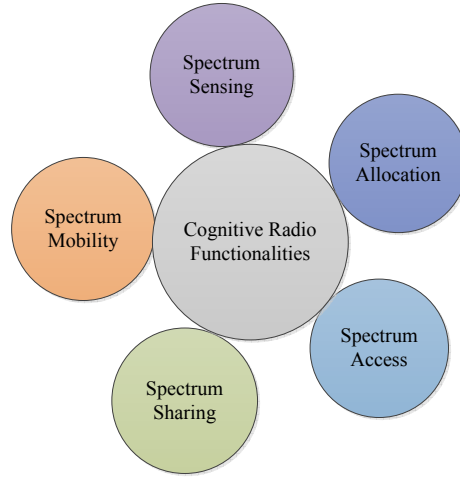
Figure 1.1: Basic elements of cognitive radio operation.
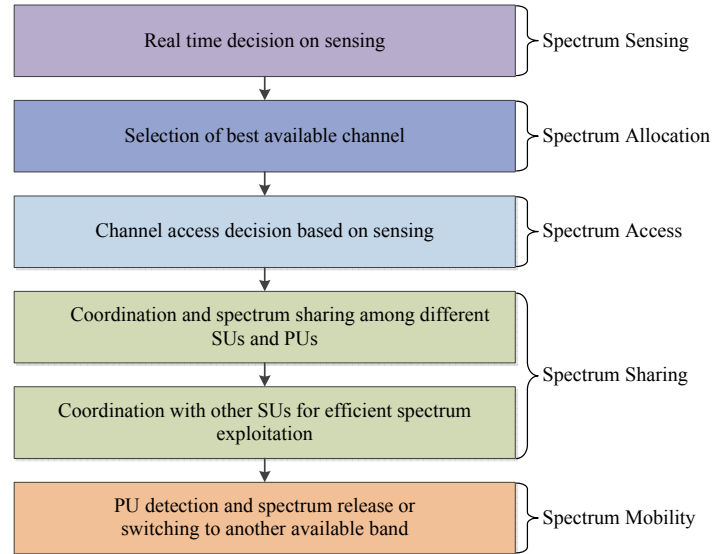
Figure 1.2: Cognitive radio functionalities.

and outage capacity of a CR system depends on the percentage of successfully detected white space which depends on the PU traffic characteristics.

Usually, the SU shall keep sensing the spectrum even when they transmit. However, implementation of this in a satisfactory manner is not easy as most transceivers are not full duplex. This can cause unintended interference to PU. Hence, licensed users don't like interweave SUs even more than underlay SUs.

Due to the multi-channel nature of CRN, the multi-dimensional nature of the resource allocation (RA) optimization problems become very difficult to solve. In addition to finding the optimal subcarrier set and power allocation for each SU, another challenge would be to avoid the co-channel interference when multiple SUs decide to use the same frequency band. Hence, a better medium access control (MAC) layer shall also cater the co-channel interference among the SUs.

Regulation and standardization efforts have already been carried out to envision some of the applications of CRN. A very important example is IEEE 802.22 Wireless Regional Area Network (WRAN) standard [8]. It provides specifications for broadband wireless access using CR technology and spectrum sharing policies and procedures for operation in the white space TV bands. IEEE 802.11af standard and its amendments [9] enable geo-location database access in the white space radio frequency (RF) spectrum. IEEE 1900.x series of standards [10] provide next generation radio and advanced spectrum management. IEEE 802.19 standard [11] enables the family of IEEE 802 wireless standards to most effectively use TV white space by providing standard coexistence methods among dissimilar or independently operated IEEE 802 networks and devices. It is also useful for non IEEE 802 networks and TV band devises. The first set of standardization study towards licensed shared access for long term evaluation (LTE) is reported in [12] that were successfully tested in a live LTE network in the 2.4-2.5 MHz frequency band [13]. In most recent times, IEEE has engaged the 802.15.4m task group [14] to characterize cognitive radio-aware PHY and MAC layers for cognitive machine-to-machine networks. These examples show standardization process for CR is well underway.

Latest developments in spectrum allocation policy and regulatory domains, including the release of the National Broadband plan, the publication of final rules for TV-white spaces, and the ongoing proceeding for secondary use of the 2,3602,400 MHz band for medical body area networks, have opened up various opportunities for the secondary use of spectrum. CR is therefore addressed to enable and support a variety of emerging applications, ranging from

smart grid, public safety and broadband cellular, medical applications to WSNs. The wide range of CR applications have various design requirements. For instance, from the data rate point of view, a temperature sensor may have a very low data rate whereas cellular handset may have a very high data rate. The IEEE 802.15.4 standard supports different data rates varying from 20 Kbps (868MHz band) to 250Kbps (2.4 GHz band).

1.2 Device-to-device (D2D) Communication

D2D communication is one of such paradigms that appears to be a promising component in next generation cellular technologies. D2D communication in cellular networks is defined as direct communication between two mobile users without traversing the base station (BS) or core network. In a traditional cellular network, all communications must go through the BS even if both communicating parties are in range for D2D communication. This architecture suits the conventional low data rate mobile services such as voice call and text message in which users are not usually close enough to have direct communication. However, mobile users in todays cellular networks use high data rate services (e.g., video sharing, gaming, proximity aware social networking) in which they could potentially be in range for direct communications (i.e., D2D). Hence, D2D communications in such scenarios can highly increase the spectral efficiency of the network. Nevertheless, the advantages of D2D communications are not only limited to enhanced spectral efficiency. In addition to improving spectral efficiency, D2D communications can potentially improve throughput, energy efficiency, delay, and fairness [15].

D2D communication is generally non-transparent to the cellular network and it can occur on the cellular spectrum (i.e., inband) or unlicensed spectrum (i.e., outband). In inband D2D communication, D2D users can setup communication through underlay or overlay spectrum sharing method. In underlay D2D communication, D2D users use the same spectrum of cellular users whereas in overlay, D2D users use a dedicated portion of cellular spectrum

[15]. The most crucial part of underlay inband method is to reduce the interference between cellular and D2D users as they share the same radio resources [16]. In the overlay inband method, D2D users occupy the dedicated portion of spectrum of cellular users, which is not an efficient approach in terms of spectrum efficiency. Other researchers propose to adopt outband rather than inband D2D communications in cellular networks so that the precious cellular spectrum be not affected by D2D communications [15]. In outband communications, the coordination between radio interfaces is either controlled by the BS (i.e, controlled) or the users themselves (i.e., autonomous). Outband D2D communication faces a few challenges in coordinating the communication over two different bands because usually D2D communication happens on a second radio interface (e.g., WiFi Direct [17] and Bluetooth [18]).

1.3 Motivations

Enhancing spectrum efficiency and energy efficiency are the most significant tasks for the regulatory authorities worldwide. Different measurement studies of spectrum utilization from the literature have indicated that spectrum is sporadically used in many geographical areas and times [2]. Low utilization and increased demand for the radio resources suggest the notion of the second time utilization of the spectrum, which allows unused parts of the spectrum to become temporarily available for the commercial purposes. This promising idea can mitigate unsatisfied spectrum demand, potentially without major changes to incumbents. It also provides us the ability to consider basic obstacles to the SUs, including why PUs would allow SUs and, equally important, under what circumstances SUs might emerge. The reality of identifying the pre-conditions for the SUs is a crucial step towards higher level of efficient spectrum utilization.

CR approach is well known to solve the under-utilization issue of the radio spectrum. However, CR technology only improves spectrum efficiency from the perspective of time

and channel, neglecting the potential optimization from the space perspective [19]. On the other hand, D2D technology [20, 21] has been proposed as an effective solution for efficiently utilizing the scarce radio resources from the space perspective. Both CR technology, and D2D communication must not cause harmful interference to cellular networks.

Now, the question arises, can D2D communication be better optimized using the cognitive radio approach? Can D2D users be modeled as secondary cognitive users and opportunistically access the under-utilized radio spectrum to increase the spectral efficiency? Can D2D systems be modeled considering both underlay and overly CR approaches to maximize the energy efficiency? These are the focus of this thesis. Note that, there are key differences between CR and original D2D systems. Mainly, the D2D communication is mostly managed by the network (that provides the spectrum) while a CR system is managed by the CR terminals distributively by spectrum sensing and interference-aware decisions [22], [23].

Driven by the aforementioned motivations, the major objective of this research is to investigate RA schemes for CRNs and how D2D communication can coexist with CR technology in order to optimize both the spectral efficiency and the energy efficiency (EE) with a more practical insight.

1.4 Contributions

Taxonomy for the Resource Allocation in CRNs:

- The RA problems are categorized and discussed according to the adopted approaches and network architecture.

- Basic elements or objectives of the RA problem are well studied to provide the RA design structure.

- The optimization strategies for the RA are explored and reviewed in the context of CRNs. Then, a comprehensive overview of these categories and optimization strategies

is provided, and also highlighted the advantages, disadvantages, and the application areas associated with each optimization strategy.

Resource Allocation in OFDM-based Cognitive Radio Systems:

- Power allocation problem in OFDM-based CRNs is modeled considering both individual subcarrier peak power constraints and subchannel (group of subcarriers) power constraints with total power constraint.

- A more efficient algorithm, named as iterative partitioned weighted geometric water-filling with individual peak power constraints (IGPP) is proposed along with subcarrier assignment.

- The proposed algorithm is shown to maximize the sum rate by providing better utilization of power resources than the existing algorithms. Power allocation is also performed considering the weight factor of each channel.

Resource Allocation for Cognitive Radio Systems with D2D Communication:

- An OFDM based cognitive cellular network with D2D communication has been modeled and analyzed using Lagrange formulation, and then solved using geometric water-filling (GWF) method. In order to maximize the transmission rate of the D2D users, the optimization task is characterized by the following five features: a) total power constraint, b) peak power constraint on each subcarrier, c) maximum power constraint of each D2D user, d) interference constraint to the PU band and e) minimum transmission rate requirements for the D2D users.

- A two-stage approach is considered to allocate the radio resource efficiently. In the first stage, a new adaptive subcarrier allocation (ASA) scheme is designed based on three parameters that form a well-designed metric. These parameters are exploited as

the weighting factors to make trade-off among the amount of power, interference and transmission rate. Then, a novel power allocation scheme is developed utilizing proven GWF approach that outperforms other existing algorithms in the literature.

Energy Efficient Power Allocation in Underlay and Overlay Cognitive Device-to-Device Communications:

- For a cognitive D2D system, two approaches (underlay and overlay) are considered to manage the spectrum sharing among the PUs and SUs in complementary scenarios.

- The power allocation problem for such a scenario is formulated as the maximization of the D2D users EE subject to the minimum rate requirement for both the D2D users and the cellular users (PUs).

- A proven power allocation algorithm based on GWF approach has been utilized to solve the EE optimization problem that outperforms the other existing algorithms.

1.5 Thesis Organization

The remainder of the thesis is organized as follows:

Chapter 2: Taxonomy for the Resource Allocation in CRNs. Presents the RA problems those are categorized first according to the adopted approaches and network architecture. Then, the optimization strategies for the RA are explored and reviewed in the context of CRNs. Finally, a comprehensive overview of these categories and optimization strategies is provided, and also highlighted the advantages, disadvantages, and the application areas associated with each optimization strategy.

Chapter 3: Resource Allocation in OFDM-based Cognitive Radio Systems. Provides the system model for OFDM-based CRNs and construct the power allocation problem considering three constraints. Describes the methods for the solution of power allocation

problem utilizing the GWF scheme along with the subcarrier allocation. Also provides comparison of the proposed algorithm results with the related works.

Chapter 4: Resource Allocation for Cognitive Radio Systems with D2D Communication. Provides the system model to jointly employ CR technology and D2D communication in cellular networks and construct the RA problem considering five constraints. Describes a two-stage approach where a new ASA scheme is designed first and then, a novel PA scheme is developed utilizing GWF approach. Present simulation results that validate the proposed solutions than the existing schemes.

Chapter 5: Energy Efficient Power Allocation in Underlay and Overlay Cognitive Device-to-Device Communications. Investigates the energy-efficient power allocation problem of co-existing D2D and cellular users considering both underlay and overlay CR approaches. In both the (underlay and overlay) spectrum sharing schemes, the optimization problem is formulated as the EE maximization of the D2D users subject to the minimum rate requirement for both the D2D users and the cellular users. A proven power allocation algorithm based on the GWF approach is utilized to solve this EE optimization problem. Contrast to the widely used Dinkelbach method for EE maximization, this algorithm can directly compute the optimal solution by applying the geometry-based approach, with exactness and low-degree polynomial complexity. Simulation results reveal the benefits of the proposed algorithm.

Chapter 6: Conclusion and FutureWork. Includes a summary of the research work, its outcomes, possible directions and timeplan for future research work.

Chapter 2

Resource Allocation Problems and Mathematical Preliminaries

In this chapter, a taxonomy for the resource allocation (RA) process in CRNs is provided. In particular, the RA problem is categorized first according to the adopted approach which could be centralized, or distributed. Second, based on the network architecture, the RA problem is also classified as infrastructure based or ad-hoc. Third, according to the problem objective, the basic elements of RA in CRNs may include: throughput (sum-rate), power, delay, QoS, fairness etc. Finally, the algorithms are also classified according to the strategy used for solving the problem which can be an optimization technique, heuristic, game theory, graph theory etc. Fig. 2.1 provides the adopted taxonomy in detail.
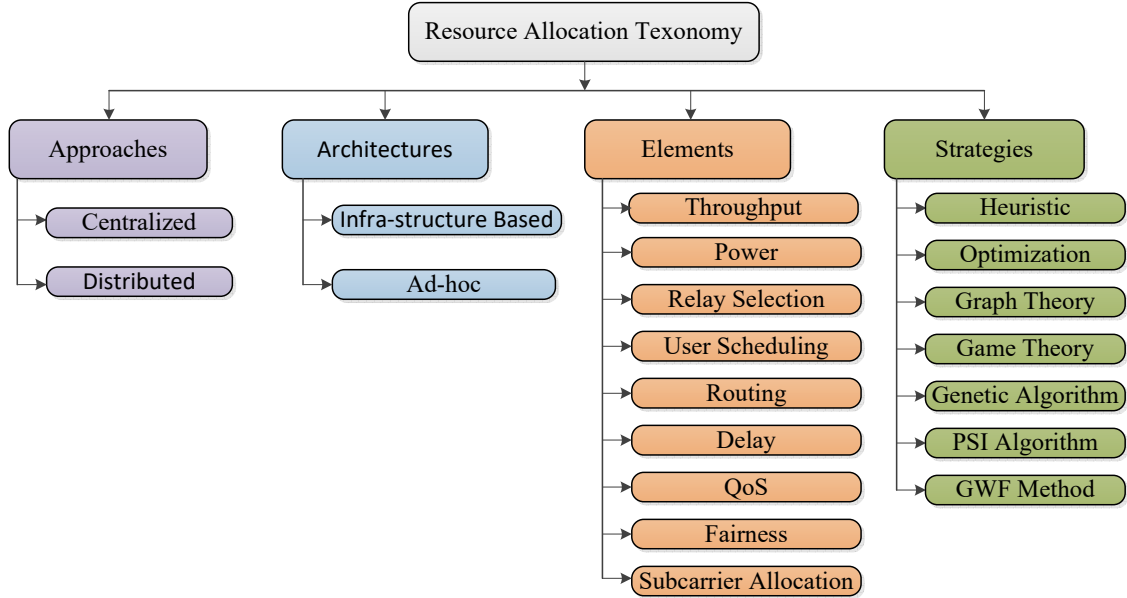
Figure 2.1: Taxonomy for the resource allocation in CRNs

2.1 Resource Allocation Approaches

In the literature, two key approaches are utilized to solve the RA problem: centralized and distributed. Each of these approaches has its merits and demerits. So that, depending on the problem requirement and priorities one of them could be adopted.

1) Centralized: The centralized approach mainly based on the existence of a central

entity that handles the RA process. This entity could be a base station (BS), eNodeB, or separate node for control purposes (server). In the centralized RA or scheduling algorithms, the central node gathers the measurements and information from the whole network, transmits control information to different users and nodes to coordinate their access, and takes the final decision. This approach has been widely investigated in literature (e.g., [24–30]). It was shown that the centralized schemes have several advantages. Due to the global view of the whole network, this approach is able to obtain the optimal solution of a desired performance metric (e.g., maximize the network sum rate, spectrum efficiency, etc.). Also, it can optimally minimize the network interference and attain an overall better network performance. Moreover, it can easily achieve optimal fairness since all the network information is available at one node. This can be done by regulating greedy nodes that devour large portion of the resources on the cost of other weak nodes. Moreover, centralized controllers can control priorities more efficiently. In contrast, there are some disadvantages that limit the practicality of the centralized approach. In particular, centralized schemes create large signaling overhead which results in a wasteful utilization of the resources (e.g., bandwidth, power, etc.). Also, due to the adopted nature which directs to make the RA process of the whole network based strongly on a single entity (central node), the failure of this central node can cause severe effects on the network performance. In a failure case, which may arise from power failure or crashes, each node in the network will independently make the RA decision. Consequently, the network performance could be significantly deteriorated. Furthermore, contention and unfairness situation could be attained.

2) Distributed: In the distributed approach, there is no central entity that manages the scheduling process. Instead, each node (or user) takes its decision autonomously or via a limited cooperation by exchanging neighboring information. In particular, each node carries out some measurements and calculations that are enough to reach the decision or should be shared among its neighbors to take the decision. Several distributed approaches have been taken into account in many researches (e.g., [31–34]). Flexibility is a major advantage

of this approach over the centralized one. Distributed schemes quickly adapt to wireless environment variations. This is due to the fact that only the nodes in the area of the variation are affected and require to amend their calculations. Therefore, there is no need to replicate the overall RA process, but only the affected part. This definitely involves the fast recovery feature which is crucial, for example, in emergency situations. This contradicts the centralized case, where any change affects the whole process and delays the decisions. Thus, distributed approaches present more robust communications. Another advantage is that distributed approaches decrease the amount of overhead and delay of switching information as a result of being only limited to a small neighboring area. In comparison, distributed approaches cannot acquire the optimal solution for the desired performance metric due to the lack of information at each node. Moreover, only local fairness between neighboring nodes can be attained. Finally, distributed approaches are more appropriate for light load networks but for high load networks a centralized approach can achieve better performance.

2.2 Architecture

1) Infrastructure Based: This model incorporates the existence of a base station and multiple users connected to it. The network can be driven either in downlink or uplink modes, and offers one-hop communications. Generally, centralized techniques are utilized for this model to employ the central entity. The users observations and measurements are fed back to the central point to take the decisions. Then, the users configure their parameters according to the central decision. This model is useful in case of setting up a permanent network. In CRNs, using proper RA strategies the base station can significantly help in protecting the primary network from secondary transmissions. Cognitive radio cellular networks (CRCN) [35,36], and IEEE 802.22 wireless regional area network (WRAN) [37,38] are examples of such networks. Although most of the strategies in literature for this model are centralized, distributed schemes can also be supported [39].

2) Ad-Hoc: In the ad-hoc model, also called infrastructureless model, the communication is performed directly between the CR nodes without the support of a central controller or a base station. Unlike infrastructure based model where the nodes communicate with the base station via single hop, the communication between the nodes of an ad-hoc network could be single-hop or multi-hop communications. In a multi-hop network, routing is an essential function to find the best route for data transmission. Indeed, the use of distributed techniques is more appropriate for this network model as the ad-hoc networks are distributed by nature [40, 41]. This includes extra challenges on the communicating nodes of the ad-hoc networks compared to those of infrastructure based since the nodes have to coordinate their access themselves. As a result, the operational load increases on the CR nodes whose resources, such as power, are limited which enforces a critical demand for computationally efficient methods.

Ad-hoc networks have several advantages. For instance, ad-hoc networks are easier to set up because the nodes are connected directly without an access point. Besides the ease of deployment, ad-hoc networks decreased dependence on infrastructure allows for fast integration with already existing infrastructure networks. This makes wireless ad-hoc networks applicable and useful in many situations such as crisis response, military environments and sensor networks [40]. In CRNs, ad-hoc networks were broadly adopted (e.g., [41, 42]). Dynamic network topology, distributed multi-hop architecture, and time and location varying spectrum availability are some prime factors of CR ad-hoc networks (CRAHNs) [41]. The specific functions associated with CRAHNs were discussed in [43]. The authors described that these functions are highly dependent on cooperation among the users due to the lack of a central coordinator. Therefore, RA is done based on local observations of each user and by exchanging information with the neighboring nodes.

2.3   Resource Allocation and Design Objectives

Fig. 2.2 shows the generic RA problem in CRNs. A generic RA design structure consists of four portions: (1) inputs; (2) outputs; (3) objectives; and (4) constraints. Different input parameters are provided by network administrator or regulatory authorities. In CRNs, central controller generally knows about the SUs and relays in the network. In case of primary and secondary network cooperation, it is possible that CRNs central controller has the information about the number of PUs and their respective geographical locations. Interference threshold is set by the regulatory authorities. Value of interference threshold depends on the spectrum sharing regime. Knowledge of channel state information (CSI) is a significant input parameter. Most of the RA algorithms assume that CSI is known at both transmitter and receiver. Under different constraints, the RA schemes are analyzed and evaluated where performance is measured in different metrics in order to produce desired outputs.

There are several elements or objectives that could be targeted by the RA problem. These elements may be incorporated as the optimization principle objective or as a constraint that should hold.

1) Throughput: Maximizing the network throughput is a very familiar criterion that is generally targeted in the RA problem. The problem could consider the individual user throughput maximization or the sum-rate of the aggregate network. Also, some efforts consider maximizing the sum-rate of both primary and secondary networks as a whole.

2) Power allocation: Power allocation for CRNs is a crucial task for better interference management. In case of CRNs, the efficient power allocation is more challenging than non-cognitive wireless network. Traditional power allocation schemes for non-cognitive networks are not applicable to CRNs as these schemes may cause unacceptable interference to the primary network. In CRNs, power allocation is performed under the constraint of acceptable interference to the PUs.

3) Relay assignment/selection: The use of relays in a CRN can benefit in two ways.

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Input Metrics
(any combination)
Number of SUs,
Number of PUs,
Number of transceivers,
Channel sensing procedure,
Protocol type,
CC mechanism,
Queueing model,
Channel access technique,
Channel state information,
Channel allocation scheme,
Network environment,
Customized network related
parameters.

Constraint (any combination)
Interference with PUs,
Adjacent channel interference const,
Channel selection/assignment,
Sensing errors, QoS, Delay,
Bandwidth, Fairness, Topology,
Traffic characteristic, Security.

Objective (any combination)

Maximize	**Minimize**
Spectrum utilization, Channel grabbing, Bandwidth utilization, Link maintenance, Incumbent protection, Traffic admission probability, Acceptable sensing error probability Packet delivery ratio, Energy efficiency, Network connectivity.	Queueing delay, Packet transmission delay, Access delay, System time for buffering, Join time of SUs, Collision rate, Sensing overheads, Communication overheads, Blocking probability, False alarm and miss detection probability, Probability of collision with PUs.

Output Metrics
(any combination)
Aggregate throughput,
Optimal number
of sensed channels,
Channel access delay,
Packet transmission delay,
Blocking probability,
Continuty probability,
Interference time,
Number of interfered
incumbent systems,
Successful packet
transmission ratio,
Collisions per slot,
Collision probability with
PUs, Forced termination
Probability.

Figure 2.2: Generic resource allocation problem

First it can increase the transmission rate and, secondly the use of relays can reduce the overall transmission power of the systems. The use of multiple relays simultaneously can further increase the performance of a cognitive radio network. A well designed multiple relay assignment and power allocation scheme can be helpful in two ways. It reduces the interference induced to the primary users in multiuser CRNs and increases the connectivity of the wireless network. In a multiple relay system, if any relay is dead or in deep fade the receiver can still get data from other relays.

*4) **User scheduling***: In multiuser CRNs, due to resource limitations and interference constraints, user scheduling in intelligent way can achieve high throughput. User scheduling schemes select the best group of users at each time slot to maximize the total throughput. The complexity of an exhaustive search for user scheduling increases exponentially with the number of users. For example, if U is the total number of users, then the number of possible ways of scheduling/selecting u users is $\binom{U}{u}$. Enumerating all possible combinations to find the one that gives the best performance is computationally inefficient. Due to the high computational complexity of the optimal selection (e.g., exhaustive search algorithm), efficient user scheduling in CRNs is an active area research.

*5) **Routing***: Most of the research on CRNs to date has focused on one or two-hop scenarios. With the advancement on ad hoc networks, recently, researchers have started to realize the importance and potential of multi-hop CRNs. To get the benefits of multi-hop transmission, new challenges must be addressed and solved. In particular, efficient routing techniques and solutions must be integrated into the ad hoc CRNs.

*6) **QoS***: QoS is a general term used for many user satisfaction related requirements. It comprises response time, throughput loss, rate requirements, outage and blocking probabilities. The main aim of QoS in CRNs is to guarantee a minimum rate, reduction in latency jitter and packet errors.

*7) **Delay***: Delay is an important metric in any wireless network especially for real-time applications such as voice and multimedia. Delay performance in CRNs has important

engineering implications, e.g., it can be used to characterize the number of SUs that can be supported under a given delay constraint. Queuing delay and transmission delay need to be analyzed in order to characterize the delay performance, which is still an unexplored area of research.

8) Subcarrier allocation: Subcarrier allocation and pairing play a significant role in future CRNs that employs orthogonal frequency division multiplexing (OFDM) in physical layer. One can increase the throughput of CRNs with the intelligent utilization of subcarriers.

2.4   Solution Approaches and Techniques

In this section, we explore and review the optimization strategies for RA in the context of CRNs. Depending upon the objectives, these strategies can be categorised under several performance optimization criteria. In the following, we provide a comprehensive overview of these categories and optimization strategies, and highlight the advantages, disadvantages, and the application areas associated to each of them.

2.4.1   Heuristic

In some cases it is tremendously tough, or even not possible, to get the optimal solution of certain problems. Hence, one may impose non-realistic assumptions to simplify the problem structure, and then find the optimal solution for the simplified structure. However, it is rather better to look for a reasonable (non-optimal) solution for the real problem structure than searching the optimal solution for inaccurate oversimplified structure. Heuristic strategies give logical solutions, that are not guaranteed to be the optimal, with acceptable time and space complexity [44]. Additionally, heuristic strategies are less restrictive than optimization methods, and thus they allow the usage of structures that are more presentable to the real world problems [45]. For CRNs, optimal solutions for RA problems are typically of high complexity. Hence, heuristic strategies are appropriate to find a fine solution

quickly. Usually, there is no methodical structure for developing heuristic strategies. Thus, researchers build up their own methods according to the problems found in the literature [44].

Several efforts (e.g. [46–49]) proposed heuristic strategies for the RA problem in CRNs. The authors in [46] proposed two heuristic distributed RA algorithms based on opportunistic splitting. A heuristic packet transmission scheduling technique was developed in [47] that depends on measured link and interference conditions at CR nodes. In [48], a low complexity huristic algorithm is proposed that efficiently solves the problem of spectrum sharing and downlink user scheduling. A two-step heuristic algorithm for sub-channel allocation and power distribution was developed in [49]. This algorithm extensively decreases the problem complexity while presenting an excellent approximate solution near optimal.

It is meaningful to mention that one disadvantage of heuristic strategies is that they are problem-specific and could not be universal. Also, there is no guarantee for convergence, especially for iterative strategies that may trapped into local optimal points far from the global optimal solution [18]. However, they stay on an essential substitution that can offer reasonable, fast, and yet easy solutions to be employed in many conditions. Additionally, heuristic solutions are more robust to problem variations than optimal solutions [57].

2.4.2 Optimization

Optimization problems intend to search the optimal of all possible solutions, which is the one that minimizes or maximizes a certain objective function. This objective function is a function used to assess a quality of the generated solution. The general mathematical structure of an optimization problem can be written as [50]:

$$
\begin{aligned}
\text{minimize} \quad & f_0(x) \\
\text{subject to:} \quad & f_i(x) \leq b_i, \quad i = 1, ..., m
\end{aligned}
\tag{2.1}
$$

where the problem components are as follows:

- $x = (x_1, ..., x_n)$: optimization variables

- $f_0 : \mathbb{R}^n \to \mathbb{R}$: objective function

- $f_i : \mathbb{R}^n \to \mathbb{R}, i = 1, ..., m$: constraint functions

- and the optimal solution x^* has the smallest value of f_0 among all vectors that satisfy the constraints

There are numerous types of objective functions occurring in RA for CRN of which three emerge to be very famous. Most of the other types are related to those three. The three are:

- Maximization of network sum throughput,

- Maximization of overall user data rate,

- Maximization of user capacity.

The other types of objective functions that have been studied in the literature include; maximization of spectrum utilizations, maximization of total channel utility, maximization of fairness scaling factor, maximization of downlink channel capacity, minimization of total transmission power, and minimization of total power consumption. Even the three stated earlier appear to have been utilized interchangeably by authors. Thus, all those three objective functions are combined together into a class of "capacity"measure. As for constraints, there are three that are usually occurring and they are:

- Power constraint,

- Constraint on interference,

- Minimum data rate for users.

The most commonly occurring decision variables are:

- Transmission power,

- Sub-channel allocation, which results in a zero-one decision variable.

In CRNs, optimization problems are generally used to formulate the RA problem for efficient utilization of the available resources. The formulated problems could be convex, non-convex, linear, or non-linear with different objectives such as sum-rate maximization, power minimization, fairness, etc. Certainly, complexity depends on the optimization problem model. For instance, convex optimization problems can be solved using standard optimization methods. Furthermore, a linear program (LP), wherein the objective function and constraints are all linear, is generally solved through iterative optimization problem solvers with less complexity and higher speed as compared to non-linear convex optimization problems with similar dimensions [50]. In non-linear programming (NLP), the objective function or some of the constraints are non-linear. For computationally intensive problems, greedy, heuristic algorithms appear as essential alternatives to accelerate the process of obtaining an acceptable approximate solution. For example, incorporating integer constraints in the problem such as the number of allocated time slots, makes it very complicated [51]. Generally, integer and mixed integer non-linear programming (MINLP) are computationally extensive (NP-hard) [52]. Hence, heuristic alternatives are usually utilized.

2.4.3   Graph Theory

Graph theory is one of the most extensively used tools for modeling and analyzing the interaction (or contention) in networks. A graph G consists of a set of vertices V and edges E, and is denoted by $G = (V, E)$. These components are mapped to the network elements according to the studied problem. Usually, vertices correspond to entities and edges represent the interaction between these entities. The graph theory could be employed to vast range of networks such as mechanical, transportation, and communication networks, among others. It can offer appropriate tools for solving network-related problems. Generally, graph theory

is utilized when the network structure is known a priori [53]

In wireless communications, graph theory is largely used to solve the scheduling and RA problems, especially for problems of high computational effort [54]. In literature, the RA problem was solved using different types of graphs such as vertex-coloring graph, conflict graph, and bipartite graph [55, 56]. For CRNs, the SUs are generally mapped to the vertices and the edges mapping varies according the model definition to characterize certain relation between two vertices. For example, in a conflict or vertex-coloring graph model, an edge between two vertices (SUs links) shows that the SUs are in the interference range of each other [48, 54]. Also, the RA for coloring graph problem is comparable to assigning each vertex a color (i.e., assign each link or SU).

If the vertex set V of a graph G can be split into two disjoint subsets $V1, V2$ such that each edge connects two vertices in different subsets, then G is a bipartite graph [57]. A bipartite matching problem is largely used for spectrum assignment and RA in CRNs [58–61]. Generally the two partitions of the bipartite graph are mapped to the SUs and the frequency bands available for assignment. The edges connecting two vertices (SU link and frequency band) for such a problem means that the SU requests (or accepts to be assigned) the corresponding frequency band.

In order to be application specific, coloring and conflict graphs are more appropriate for interference-limited environment. This is similar to the cases of having multiple SUs transmit simultaneously, and thus they can generate high interference to each other. Therefore, using the prescribed conflict or coloring graphs, also called node contention graphs (NCG), assists in modeling this interference in a way that makes simpler the development of a proper RA [54, 62]. On the other hand, the works adopted bipartite graphs usually allowed one SU per band with the owner PU to limit the interference in the system [58, 59]. However, adding preferences to the SUs and PUs guarantees better protection for the primary network as well as improved secondary performance. This is because the PUs preferences are typically set according to their tolerated interference. Certainly, graph-based algorithms cannot integrate

multiple performance metrics and so, normally, QoS is not guaranteed.

2.4.4 Game Theory

Game theory is a mathematical framework utilized to model and analyze the interaction among multiple individuals whose actions affect each other, or possibly who have conflict of interest [63, 64]. Usually, the game is modeled by considering a set of players (decision makers) who obtain the decisions (or actions) to maximize their payoff (utility). Although it is originally developed for economics, game theory found success in multiple fields such as engineering, biology, political science, physiology, etc [65]. This is due to its advanced theoretical foundations which make it a powerful tool in decision making. Mathematically, the game is denoted as $G(\mathcal{N}, \mathcal{A}, \{u_i\})$, and the three game components are [65, 66]:

- $\mathcal{N} = \{1, 2, ..., N\}$ represents the finite set of players,

- $\mathcal{A} = A_1 \times A_2 \times ...A_N$ represents the sets of actions such that A_i is the set of actions available for player i,

- $u_i : A \rightarrow \mathbb{R}$ represents payoff/utility function of player i, which is a function of actions of all players.

Generally, game theory can be classified into two broad schemes: non-cooperative and cooperative schemes. These schemes have been broadly studied in literature (e.g. [86], [87], [97]). In a non-cooperative scheme, the players act in a selfish manner to maximize their own utility regardless of the impact of this on others. Nash Equilibrium (NE) is commonly known to be the solution point of non-cooperative game [89]. In a cooperative game model, collaboration among the players and information exchanging are the ways to enhance the overall utility of the network and maximize their mutual benefits. Nash Bargaining (NB) is the common solution point for this game model. Also, other game categories exist such as static/dynamic, and complete/incomplete information [86].

In wireless communications, game theory is utilized to model and analyze several functions related to different layers (physical, data link, network, etc.) [90]. Usually, game theoretic approaches are used for power control [91], interference management [92], resource allocation [93], network selection in an environment of multiple deployed technologies [94], hand-off management [95], among others. These functions can be employed in the context of wireless sensor networks, CRNs, ad-hoc networks, etc. One major advantage of using non-cooperative game theory in wireless communication is its ability to offer robust and efficient distributed algorithms that rely only on local information and reduce the signaling overhead and computation complexity of the centralized approaches [93], [96]. However, the game model should be formulated carefully to be able to search a stable solution.

Unlike users of conventional wireless networks, CR users are intelligent and have the ability to observe, learn, interact with the surrounding environment, and adjust their parameters accordingly for an optimized performance. However, these users can be belonging to different authorities or have different goals. Thus, cooperation between them cannot be taken for granted. Instead, these users may act selfishly for each one to maximize its own payoff. Generally, an underlay CR spectrum sharing game model includes the following:

- Players: represented by the set of SUs or both SUs and PUs,

- Actions or strategies: depend on the player whether it is an SU or a PU,

- Utilities: an objective function to be maximized such as throughput, SINR, QoS, fairness, revenue, etc.

Thus, game theory occurs as a very important tool that can efficiently model and analyze the spectrum sharing process among the users that have conflict of interests in CRNs. Furthermore, game theory helps to design self-organized algorithms that are more appropriate to the dynamic wireless nature.

2.4.5 Genetic Algorithms

Genetic Algorithm is adaptive search algorithm based on the evolutionary ideas of natural selection [67]. An iterative process starts with a randomly generated set of solutions called population. Best individuals are selected through the utility function (called here fitness function). Then, starting from this subset, a second population is produced through genetic operators: crossover and/or mutation. The new population shares many of the characteristics of its parents, and it hopefully represents a better solution. The algorithm typically terminates when it converges to the optimal solution or after a fixed number of iterations. Genetic algorithms are chosen to solve RA problems due to their fast convergence and the possibility of obtaining multiple solutions. There are quite a few efforts [68–70] are found in the literature that utilizes genetic algorithms to solve RA problems.

2.4.6 Particle Swarm Intelligence Algorithms

Particle swarm intelligence (PSI) algorithms are population based stochastic optimization technique inspired by the collective behaviour of social biological individuals (e. g. bird flocking or fish schooling). PSI algorithms model network users as a population of simple agents interacting with the surrounding environment. Each individual has relatively little intelligence, however, the collaborative behaviour of the population directs to a global intelligence, which allows to solve complex tasks. For example, in social insect colonies, different activities are often executed by those individuals that are better equipped for the task. This phenomenon is named division of labour [71]. PSI algorithms are scalable, fault tolerant and moreover, they adapt to changes in real time. There are quite a few efforts [72–75] are found in the literature that utilizes PSI algorithms to solve RA problems.

2.4.7 Geometric Water-Filling Method

The conventional water-filling (CWF) [76, 77] problem can be described as follows. Given $P_T > 0$, as the total signal power (or volume of the water); the allocated power and the propagation path gain for the ith channel are given as P_i and h_i respectively where, $i = 1...N$; and N is the total number of subcarriers. Now without loss of generality, if $\{h_i\}_{i=1}^{N}$ be positive and monotonically decreasing, then the optimization problem can be written as:

$$\max_{\{P_i\}} \ \sum_{i=1}^{N} \log(1 + h_i P_i) \qquad (2.2)$$

$$\text{subject to: } C1: \ 0 \leq P_i, \forall i;$$

$$C2: \ \sum_{i=1}^{N} P_i = P_T$$

where, constraint C1 is the allocated power to be nonnegative and constraint C2 is the total power constraint. To find the solution to problem (2.2), we usually start from the Karush-Kuhn-Tucker (KKT) conditions of the problem, as a group of the optimality conditions. The water level (μ) needs to be chosen to satisfy the power sum constraints with equality ($\sum_{i=1}^{N} P_i = P_T$) to find the optimal solution.

In [78], GWF approach is proposed to solve the CWF problem and its weighted form. It has two advantages, they are: 1) the geometric approach can compute the exact solution to the CWF, including the weighted case, with less computation and easier analysis without determining the water level through solving the non-linear system, 2) machinery of the proposed geometric approach can overcome the limitations of the CWF algorithm to include more stringent constraints.

Fig. 2.3 gives an illustration of the GWF algorithm proposed in [78]. Suppose there are 4 steps/stairs ($N = 4$) with unit width inside a water tank. For the conventional approach, the dashed horizontal line, which is the water level μ, needs to be determined first and then
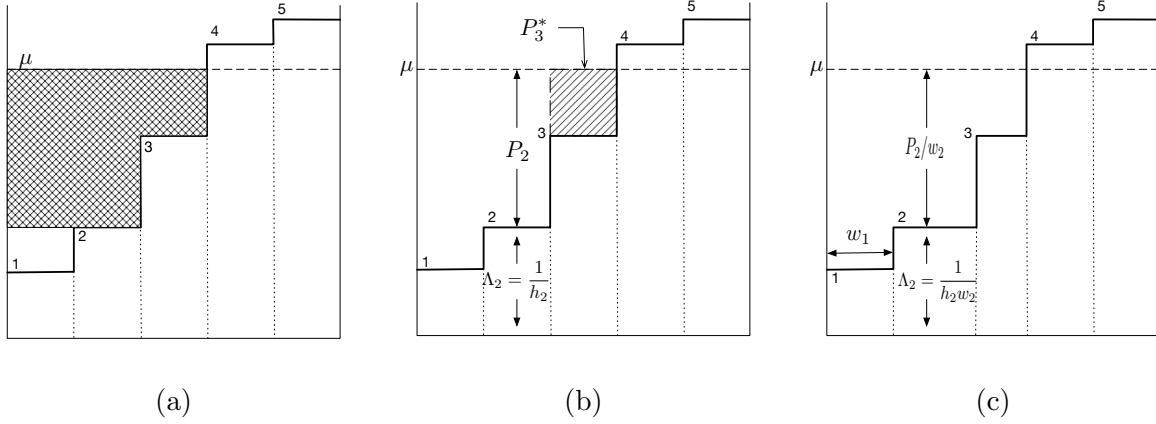
Figure 2.3: Illustration for the proposed GWF algorithm (a) Illustration of $P_t(n)$ (shadowed area, representing the total water/power above step n) when $n = 2$, (b) Illustration of water level step $n^* = 3$, allocated power for the third step P_3^*, and step/stair depth $\Lambda_i = \frac{1}{h_i}$ and (c) Illustration of the weighted case.

the power allocated (water volume) above is solved. Let λ_i denotes the "step depth" of the ith stair which is the height of the ith step to the bottom of the tank, and is given as

$$\lambda_i = \frac{1}{h_i} \quad \text{for } i = 1, 2, ..., N. \tag{2.3}$$

Since the sequence h_i is sorted as monotonically decreasing, the step depth of the stairs indexed as $[1, ..., N]$ is monotonically increasing. Now $\delta_{i,j}$ be the "step depth difference" of the ith and the jth stairs, can be expressed as,

$$\delta_{i,j} = \lambda_i - \lambda_j = \frac{1}{h_i} - \frac{1}{h_j} \quad \text{as } i \geq j \text{ and } 1 \leq i, j \leq N. \tag{2.4}$$

Instead of trying to determine the water level μ, which is a real nonnegative number, the water level step, denoted by n^*, is the target to solve, that is the highest step under water. Based on the result of n^*, the solutions for power allocation, can be written instantly. Let $P_t(n)$ denote the water volume above step n or zero, whichever is greater. The value of $P_t(n)$ can be solved by subtracting the volume of the water under step n from the total power P_T,

as,

$$P_t(n) = \left\{ P_T - \left[\sum_{i=1}^{n-1} \left(\frac{1}{h_n} - \frac{1}{h_i} \right) \right] \right\}^+$$
$$= \left\{ P_T - \left[\sum_{i=1}^{n-1} \delta_{n,i} \right] \right\}^+, \quad \text{for } n = 1, ..., N \tag{2.5}$$

Due to the definition of $P_t(n)$ being the power (water volume) above step n, it cannot be a negative number. Therefore we use $\{.\}^+$ in 4.16 to assign 0 to $P_t(n)$ if the result inside the bracket is negative. The corresponding geometric meaning is that the nth level is above water.

According to [78], the explicit solution to (2.2) is:

$$P_i = \begin{cases} P_{n^*} + (\lambda_{n^*} - \lambda_i) & 1 \le i \le n^* \\ 0, & n^* < i \le N, \end{cases} \tag{2.6}$$

where the water level step n^* is given as

$$n^* = \max \left\{ n | P_t(n) > 0, 1 \le n \le N \right\} \tag{2.7}$$

and the power level for this step is

$$P_{n^*} = \frac{1}{n^*} P_t(n^*) \tag{2.8}$$

GWF method for the weighted case called weighted geometric water-filling method (WGWF) and weighted geometric water-filling with individual peak power constraints (GWFPP), is also proposed in [78].

2.5 Chapter Summary

This chapter presents the RA problems those are categorized first according to the adopted approaches and network architecture. Then, the optimization strategies for the RA are explored and reviewed in the context of CRNs. Finally, a comprehensive overview of these categories and optimization strategies is provided, and also highlighted the advantages, disadvantages, and the application areas associated with each optimization strategy.

Chapter 3

Resource Allocation in OFDM-based Cognitive Radio Systems

3.1 Introduction

RA problem in OFDM based CRNs has been widely studied under different settings in the open literature. A power allocation grouping scheme based on the interference channel gain, pulse shape and frequency distance is presented in [79] in order to improve capacity while the interference power for PUs stays at constant level. At the first stage, power is assigned to some groups based on the grouping scheme and at the second stage, the remaining power is allocated to others with water-filling algorithm.

In order to maximize the SUs' transmission capacity by adjusting the power allocation across the subcarriers, two suboptimal schemes for subcarrier allocation with associated triangular and Gaussian power loading mechanism are studied in [80]. Here, these schemes maintain the total power used within the power budget and also the interference at the PUs within a permissible threshold limit.

A low-complexity algorithm using power-increment or power-decrement WF processes is proposed in [81]. This algorithm is based on constraining the total and transmit powers of each subchannel.

In order to maximize the download capacity of CRNs, a subcarrier and power allocation algorithm based on the linear water-filling(LWF) scheme is proposed in [82] while keeping both the total transmit power and interference introduced to the PU below the pre-constraints.

A suboptimal power allocation algorithm for multiuser OFDM-based CRNs is presented in [83] that simplifies the procedure of determining the water level to allocate the power for each subcarrier under a peak power constraint. This method not only reduces the computational complexity but also can easily be combined with a subcarrier allocation algorithm for joint subcarrier and power allocation.

Another suboptimal power allocation algorithm for multiuser OFDM-based CRNs is presented in [84] that simplifies the procedure of determining the water level to allocate the power for each subcarrier under a peak power constraint. This method not only reduces

the computational complexity but also can easily be combined with a subcarrier allocation algorithm for joint subcarrier and power allocation.

A low-complexity suboptimal power allocation algorithm is proposed in [85] where CR pairs (CRPs) may use both nonactive and active PU pair (PUP) bands as long as the total co-channel interference (CCI) and cross-channel interference (XCI) do not exceed prescribed limits. The complexity reduction is done by making a validated approximation based on the following: 1) the fact that XCI from CRUs to PUPs is mainly limited to a few subchannels adjacent to the PUP bands and 2) the assumption that the bandwidth for a PUP is typically much larger than that of an OFDM subchannel and that there is usually a guard band between two adjacent PUP bands.

An optimal scheme employing joint power allocation in overlay and underlay fashion has been proposed in [86]. The optimal scheme based on the Lagrange formulation maximizes the downlink capacity of CR users while maintaining a total power budget and keeping the interference introduced to the PU band below a threshold. A low complexity suboptimal scheme is also presented where equal low power is allocated to all the underlay subcarriers and a ladder profile is used to load power in the overlay subcarriers.

For weighted sum rate maximization in CRNs, a power limited multilevel WF iterative algorithm has been proposed in [87] where subcarrier power constraints were added to the traditional problem.

With the total power constraint and the power constraint on each subchannel, an iterative partitioned water-filling (IPWF) algorithm was proposed in [88] to realize optimal power allocation in OFDM based CRNs.

Table 3.1 provides different approaches for power allocation in OFDM-based CRNs.

Table 3.1: Different approaches for power allocation in OFDM-based CRNs

Ref.	Objective	Constraints	Solution approach
[79], 2014	Improve capacity while the interference power for PUs stays at constant level	Total transmit power and interference constraints	A grouping scheme based on the interference channel gain, pulse shape and frequency distance is considered
[80], 2013	Maximize transmission capacity	Total transmit power and interference constraints	Two suboptimal schemes for subcarrier allocation with associated triangular and Gaussian power loading mechanism are studied.
[81], 2012	Maximize capacity	Total transmit power and individual sub-channels' power constraints	A low-complexity algorithm using power-increment or power-decrement water-filling processes is considered.
[82], 2011	Maximize downlink capacity	Total transmit power and interference constraints	An iterative suboptimal power allocation algorithm based on LWF is proposed along with subcarrier allocation.
[83], 2011	Maximize overall throughput while keep the average interference to the PU within a target outage probability level.	Total transmit power and interference constraints	WF process runs only once, and then directly calculates the final result without the need for searching the Lagrange multiplier.
[84], 2010	Maximize uplink capacity	Total transmit power and peak power constraints	A simple and low complexity suboptimal scheme is considered for determining the water level to allocate the power for each subcarrier.
[85], 2010	Maximize the overall rate while keeping the interference experienced by the PU pairs below certain thresholds	Total transmit power and interference constraints	A low-complexity suboptimal power allocation algorithm is proposed where CR pairs may use both nonactive and active PU pair bands as long as the total cochannel interference and cross-channel interference do not exceed prescribed limits.
[86], 2010	Maximize downlink capacity while keeping the interference introduced to the PU band below a threshold	Total transmit power and interference constraints	A low complexity suboptimal scheme for joint overlay and underlay power allocation is presented where equal low power is allocated to the underlay subcarriers and a ladder profile is used to load power in the overlay subcarriers.
[87], 2009	Maximize the weighted sum rate of SUs in the downlink, without causing interferences to PUs	Total transmit power and interference constraints	A power limited multilevel WF iterative algorithm is considered.
[88], 2007	Maximize the capacity maintaining the PU's interference limits.	Total transmit power and per subchannel power constraints	An iterative partitioned water-filling algorithm is proposed.

3.2   Cognitive Radio System Model and Transmission Power Constraint

A typical cognitive radio systems is shown in Fig. 3.1 where PUs and SUs share the same bandwidth. In order to avoid harmful interference to each other, the SU needs to detect the opportunities when PUs are not utilizing the spectrum. Higher detection probability without errors provide successful exploitation of opportunities for transmission. In Fig. 3.1, a disk propagation model is considered to illustrate SU transmission. SU can detect any PU's activity within the detection region. However, those PUs that fall outside the detection region (like PU2 in Fig. 3.1), are undetectable by the SU. To deal with this situation, as in [89], PU2 defines a protection region with radius P and needs to maintain a certain interference level η within this area. In this scenario, SU's transmission power P_{tx}, subjected to interference constraint, can be written as:

$$P_{\text{tx}} \leq \eta(D - P)^{\beta} \tag{3.1}$$

where D is the distance between the SU transmitter and the nearest undetectable PU transmitter, β is the path attenuation factor and η is the maximum allowable interference level. OFDM is a potential technology in terms of modulation and power control. It is also highly flexible due to reconfigurable subcarrier structure to fit in CRNs for efficient utilization of spectrum opportunities. Fig. 3.2 depicts a typical spectrum structure in OFDM-based CRNs. There are M subchannels licensed to M PU systems that can be potentially used by the SU based on opportunity detection. There are N subcarriers that are distributed among the M subchannels. For example, let the jth subchannel has total L_j subcarriers that can be utilized by the SU when PU is absent. For successful transmission, the SU first needs to test any PU transmitter in the desired subchannel. If found, the sum power of all the subcarriers in that subchannel will be set to zero until the PU transmission ends. If not, the SU can utilize this subchannel with the interference constraint described in (3.1). Let G_j is
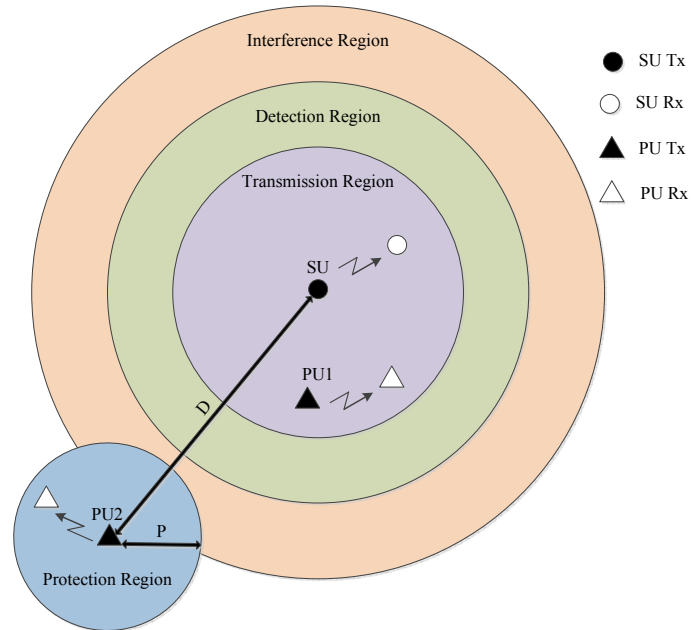
Figure 3.1: Cognitive radio system model.
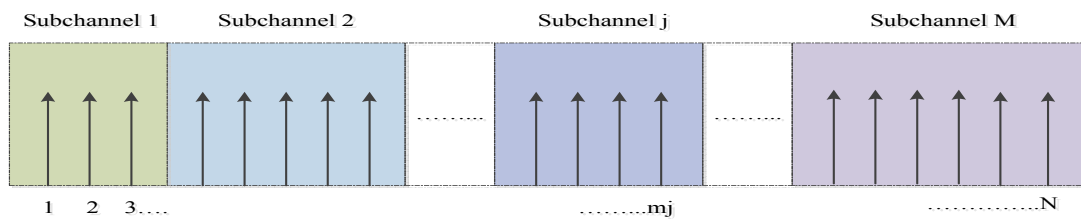
Figure 3.2: Spectrum of SU in OFDM-based CRNs

the interference constraint on the jth subchannel after spectrum detection, then,

$$
G_j \triangleq \begin{cases} 0 & PU_j \text{ is detected} \\ \eta_j (D_j - P_j)^{\beta_j} & PU_j \text{ is not detected} \end{cases} \tag{3.2}
$$

where η_j is the maximum allowable interference level for PU_j within the protection region whose radius is P_j, D_j is the distance between the SUs transmitter and the nearest undetectable PU_j's transmitter and β_j is the corresponding path attenuation factor.

3.3   Problem Formulation

Consider an OFDM communication system similar to [90]:

$$
y_n[m] = h_n x_n[m] + w_n[m], \quad \text{where } n = 1, ..., N \tag{3.3}
$$

where $x_n[m]$, $y_n[m]$, $w_n[m]$ and h_n are the input, output, noise signal and channel gain, respectively. Assume $P_T > 0$, as the total power constraint and P_i is the transmit power of an OFDM block, then the achievable data rate of reliable communication using the OFDM channel is,

$$
R(P_i) = \sum_{i=1}^{N} \Delta B \log(1 + \frac{P_i |h_i|^2}{N_0}) \tag{3.4}
$$

where N_0 is the noise power spectral density and ΔB is the subcarrier spacing (bandwidth). Thus the power allocation has to be done to maximize the sum rate in (3.4). In OFDM based CRNs, the subchannel transmit power constraints impose further restrictions on the power allocation in addition to the total transmit power constraint. Assuming the allocated signal power and the propagation path gain for the ith subcarrier are given as P_i and h_i (where $\frac{|h_i|^2}{N_0} = h_i$) respectively, $i = 1, ..., N$ and, the weights $w_i > 0, \forall i$ then the optimal

power allocation problem can be expressed as:

$$\max_{\{P_i\}} \sum_{i=1}^{N} w_i \log(1 + h_i P_i) \tag{3.5}$$

$$\text{subject to: } \text{C1: } 0 \le P_i \le S_i, \forall i;$$

$$\text{C2: } \sum_{i=1}^{N} P_i = P_T$$

$$\text{C3: } F_j \le G_j, \forall j;$$

where, N is the total number of subcarriers and $j = 1, ..., M$; and M is the total number of subchannels, $F_j = \sum_{i=m_j}^{m_{j+1}-1} P_i, j \epsilon A$ is the power allocated to the jth subchannel and m_j is the index of the first subcarrier and $m_{j+1} - 1$ is the index of the last subcarrier in the jth subchannel.

The power allocation problem in (3.5) is constructed considering three constraints. Constraint C1 consider individual peak power constraints, constraint C2 includes total power constraint and constraint C3 incorporates individual subchannel power constraints caused by the PUs's interference limits. Considering constraints C2 and C3, in [88] the authors proposed IPWF algorithm to obtain the optimal power allocation vector. Constraint C1 was introduced in [78] where the authors proposed GWFPP approach to solve the weighted RRA problems, that also provide optimal result. In this paper, we combined all those constraints to construct an optimal power allocation scheme.

In OFDM based CRNs, the subchannel transmit power constraints impose restrictions on the power allocation in addition to the total transmit power constraint. On the other hand, peak power constraint impose further restriction on the power allocation problem. Thus, a transmission rate constraint associated with the maximum modulation order limitation on each subcarrier is considered. It leads to a peak power constraint on each subcarrier. Since the combining of all three constraints made the power allocation problem more complicated, therefore previous approach cannot be easily utilized to solve the problem, and hence we

need to develop new approach.

3.4 Subcarrier Allocation

Assume I_m be the number of subcarriers allocated for one subchannel, is a variable. Since the utilization of any subchannel by the SU, is bounded by the power constraint on the jth subchannel (G_j), the transmit power for one subchannel on each subcarrier is given by

$$P_{m,i_m} = \frac{G_j}{I_m}, \quad i_m \in \hat{I}_m \tag{3.6}$$

where $\hat{I}_m$ represents the set of subcarriers allocated to one subchannel and I_m is the number of subcarriers allocated to one subchannel. The achieveable data rate (using (3.4)) can be shown as

$$D = \sum_{m=1}^{M} \sum_{i_m \in I_m} R_{m,i_m}(P_{m,i_m}), \quad i_m \in \hat{I}_m \tag{3.7}$$

For a given set $\hat{I}_m$ for a subchannel, if one more subcarrier $i_m{}^*$ is allocated to that subchannel, i. e. $\hat{I}_m$ is replaced by $\hat{I}_m \cup \{i_m{}^*\}$, the change of achievable rate for that subchannel, $\Delta d_{m,i_m{}^*}(\hat{I}_m)$, can be given by

$$
\begin{aligned}
\Delta d_{m,i_m{}^*}(\hat{I}_m) &= D_m(\frac{G_j}{I_m+1}) - D_m(\frac{G_j}{I_m}) \\
&= \sum_{i_m \in \hat{I}_m \cup \{i_m{}^*\}} d_{m,i_m}(\frac{G_j}{I_m+1}) - \sum_{i_m \in \hat{I}_m} d_{m,i_m}(\frac{G_j}{I_m})
\end{aligned} \tag{3.8}
$$

where d_{m,i_m} is the instantaneous achievable rate on the subcarrier $i, \quad i_m \in \hat{I}_m$.

In our proposed algorithm, assuming $\hat{I}_m$ has been allocated to one subchannel, whether an unallocated subcarrier i can be allocated to one subchannel, depends on whether its data rate increase $\Delta d_{m,i_m}(\hat{I}_m)$ is the maximum among all the subchannels. That is, subcarrier i will be allocated to $k^* = \max_{m,i_m} \Delta d_{m,i_m}(\hat{I}_m)$. The basics idea behind the subcarrier allocation is well depicted in 3.3 and the algorithm is described in Algorithm 1 description.
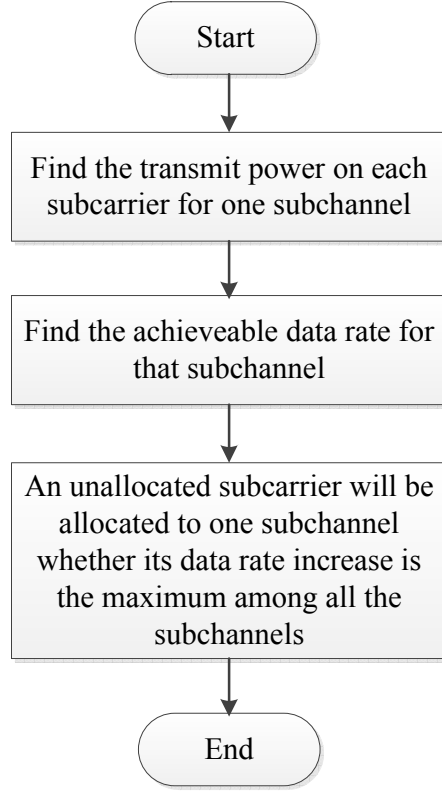
Figure 3.3: Flow chart for subcarrier aliocation.

Algorithm 1 Subcarrier Allocation

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initialization $\hat{I}_m = \phi, I_m = 0, \Delta d_{m,i_m}(I_m) = D_m(G_j)$
for $i \in N$ **do**
    for $m \in M$ **do**
        compute $\Delta d_{m,i_m}(\hat{I}_m)$ using (3.8)
        $k^* = \max_{m,i_m} \Delta d_{m,i_m}(\hat{I}_m)$;
        $\hat{I}_m^* = \hat{I}_m \cup \{i\}$;
        $I_m^* = I_m^* + 1$;
    end
end

After subcarrier allocation, in the second step, power allocation is carried out on its allocated subcarrier $\hat{A}_m$.

3.5 Power Allocation using GWFPP

3.5.1 Iterative Partitioned Weighted Geometric Water-Filling with Individual Peak Power (IGPP)

In this work, utilizing IPWF [88] and GWFPP [78] approach, we proposed Iterative Partitioned Weighted Geometric Water-Filling with Individual Peak Power (IGPP) algorithm, that also provides optimal result. For IGPP the first step is to divide all the subchannels into two sets, say A and B, and there are 2^M partitions in total. E set is a subsequence of the sequence $1, 2, ..., N$ and N is the total number of subcarriers. The next step would be to perform GWFPP for every j^{th} subchannel and calculate P_i using (??), (4.18) and (4.19). Let the set Λ is defined by the set $\{i | P_i > S_i, i \in E\}$. If Λ is an empty set, then P_i will be the output, otherwise, P_i will be set by the individual peak power S_i. Everytime we need to update the set E and the total power P_T. Since the finite set E is getting smaller and smaller until the set Λ is empty, algorithm GWFPP carries out at most, N loops to compute the optimal solution [78]. The next steps are to remove partitions that are represented by set D which is a set of subchannels that satisfies $F_j < G_j$ where $j \in A$. For each of the remaining partitions in the remainder set A, the geometric water-filling is performed on the subcarriers that belong to the jth subchannel. Algorithm IGPP carries out the loops to compute the optimal solution until the set A is empty. The last step would be to verify each partition whether they satisfy $F_j < G_j$ where $j \in B$. According to the paper [88], there is only one available partition and the corresponding power allocation vector is the solution. Based on the property of IGPP and the strict constraints on the objective function, there can be only one power allocation vector which satisfies all the conditions. In CWF problem, it is dificult to obtain the explicit expression of the optimal power allocation vector. A derived algorithm

obtained from [88] and [78] forming IGPP, is described in Algorithm 2 description.

Algorithm 2 Iterative Partitioned Weighted Geometric Water-filling with Individual Peak Power Constraints (IGPP)

Input: vector $\{\frac{1}{h_i}\}, \{w_i\}, \{S_i\}$ for $i = 1, 2, ..., N$,

the set $E = 1, 2, ..., N$ and P_T

initialization $A = \{j | j = 1, 2, ..., M\}$

$B = \phi, F = \phi, \Lambda = \phi, P^* = P_T$;

$C = \{i | \text{the } i^{\text{th}} \text{ subcarrier belongs to the } j^{\text{th}} \text{ subchannel}, j \in A\}$;

for $j \in A$ **do**

  for $i \in C$ **do**

    compute $\{P_i\}$ using GWF

    $\Lambda = \{i | P_i > S_i, i \in E\}$

    if $\Lambda = \phi$ **then**

      | output: $\{P_i\}$

    else

      | $P_i = S_i, i \in A$

    end

    $E = E \setminus \Lambda$

  end

  $F_j = \sum_{i=m_j}^{m_{j+1}-1} P_i, j \in A$

  $D = \{j | F_j \leq G_j, j \in A\}$;

  $L = \{i | \text{the } i^{\text{th}} \text{ subcarrier belongs to the } j^{\text{th}} \text{ subchannel}, j \in D\}$

  $A = A \setminus D, B = B \cup D$

  $C = C \setminus L, F = F \cup L$

  if $A = \phi$ **then**

    | output: $\{P_i\}$

  else

    | $P^* = P^* - \sum_{i \in L} P_i$

  end

end

3.6 Performance Evaluation

The proposed algorithm IGPP along with the existing methods (IPWF, GWFPP), have been implemented using MATLAB. Randomized fading have been used to generate the outcomes of each algorithms. Here, we assumed that the distance between the SU and the PU is

known, thus equation (3.2) has been used to calculate the subchannel power constraints (G_j). According to the subcarrier assignment strategy, described in previous section, we got subcarriers 1, 2, 3, 4 to be in subchannel 1, subcarriers 5, 6, 7 to be in subchannel 2, subcarriers 8, 9, 10, 11 to be in subchannel 3 and the last set of subcarriers 12, 13, 14, 15 to be in subchannel 4. The simulation parameters are summarized in Table 3.2.

Table 3.2: Simulation Parameters

Parameters	Values
No. of SU and PU	1, 4
Number of subchannels	4
Number of subcarriers	15
Protection region (P_j)	1m
Path attenuation factor (β)	2
Total power (P_T)	159
Subcarrier Bandwidth (ΔB)	15KHz
Subchannel power constraints (G_j)	{72, 44, 29, 17}
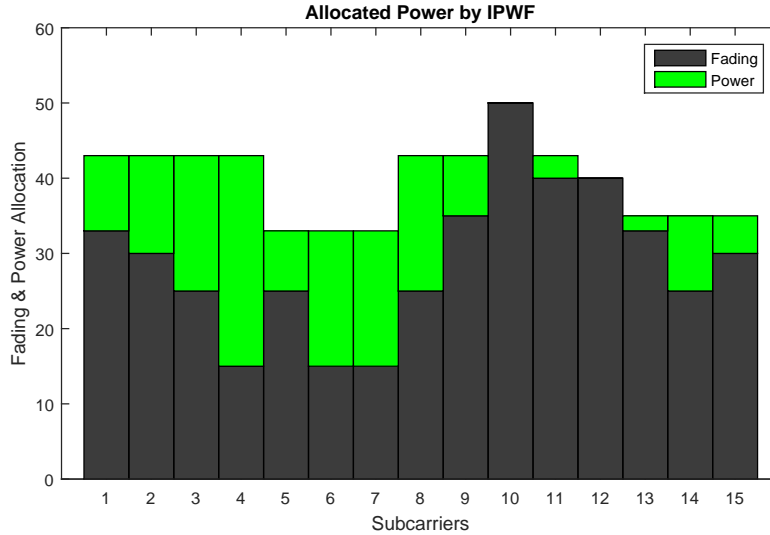
Figure 3.4: Power allocation using Iterative Partitioned Water-Filling Method

Fig. 3.4 shows power allocation when IPWF method has been applied. Since IPWF mainly works based on partitionof sunchannels, the water levels are different for each sub-channel due to the total subchannel power constraint for the partitions.
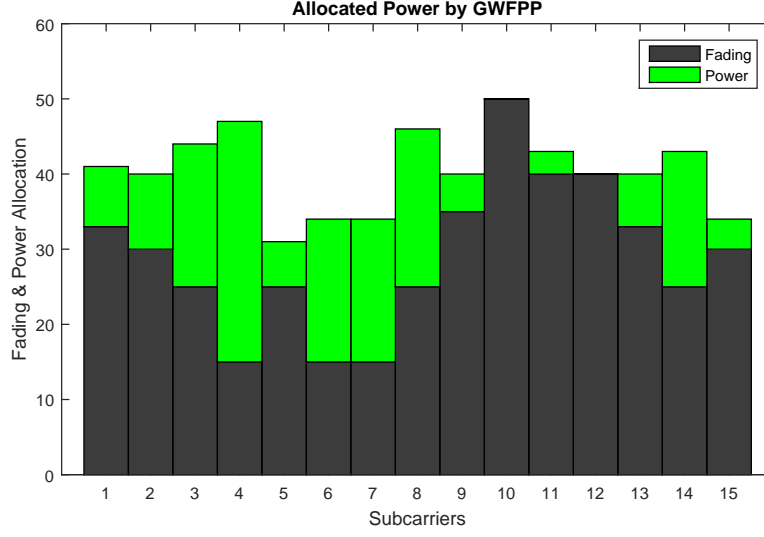
Figure 3.5: Power allocation using Geometric Water-Filling Method with Peak Power Constraints

Fig. 3.5 shows power allocation when GWFPP algorithm has been applied. This algorithm mainly consider individual peak power constraints. As a result, for each channel we get a different set of water level which follows the individual peak power constraints.
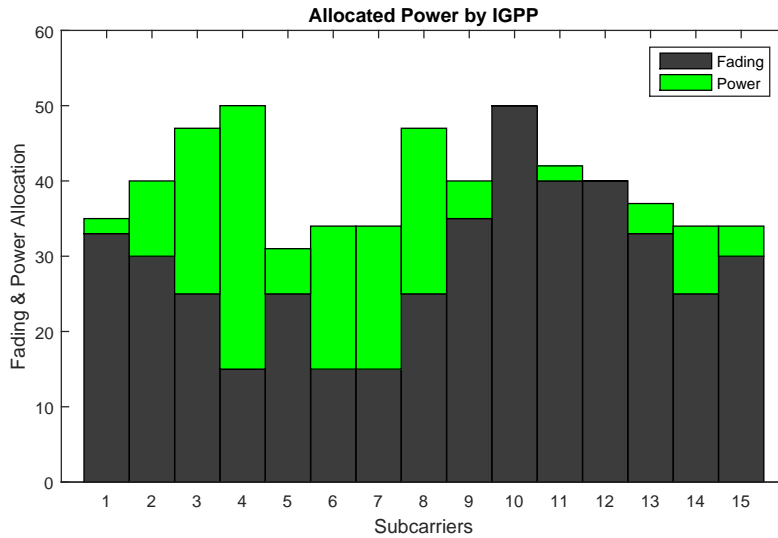
Figure 3.6: Power allocation using Iterative Partitioned Weighted Geometric Water-Filling with Individual Peak Power Constraints Algorithm

Fig. 3.6 shows power allocation when IGPP algorithm has been applied. Due to the total subchannel power constraint and individual peak power constraints the simulation result varies from the results of IPWF and GWFPP. For each subcarrier we get a different set of water level which follows the individual peak power constraints but they are different from the GWFPP algorithm due to the total subchannel power constraints. Fig. 3.7 shows power allocation by IGPP when considering different weight factors of subcarriers.
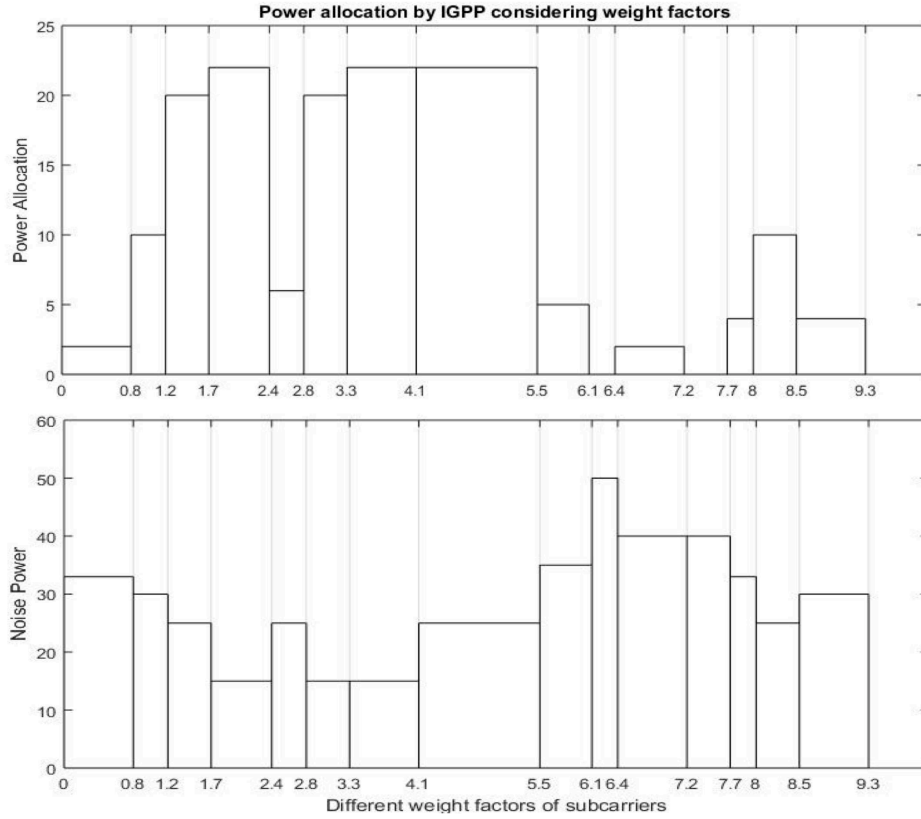
Figure 3.7: Power allocation by IGPP considering weight factors

Fig. 3.7 shows allocated power with corresponding noise power by IGPP when considering different weight factors for subcarriers. In X axis, cumulative summation of weighted coefficients are presented, as we moved towards right. In Fig. 3.7, the width of each bar

varies due to the different weight factors of the subcarriers.
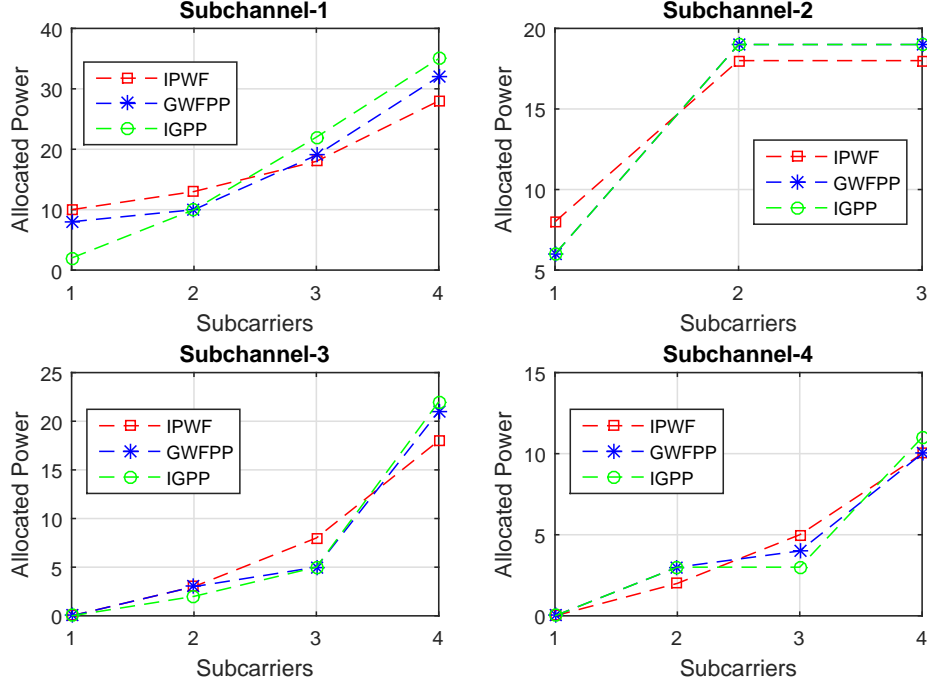
Figure 3.8: Comparison of the sum rates for IPWF, GWFPP and IGPP

Fig. 3.8 compares the allocated power for the IPWF, GWFPP and IGPP algorithms. For each subchannel, we sorted the subcarriers according to their noise power. Thus, the subcarrier that has highest noise power, comes first and the subcarrier that has lowest noise power, comes last for each subchannel. From Fig. 3.8, we found that, for each subchannel, the algorithm IGPP allocated less power in the subcarrier that has highest noise power and allocated more power in the subcarrier that has lowest noise power than the other two algorithms. Thus, the IGPP allows better utilization of the available power resources than IPW and GWFPP.

Fig. 3.9 compares the sum rates for the IPWF, GWFPP and IGPP algorithms. IGPP algorithm allows the sum rate to be better than IPW and GWFPP, due to the better utilisation of the power resources.
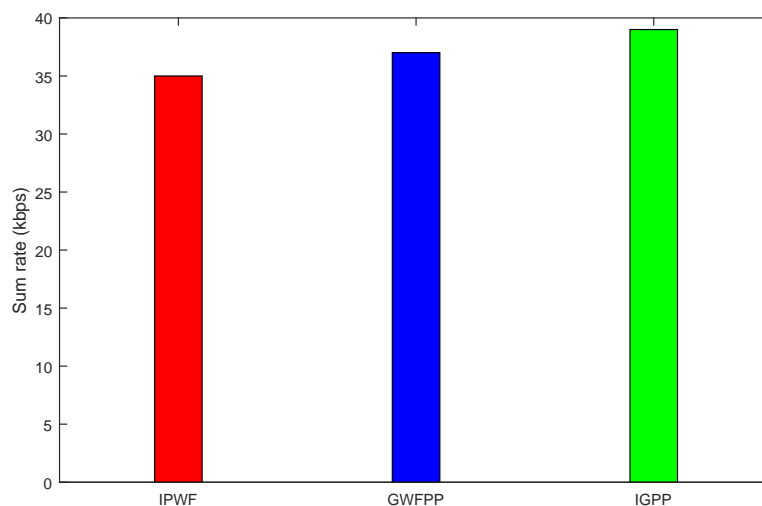
Figure 3.9: Optimal power allocation vs subcarriers for each subchannel using IPWF, GWFPP and IGPP

3.7 Chapter Summary

This Chapter provides the system model for OFDM-based CRNs and construct the power allocation problem considering three constraints. Describes the methods for the solution of power allocation problem and presents the proposed algorithms for power allocation along with subcarrier allocation. Also provides comparison of the proposed algorithm results with the related works.

Chapter 4

Resource Allocation for Cognitive Radio Systems with D2D Communication

4.1 Introduction

There have been several burgeoning research efforts found in the literature [91–99] on the RA schemes for CRNs. On the other hand, due to the benefit of D2D communication, International Mobile Telecommunications (IMT)- Advanced Standard systems, such as Long Term Evolution (LTE) and WiMax, allow D2D communication sharing the same radio resources with the cellular network to increase the spectral efficiency [19]. D2D communication is, in fact integrated into LTE-Advanced networks in [100, 101]. RRA for D2D communication underlaying cellular networks are currently being extensively investigated by researchers in terms of spectral efficiency [16, 102–107] and in terms of energy efficiency [108, 109].

From the literature survey, it is found that, most of the recent works focus on how to exploit D2D communication in cellular networks under different constraints. However, only a few efforts [19, 110–114] have been made to incorporate D2D communication with CR technology to jointly maximize the spectrum efficiency. In [19], the SUs mode selection strategies are optimized in a cognitive cellular network with D2D communication. A mixed overlay-underlay spectrum sharing method is proposed in [110] for CR-assisted D2D communications in a cellular network. Two spectrum access policies (random and prioritized) are investigated in [111] for cognitive and energy harvesting-based D2D communication in cellular networks. A RA scheme based on CR approach for D2D underlay multicast communication is proposed in [112] to improve system performance. The joint use of full-duplex relay and D2D communication are investigated in [113] for CRNs. An optimal power allocation algorithm is presented in [114] for cognitive D2D communication assisted by two-way relaying.

Table 4.1 provides different approaches to incorporate D2D communication with CR technology.

In this section, the resource allocation problem is studied by jointly employing CR technology and D2D communication in cellular networks. D2D users are modeled as cognitive secondary users where they can opportunistically access the spectrum. An OFDM based

Table 4.1: Comparative analysis of resource allocation optimization problem in cognitive D2D communication

Ref.	Objective	Constraint	Solution approach	Performance metric
[19], 2012	Maximize the total data rates of the CUs and D2D users	Transmission power budgets and interference constraints for the CUs and D2D users	D2D users optimal power is analyzed and transmission mode is selected using the mixed strategy which is updated by replicator dynamics within the framework of evolutionary game theory	Replicator dynamics, population share, average utilities, system converge
[110], 2015	Maximize the allowable density of D2D devices	Interference threshold constraint, collision probability constraint	A mixed overlay-underlay spectrum sharing system is analyzed and a solution is derived to accurately capture the interactions between devices and cellular infrastructures using stochastic geometry	Coverage probability, isolation probability, interference probability
[111], 2015	Calculate the overall outage probability for D2D users	Signal-to-interference-plus-noise ratio threshold	A complete framework based on stochastic geometry has been developed for statistical analysis of cognitive D2D communication using energy harvested from the ambient interference	Transmission probability, outage probability
[112], 2014	Maximize the total system capacity of the PU and SU multicast group	Transmission power budgets and interference constraints for the PUs and SUs	An optimal channel allocation method that reduces the interference from cellular to multicast D2D group is proposed	Total capacity of the system
[113], 2016	Maximize the achievable rate of D2D links	Signal-to-interference-plus-noise ratio threshold	D2D communication and full-duplex relay are utilized in CRN to optimized the rates of the D2D link	Achievable rate gain
[114], 2013	Minimize the SUs outage probability	Peak transmit power constraints, interference power constraints	An optimal power allocation algorithm is proposed for a CR network where a D2D pair as two SUs exchange their information through a relay node using network coding	Outage probability

cognitive cellular network with D2D communication has been designed and analyzed using Lagrange formulation and then solved using geometric water-filling (GWF) method [78]. The optimization problem is characterized by the following five features in order to maximize the transmission rate of the D2D users: a) total power constraint, b) peak power constraint on each subcarrier, c) maximum power constraint of each D2D user, d) interference constraint to the PU band and e) minimum transmission rate requirements for the D2D users. The senario that we considered to jointly employ CR technology and D2D communication in cellular networks is more practical and yet didn't study by the researchers. For such a cognitive D2D system model, the five sets of constraints are necessary and sufficient in order to maximize the transmission rate of the D2D users. To the best of the authors knowledge, the prior resource allocation researches did not consider the above five features simultaneously for such a cognitive D2D system.

4.2   System Model

A single cell downlink OFDM based cognitive cellular system with multiple cellular users as PUs and multiple D2D users as SUs is considered as shown in Fig. 4.1.

In spectral domain, we consider the side-by-side CR access model as shown in Fig. 4.2. It is assumed that the frequency bands with bandwidth B (B_1, B_2, ..., B_K in Hz), are occupied by K PUs (1, 2, ..., K). The unoccupied band that can be sensed by the M D2D users (1, 2, ..., M) for possible transmission, is located on both sides of PU bands. It is possible for the D2D users to opportunistically utilize those unused spectrum by the of knowledge of the environment and cognition capability, to adapt to their radio parameters accordingly [23]. Let, $\mathcal{K}$ be the set for PUs where $\mathcal{K} = \{1, 2, ..., K\}$ and $\mathcal{M}$ be the set for D2D users where $\mathcal{M} = \{1, 2, ..., M\}$. The frequency band which is available for CR transmission, is divided into N subcarriers and each subcarrier occupies a bandwidth of ΔB Hz.

Each subcarrier transmits in the fading channel where channel gain is integrated by the
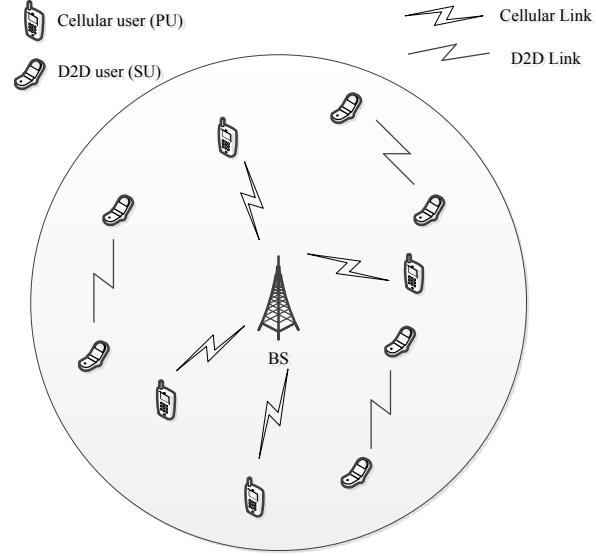
Figure 4.1: A D2D enabled cognitive radio system.
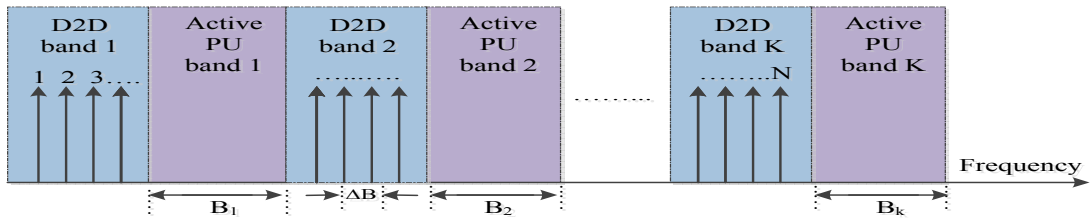
Figure 4.2: Spectrum distribution of PUs and D2D users in OFDM based cognitive D2D system.

effects of propagation path loss and shadowing. Thus, the D2D users need to detect the channel gain $h_{m,n}^{dd}$, $h_{m,k}^{dp}$ and $h_{k,m}^{pd}$, by the channel estimation mechanism before transmission. In practice, CSI on the D2D users own channel can be obtained via the classical channel training and feedback techniques. However, the CSI from the D2D user to the PU is not directly available. This can be obtained by the D2D-Tx from the PU-Rx by estimating the reversed channel under the assumption of channel reciprocity. Since our focus is on the resource allocation, we assumed that all the channel estimations are performed using advanced methods, otherwise it will effect the resource allocation scheme. Here, $h_{m,n}^{dd}$ denotes the channel gain between the mth D2D user's transmitter and receiver; $h_{m,k}^{dp}$, is the channel gain between the mth D2D user's transmitter and the kth PU's receiver; and $h_{k,m}^{pd}$, is the channel gain between the kth PU's transmitter and the mth D2D user's receiver. The subscript of index n denotes the nth subcarrier. Table 4.2 provides a list of frequently used variables and abbreviations.

Due to the coexistence of PU and D2D users in the side-by-side bands, the mutual interference is introduced. Now, the mutual interference introduced by the nth subcarrier of the mth D2D user to the kth PU band can be written as [115]

$$\Upsilon_{m,n}^{(k)} = |h_{m,k}^{dp}|^2 P_{m,n} T_s \int_{d_{m,n}^{(k)}-B_k/2}^{d_{m,n}^{(k)}+B_k/2} \left(\frac{sin\pi fT_s}{\pi fT_s}\right)^2 df \qquad (4.1)$$

where, $P_{m,n}$ is the transmit power for the mth D2D user allocated to the nth subcarrier, T_s is the symbol duration, $d_{m,n}^{(k)}$ represents the spectrum distance between the nth subcarrier of the mth D2D user and the kth PU band and B_k represents occupied bandwidth by the kth PU.

Let $I_{m,n}^{(k)} = |h_{m,k}^{dp}|^2 T_s \int_{d_{m,n}^{(k)}-B_k/2}^{d_{m,n}^{(k)}+B_k/2} \left(\frac{sin\pi fT_s}{\pi fT_s}\right)^2 df$, be the interference factor for the mth D2D user between the nth subcarrier and the kth PU band. Then equation (4.1) can be rewritten as

$$\Upsilon_{m,n}^{(k)} = P_{m,n} \cdot I_{m,n}^{(k)}. \qquad (4.2)$$

Table 4.2: List of frequently used variables and abbreviations

Group	Variable	Meaning
Index	k	index of PUs, for $k = 1, 2, \cdots, K$
	m	index of D2D users, for $m = 1, 2, \cdots, M$
	l	index of other active D2D users, for $l = 1, 2, \cdots, M$
	n	index of subcarriers, for $n = 1, 2, \cdots, N$
	B	index of PUs bandwidth B_1, B_2, ..., B_K in Hz
Set	$\mathcal{K}$	set of PUs $\{1, 2, \cdots, K\}$
	$\mathcal{M}$	set of D2D users $\{1, 2, \cdots, M\}$
	$\mathcal{N}$	set of subcarriers $\{1, 2, \cdots, N\}$
	$\mathcal{N}_m$	set of subcarriers allocated to the mth D2D user $\{1, 2, \cdots, N_m\}$
	$\bar{N}_m$	number of subcarriers allocated to the mth D2D user
	λ	set of subcarriers that exceeds the peak power constraint
	Ω	set of subcarriers that need to be reallocated
Channel related term	$h_{m,n}^{dd}$	channel gain between the mth D2D user's transmitter and receiver
	$h_{m,k}^{dp}$	channel gain between the mth D2D user's transmitter and the kth PU's receiver
	$h_{k,m}^{pd}$	channel gain between the kth PU's transmitter and the mth D2D user receiver
	$\Gamma_{m,n}$	channel gain-to-noise ratio
	d_m	link distance between the devices of D2D user
	η	path attenuation factor
	σ_{AWGN}^2	additive white Gaussian noise variance
Bandwidth related term	$d_{m,n}^{(k)}$	spectrum distance between the nth subcarrier of the mth D2D user and the kth PU band
	ΔB	bandwidth of each subcarrier in Hz
Power related term	$P_{m,n}$	transmit power for the mth D2D user allocated to the nth subcarrier
	S_m	total allocated power for the mth D2D user
	E_m	extra power for the mth D2D user
	R_m	remaining power for the mth D2D user that needs to be reallocated in the next round
Interference related term	$\Upsilon_{m,n}^k$	interference introduced by the nth subcarrier of the mth D2D user to the kth PU band
	$I_{m,n}^k$	interference factor for the mth D2D user between the nth subcarrier and the kth PU band
	$\rho_{m,n}^k$	interference introduced by the kth PU signal to the mth D2D user on the nth subcarrier
	$L_{l,n}$	interference signal comes from other active D2D users.
	$\mathcal{I}_{agg}$	aggregated interference
Transmission rate related term	$\Re_{m,n}$	transmission rate for the mth D2D user on the nth subcarrier
	$\bar{\Re}_{m,n}$	transmission rate when peak power constraint is considered
Constraint Group	P_T	total power constraint
	$P_{m,max}$	maximum power constraint of the mth D2D user
	$\bar{P}_{m,n}$	peak power constraint for the mth D2D user at the nth subcarrier
	I_{th}^k	interference threshold of the kth PU band
	$\Re_{m,min}$	minimum transmission rate requirements for the D2D users
	$x_{m,n}$	binary decision variable of subcarrier allocation
Others	$\alpha, \beta, \gamma, \delta, \psi$	Lagrange multipliers
	$\Pi_{m,n}$	proposed metric for subcarrier allocation
	w_1, w_2, w_3	weighting factors for subcarrier allocation
Reference Level	μ	water level
	j^*	water level step (highest step under the water)
Matrix	$\mathbf{X}$	$M \times N$ matrix of subcarrier allocation
	$\mathbf{P}$	$M \times N$ matrix of allocated power
	$\mathbf{T}$	$M \times N$ matrix of allocated power when binary decision variable is considered
Abbreviations	PSD	power spectrum density
	ASA	Adaptive subcarrier allocation
	PA	Power allocation
	GWF	Geometric water-filling
	GWFPP	Geometric water-filling with peak power constraint

Now, with an ideal coding scheme, the transmission rate for the mth D2D user on the nth subcarrier, is given by the following formula

$$\Re_{m,n}(P_{m,n}, d_m) = \Delta B \log \left(1 + \frac{P_{m,n} |h_{m,n}^{dd}|^2 d_m^{-\eta}}{\mathcal{I}_{agg}} \right) \tag{4.3}$$

where, d_m represents the link distance between the devices of D2D user and η is the path attenuation factor. In (4.3), $\mathcal{I}_{agg} = \sigma_{AWGN}^2 + \sum_{k=1}^{K} \rho_{m,n}^k + \sum_{l=1,l\neq m}^{M} L_{l,n}$ denotes the aggregated interference, where σ_{AWGN}^2 denotes the additive white Gaussian noise (AWGN) variance, the second term be the interference introduced by the kth PU signal to the mth D2D user on the nth subcarrier and the third term represents the interference signal comes from other active D2D users.

Let $\Gamma_{m,n} = \frac{|h_{m,n}^{dd}|^2 d_m^{-\eta}}{\mathcal{I}_{agg}}$ represents the channel gain-to-noise ratio, then (4.3) can be rewritten as

$$\Re_{m,n}(P_{m,n}, d_m) = \Delta B \log \left(1 + P_{m,n}\Gamma_{m,n} \right). \tag{4.4}$$

In this paper, a transmission rate constraint associated with the maximum modulation order limitation on each subcarrier is considered. It leads to a peak power constraint $(\bar{P}_{m,n})$ for the mth D2D user on the nth subcarrier which can be written from (4.4) as

$$\bar{P}_{m,n} = \frac{2^{\bar{\Re}_{m,n}} - 1}{\Gamma_{m,n}} \tag{4.5}$$

where $\bar{\Re}_{m,n}$ is the corresponding transmission rate when $\bar{P}_{m,n}$ is considered.

Let $x_{m,n}$ be a binary decision variable of channel (subcarrier) allocation. If subcarrier n is allocated to D2D user m, then $x_{m,n}$ is equal to 1; otherwise it is equal to zero. Since each subcarrier is exclusively allocated to one D2D user, then

$$\sum_{m=1}^{M} x_{m,n} = 1, \quad n = 1, 2, ..., N. \tag{4.6}$$

Now, the total system transmission rate is given by

$$\Re(\mathbf{X},\ \mathbf{P}) = \Delta B \sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n} \log\left(1 + P_{m,n}\Gamma_{m,n}\right) \tag{4.7}$$

where, $\mathbf{X}$ is a $M \times N$ matrix of subcarrier allocation indices $x_{m,n}$, and $\mathbf{P}$ is a $M \times N$ matrix of allocated power $P_{m,n}$.

4.3 Problem Formulation

Our objective of RA (subcarrier and power allocation) is to maximize the total downlink transmission rate of the D2D system under both power and interference constraints along with the minimum rate requirements. Therefore, the optimization problem can be formulated as follows

$$\max_{\mathbf{X},\ \mathbf{P}} \Delta B \sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n} \log\left(1 + P_{m,n}\Gamma_{m,n}\right) \tag{4.8}$$

subject to:

$$C1: \sum_{m=1}^{M} x_{m,n} = 1,\ x_{m,n}\ \in\ \{0,1\};\ \ \forall n\ \in\ \mathcal{N}$$

$$C2: \sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n} P_{m,n} \leq P_T, P_{m,n} \geq 0;$$

$$C3: \sum_{n=1}^{N} x_{m,n} P_{m,n} \leq P_{m,max};\ \ \forall m\ \in\ \mathcal{M}$$

$$C4: x_{m,n} P_{m,n} \leq \bar{P}_{m,n};\ \ \forall m\ \in\ \mathcal{M},\ \ \forall n\ \in\ \mathcal{N}$$

$$C5: \sum_{k=1}^{K} \sum_{n=1}^{N} x_{m,n} \Upsilon_{m,n}^{(k)} \leq I_{th};\ \ \forall m\ \in\ \mathcal{M}$$

$$C6: \sum_{n=1}^{N} x_{m,n} \Re_{m,n} \geq \Re_{m,min};\ \ \forall m\ \in\ \mathcal{M}$$

where, constraint C1 depicts that each subcarrier can not be reused by more than one D2D user. Constraint C2, C3 and C4 denote total power constraint (e. g. P_T), maximum power constraint of each D2D user (e. g. $P_{m,max}$), and peak power constraint on each subcarrier (e. g. $\bar{P}_{m,n}$) respectively. Constraint C5 describes interference constraint where I_{th} denotes the total interference threshold by the K PU bands. Lastly, constraint C6 provides minimum transmission rate requirements for the D2D users.

The optimization problem in (4.8) is nonconvex due to binary decision variable $x_{m,n}$. This variable can be relaxed by applying a time sharing approach [116] to allow any value in the interval $(0,1]$ instead of $\{0,1\}$ set, which is equivalent to allowing time-sharing of a single subcarrier between different users. By time-sharing we mean that several users can transmit on a given subcarrier during a given scheduling interval, with each user transmitting alone for a fraction of the interval. This corresponds to a sort of time division multiple access subdivision of the scheduling time unit and is not to be confused with overlapping transmission. Let $t_{m,n} = x_{m,n}P_{m,n}$, then the optimization problem in (4.8) can be rewritten

as follows:

$$\max_{\mathbf{X}, \mathbf{T}} \Re(\mathbf{X}, \mathbf{T}) = \Delta B \sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n} \log \left(1 + \frac{t_{m,n}}{x_{m,n}} \Gamma_{m,n} \right) \quad (4.9)$$

subject to:

$$C1: \quad \sum_{m=1}^{M} x_{m,n} = 1, \ x_{m,n} \in (0,1]; \quad \forall n \in \mathcal{N}$$

$$C2: \quad \sum_{m=1}^{M} \sum_{n=1}^{N} t_{m,n} \le P_T, \ t_{m,n} \ge 0;$$

$$C3: \quad \sum_{n=1}^{N} t_{m,n} \le P_{m,max}, \quad \forall m \in \mathcal{M}$$

$$C4: \quad t_{m,n} \le \bar{P}_{m,n}; \quad \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}$$

$$C5: \quad \sum_{k=1}^{K} \sum_{n=1}^{N} t_{m,n} I_{m,n}^{(k)} \le I_{th}; \quad \forall m \in \mathcal{M}$$

$$C6: \quad \sum_{n=1}^{N} x_{m,n} \Re_{m,n} \ge \Re_{m,min}; \quad \forall m \in \mathcal{M}$$

The problem in (4.9) is convex with a concave objective function which is equivalent to the original problem in (4.8) when the condition on $x_{m,n}$ is relaxed for each D2D user m and subcarrier n. Finding the optimal pair $(x_{m,n}^*, t_{m,n}^*) = (x_{m,n}^*, x_{m,n}^* P_{m,n}^*)$ leads to the same solution as finding $(x_{m,n}^*, P_{m,n}^*)$.

The analytical solution of the problem in (4.9) is

$$P_{m,n}^* = \left[\frac{1 + \psi_m}{\ln \left(\alpha_n + \beta_m + \gamma_n + \sum_{k=1}^{K} \delta_k I_{m,n}^{(k)} \right)} - \frac{1}{\Gamma_{m,n}} \right]^+. \quad (4.10)$$

Proof: See **Appendix**

The $P_{m,n}^*$ denotes the optimal power allocation for the mth D2D user on the nth subcarrier

when $m = m^*$. Thus, the indices of the subcarrier allocation matrix X will be

$$
x_{m,n} = \begin{cases} 1 & m = m^* \ \text{ for } n = 1, 2, ..., N \\ 0, & \text{otherwise.} \end{cases} \tag{4.11}
$$

The power allocation strategy in (4.10) is indeed corresponding to the CWF strategy [76] and depends on the Lagrange multipliers $(\alpha, \beta, \gamma, \delta, \psi)$ associated with the per user power and interference constraints. By using the CWF, the optimal power allocation strategy can be calculated which is practically intractable. Thus, in this paper, GWF approach [78] is utilized to solve the CWF problem which is described in the following section. It has two advantages:

1. The geometric approach can compute the exact solution to the CWF, including the weighted case, with less computation without determining the water level through solving the non-linear system,

2. Machinery of the proposed geometric approach can overcome the limitations of the CWF algorithm to include more stringent constraints.

In terms of complexity, the CWF approach has a worst-case complexity of N iterations, i.e., total $O(N^2)$ fundamental arithmetic and logical operations under the $2(N+1)$ memory requirement. On the other hand, GWF algorithm occupies less computational resource. The worst-case computational complexity of the GWF algorithm is $8N + 3$ fundamental arithmetic and logical operations under the $2(N+1)$ memory requirement and for GWFPP, the worst-case complexity is $4N^2 + 7N$ fundamental arithmetic and logical operations.

4.4   Proposed Resource Allocation Scheme

Based on the analysis in the previous section, an efficient RA scheme is proposed in this section to address the problem defined in (4.8). A two-stage approach is considered to

solve (4.8) efficiently. Specifically, the resource allocation scheme is divided into two individual procedures: adaptive subcarrier allocation (ASA) and power allocation (PA). In the first stage, each subcarrier is assigned to one D2D user with the minimum value of the proposed metric that is adaptive in nature. In the second stage, power is allocated among all the D2D users to maximize the transmission rate. The procedure for the RA scheme is illustrated in Fig. 4.3.
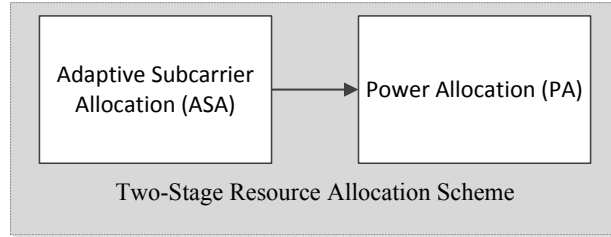
Figure 4.3: The procedure for resource allocation scheme.

4.4.1   Adaptive Subcarrier Allocation (ASA)

Most of the recent works regarding subcarrier allocation strategy to the D2D users is based on greedy approach [104, 105]. In order to assign subcarriers to the D2D users, a proposed metric is utilized that is adaptive in nature. The proposed metric is related to the amount of power, interference and transmission rate.

Let $\mathcal{N}$ be the set of subcarriers where $\mathcal{N} = \{1, 2, ..., N\}$, $\mathcal{N}_m$ be the set of subcarriers allocated to the mth D2D user and $\bar{N}_m$ denotes the number of subcarriers allocated to the mth D2D user. Now, the transmission rate increment for one more subcarrier allocation to the mth D2D user can be written as

$$\Delta \Re_{m,n} = \Re_{m,n} \left(\frac{P_{m,n}}{\bar{N}_m + 1}, d_m \right) - \Re_{m,n} \left(\frac{P_{m,n}}{\bar{N}_m}, d_m \right), n \in \mathcal{N}_m. \tag{4.12}$$

The power increment for transmitting one more increment in transmission rate $\Delta \Re$ on

subcarrier n of the mth D2D user can be written as

$$\Delta P_{m,n} = \frac{(2^{\Re_{m,n}+\Delta\Re_{m,n}} - 2^{\Re_{m,n}})}{\Gamma_{m,n}}. \tag{4.13}$$

The interference increment caused by subcarrier n of the mth D2D user for the kth PU can be written as

$$\Delta\Upsilon_{m,n}^{(k)} = \Delta P_{m,n} \cdot I_{m,n}^{(k)}. \tag{4.14}$$

A metric composed of three parts for the nth subcarrier of the mth D2D user is described as

$$\Pi_{m,n} = w_1\left(\frac{\Delta P_{m,n}}{P_{m,max} - P_{m,used}}\right) + w_2\left(\sum_{k=1}^{K}\frac{\Delta\Upsilon_{m,n}^k}{I_{th} - \Upsilon_{m,used}^k}\right) + w_3\left(\frac{\Delta\Re_{m,n}}{\Re_{m,used} - \Re_{m,min}}\right) \tag{4.15}$$

where, $P_{m,used}$ is the amount of power that has been utilized for the mth D2D user, $\Upsilon_{m,used}^k$ is the interference that has been initiated to the kth PU, and $\Re_{m,used}$ is the corresponding transmission rate of the mth D2D user. The first part consists of the amount of the power increment for transmitting one more increment in transmission rate and the amount of the unused power. The second part includes the amount of interference that is used for considering the interference constraints. Finally, the third part is associated with the minimum transmission rate requirements among the D2D users. Three non-negative parameters (w_1, w_2, w_3) are exploited as the weighting factors to make a trade-off between the power and the interference constraints together with the minimum rate requirements in the subcarrier allocation process. This is the reason why this subcarrier assignment strategy is named as adaptive subcarrier allocation (ASA).

For a specific D2D user, a subcarrier n^* with the minimum value of the metric (4.15), is assigned to that selected D2D user m^*. A subcarrier with a lower value depicts that the power and interference increments for providing one more increment in transmission rate are relatively small compared to other subcarriers. The ASA strategy is well described in

Algorithm 1.

Algorithm 3 Adaptive Subcarrier Allocation (ASA)

Input: The set $\mathcal{N} = \{1, 2, ..., N\}$
initialization: $\mathcal{N}_m = \phi, \bar{N}_m = 0, \Re_{m,used} = 0,$
$P_{m,used} = 0, \Upsilon^k_{m,used} = 0; \ \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}, \ \forall k \in \mathcal{K}$
for $n \in \mathcal{N}$ **do**

> compute $\Delta P_{m,n}$ using (4.13),
> $\Delta \Upsilon^{(k)}_{m,n}$ using (4.14)
> and $\Delta \Re_{m,n}$ using (4.12);
> calculate $\Pi_{m,n}$ using (4.15);
> $(m^*, n^*) = \arg \ \min \ \Pi_{m,n};$
> $\mathcal{N} = \mathcal{N} - \{n^*\}, \mathcal{N}_{m^*} = \mathcal{N}_m \cup \{n^*\}, \bar{N}_m = \bar{N}_m + 1;$
> update $P_{m,used}, \Upsilon^k_{m,used}, \Re_{m,used}$

end

4.4.2 Power Allocation (PA)

After subcarrier assignment described in the previous section, power allocation is performed for the selected subcarrier n^* of the D2D user m^*. For the selected subcarrier n^* of the D2D user m^*, the value of x_{m^*,n^*} becomes 1 and then the power allocation problem in (4.8) can be solved using GWF approach. Fig. 4 gives an illustration of the GWF approach.

Instead of trying to determine the common water level μ (real nonnegative number) in CWF, the highest water level step, denoted by j^*, which is an integer number, is introduced to find the solutions for power allocation. Let $P(j)$ denotes the water volume above step j or zero, whichever is greater and the value of $P(j)$ can be found as:

$$P(j) = \left[P_T - \left\{ \sum_{n=1}^{j-1} \left(\frac{1}{\Gamma_{m,j}} - \frac{1}{\Gamma_{m,n}} \right) \right\} \right]^+ ; \forall j \in \mathcal{N}_m \qquad (4.16)$$

where $\frac{1}{\Gamma_{m,n}}$ is the "step depth" of the nth stair. Due to the definition of $P(j)$ being the power (water volume) above step j, it cannot be a negative number. Therefore we use $\{.\}^+$ in (4.16) to assign 0 to $P(j)$ if the result inside the bracket is negative. The corresponding

(a)   (b)
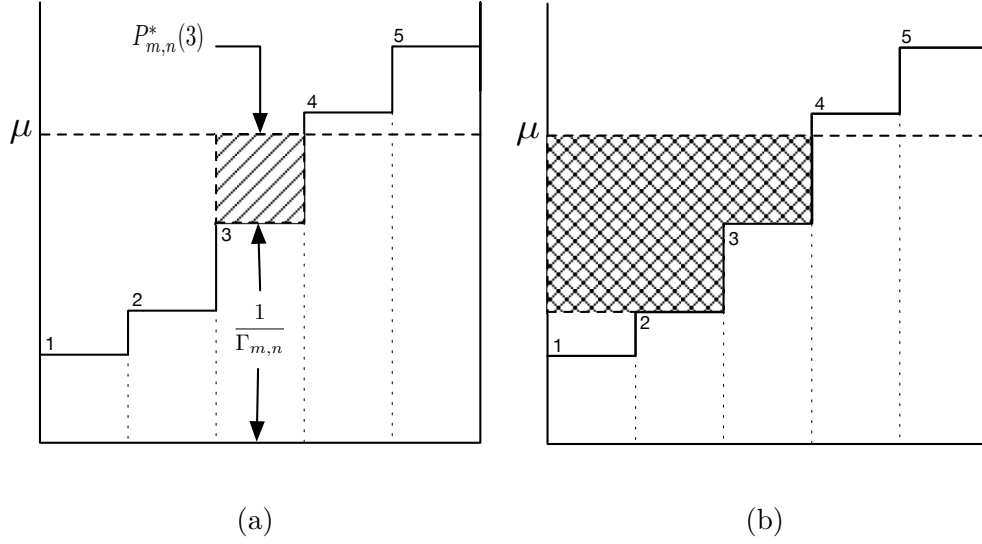
Figure 4.4: Illustration for the GWF algorithm (a) Illustration of water level step $j^* = 3$, allocated power for the third step $P^*_{m,n}(3)$, and step depth is $\frac{1}{\Gamma_{m,n}}$ and (b) Illustration of $P(j)$ (shadowed area, representing the total power above step j) when $j = 2$.

geometric meaning is that the $j^{*^{th}}$ level is above water.

According to [78], the explicit solution for power allocation is:

$$P_{m,n} = \begin{cases} P_{m,j^*} + \left(\frac{1}{\Gamma_{m,j^*}} - \frac{1}{\Gamma_{m,n}} \right) & 1 \leq n \leq j^* \\ 0, & j^* < n \leq N_m, \end{cases} \tag{4.17}$$

where the water level step j^* is given as

$$j^* = \max \left\{ j | P(j) > 0, 1 \leq j \leq N_m \right\} \tag{4.18}$$

and the power level for this step is

$$P_{m,j^*} = \frac{1}{j^*} \ P(j^*). \tag{4.19}$$

In order to allocate power to the selected subcarriers for each D2D user, first we perform geometric water-filling with peak power constraint (GWFPP) [78] for all the subcarriers and

calculate $\{P_{m,n}\}$ using (4.17), (4.18) and (4.19). Now, let λ is defined by the set $\{n|P_{m,n} > \bar{P}_{m,n}, n \in \mathcal{N}_m\}$. If λ is an empty set, then $P_{m,n}$ will be the output, otherwise, $P_{m,n}$ will be set by the individual peak power $\bar{P}_{m,n}$. Everytime we need to update the set $\mathcal{N}_m$ and the total power P_T at the end of each iteration. Since the finite set $\mathcal{N}_m$ is getting smaller and smaller until the set λ is empty. The required steps to apply the algorithm GWFPP is summarized below:

Algorithm GWFPP

Input: vector $\{\frac{1}{\Gamma_{m,n}}\}$, $\{\bar{P}_{m,n}\}$ $\forall n \in \mathcal{N}_m$ and P_T.

1) Compute $\{P_{m,n}\}$ using (4.17), (4.18) and (4.19).

2) The set λ is defined by the set $\{n|P_{m,n} > \bar{P}_{m,n}, n \in \mathcal{N}_m\}$. If λ is the empty set, output $\{P_{m,n}\}_{n=1}^{N_m}$; else, $P_{m,n} = \bar{P}_{m,n}$, as $n \in \lambda$.

3) Update $\mathcal{N}_m$ and P_T. Then return to 1) of the GWFPP.

The next step is to compute the summation of allocated power for all D2D users. Let S_m be the total allocated power for the mth D2D user, E_m be the extra power for the mth D2D user when S_m exceeds the device's maximum power ($P_{m,max}$) and R_m be the remaining power for the mth D2D user that needs to be reallocated in the next round. In order to satisfy device's maximum power constraint, three cases are considered: 1) $S_m = P_{m,max}$, 2) $S_m > P_{m,max}$ and 3) $S_m < P_{m,max}$. For the first case, after checking the interference and minimum rate requirement constraints, we can have the allocated power vector for those D2D users directly. For the second case, we first perform GWFPP with the corresponding $P_{m,max}$ and then, check the interference and minimum rate requirement constraints to get their power allocation vectors. In this case, we also calculate all the E_m that needs to be reallocated in the next round. Finally, for the third case, in order to perform GWFPP less number of times, we start with those D2D users where we can allocate the remaining power most while satisfying the required constraints. In each case, if any violation of the interference or minimum rate constraint happens, this algorithm creates a set of Ω for those subcarriers and the amount of the R_m that needs to be reallocated in the next round. The process

continues until all the reallocation being completed while satisfying all the constraints. The required steps for performing the power allocation are described in Fig. 4.5 and the detailed algorithm is well depicted in the Algorithm 2 description.
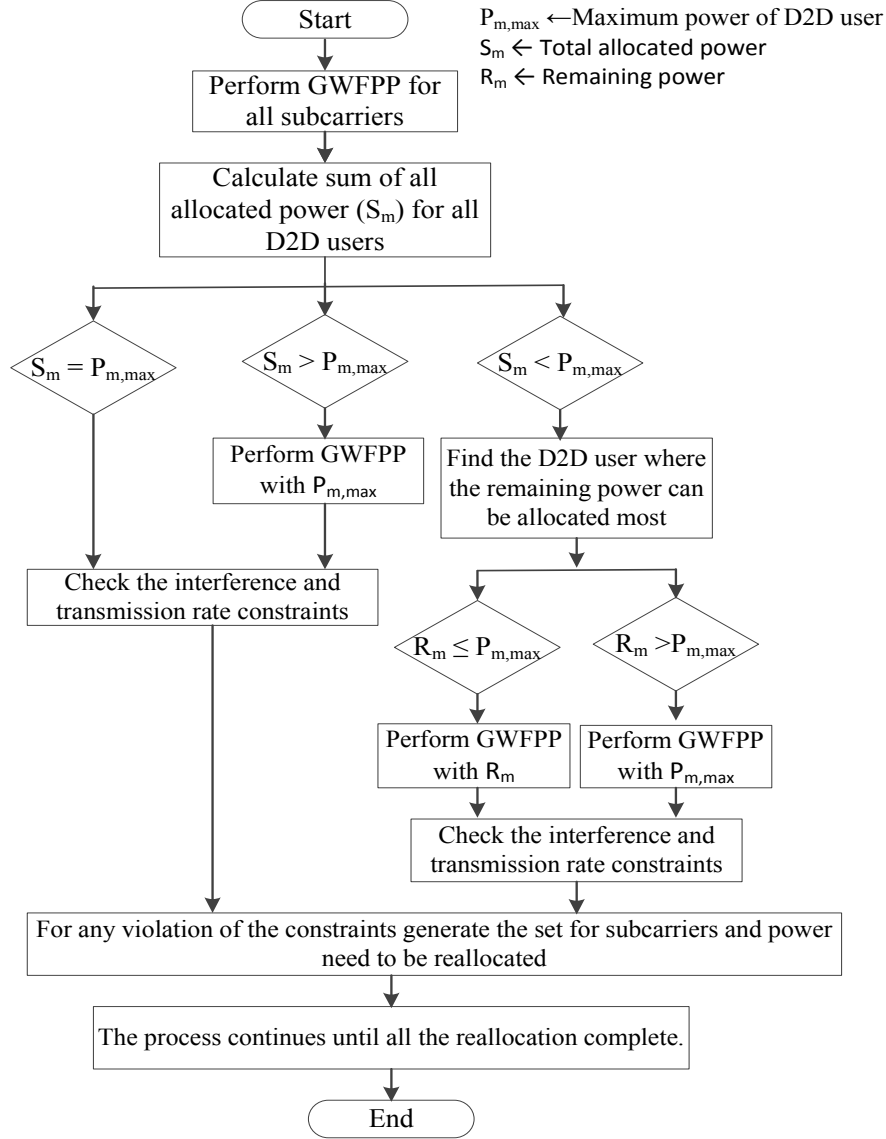
Figure 4.5: Flow chart of power allocation algorithm.

Algorithm 4 Power Allocation (PA)

Input: vector $\{P_{m,max}\}\forall m \in \mathcal{M}$, P_T;

initialization $A = \{m|m \in \mathcal{M}\}, B = \{n|n \in \mathcal{N}_m\}, C = \{m|\text{sorted D2D user}\}, \Omega = \phi$;

for $n \in B$ **do**

    compute $\{P_{m,n}\}$ using **GWFPP** with P_T

end

for $m \in A$ **do**

    calculate total allocated power, $S_m = \sum_{n=1}^{N_m} P_{m,n}$

    if $S_m = P_{m,max}$ **then**

        Interference-Rate Check$(\Upsilon_m, \Re_m)$;

    end

    if $S_m > P_{m,max}$ **then**

        Extra power, $E_m = S_m - P_{m,max}$;

        compute $\{P_{m,n}\}$ using **GWFPP** with $P_{m,max}$;

        Interference-Rate Check$(\Upsilon_m, \Re_m)$;

    end

    if $S_m < P_{m,max}$ **then**

        calculate $\{P_{m,max} - S_m\}$;

    end

end

sort $\downarrow \{P_{m,max} - S_m\}$;

for $m \in C$ **do**

    total power need to be reallocated, $R_m = S_m + E_m$;

    $\mathcal{N}_m = \mathcal{N}_m \cup \{n\}, n \in \Omega$;

    if $R_m \leq P_{m,max}$ **then**

        compute $\{P_{m,n}\}$ using **GWFPP** with R_m;

        Interference-Rate Check$(\Upsilon_m, \Re_m)$;

    else

        Extra power, $E_m = S_m - P_{m,max}$;

        compute $\{P_{m,n}\}$ using **GWFPP** with $P_{m,max}$;

        Interference-Rate Check$(\Upsilon_m, \Re_m)$;

    end

end

return $\{P_{m,n}\}$

Function Interference-Rate Check$(\Upsilon_m, \Re_m)$:

    calculate total interference, $\Upsilon_m = \sum_{n=1}^{N_m} P_{m,n} I_{m,n}^{(k)}$

    calculate total transmission rate, $\Re_m = \sum_{n=1}^{N_m} \Re_{m,n}$

    if $(\Upsilon_m \leq I_{th})$ && $(\Re_m \geq \Re_{min})$ **then**

        output: $\{P_{m,n}\}$;

        $E_m = 0$;

    end

    If$(!\mathcal{N}_m)$

    $\Omega \longleftarrow \mathcal{N}_m \setminus n, E_m = \sum_{n=1}^{N_m} P_{m,n}$

    return $\{P_{m,n}\}, E_m, \Omega$

4.5   Performance Evaluation

In order to evaluate the performance of the subcarrier assignment and power allocation algorithm for D2D communications, we simulate a multiuser single cell system with radius 100m where BS is located in the center of the cell using MATLAB. All cellular users (perform as PUs) and D2D users (perform as SUs) are uniformly distributed randomly within the cell. The distance between D2D pairs varies depending on their relative position in the cell. All other simulation parameters are considered according to Table 4.3. The simulation results are evaluated over different realization of PUs and D2D users locations, interference conditions and channel gains. Average transmitted data rates for different algorithms under consideration are obtained from several independent simulation runs.

Table 4.3: Simulation Parameters

Parameters	Values
Total no. of D2D users	5-35
Total no. of PUs	12-24
Total no. of subcarriers	5-50
Subcarrier bandwidth (ΔB)	1.5 KHz
The value of T_s	1μs
Path loss factor	4
The value of δ_d^2	10^{-12}
Max D2D T_x power	0.1W
Max PU T_x power	0.25W

In order to evaluate the performance of the proposed algorithm, we compared our algorithm with the most popular schemes : uniform power loading, water-filling schemes [76], and ladder/triangular profile power allocation [117, 118]. In the uniform power loading scheme, uniform power is loaded into each subcarrier and it only consider total power constraint C2. With the total power as the power constraint (C2), the power profile follows the water-filling scheme as in [76]. In ladder profile scheme [117], power is distributed in such a fashion so that the subcarriers that are adjacent to the PU bands, are given less power where as the subcarriers that are far away to the PU bands, are given more power. According to

the triangular power allocation scheme in [118], power allocated to the subcarriers near the PUs is small and gradually increase as move towards the middle. Thus maximum power is allocated to the middle most subcarrier. Since the idea behind the schemes (ladder profile and triangular power allocation) is the same, thus we name these schemes as ladder/triangle scheme and they only considered the interference constraint C5.
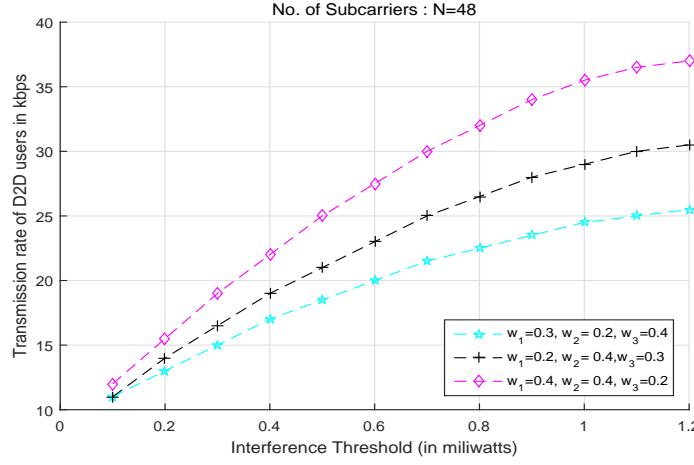
Figure 4.6: Illustration of the behavior for the proposed subcarrier assignment with different values of the weighting factors (w_1, w_2, w_3)

The behavior of the proposed subcarrier assignment strategy with different values of the weighting factors in (4.15) is illustrated in Fig. 4.6. The effect of the different weighting factors (w_1, w_2, w_3) is revealed in the performance curves. The simulation results show that an appropriate value of the weighting factors for the threer parts in the proposed indicator can achieve superior performance. We select the values of the weighting factors (w_1, w_2, w_3) to be (0.4, 0.4, 0.2) in the following simulation, since this combination returns the highest sum rate of the D2D uses in the simulation range.

Fig. 4.7 shows the effect of the distance between the D2D users on subcarrier allocation where the minimum rate requirement is 50 kbps. Here, the first row represents the number of allocated subcarriers, the second row denotes the distance between the D2D users and the third row shows the transmission rate. It can be observed from Fig. 4.7 that the distance
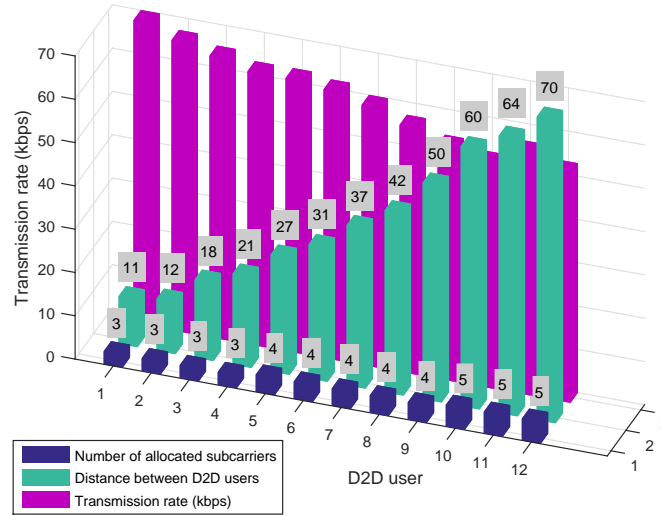
Figure 4.7: Effect of the distance between the D2D users on subcarrier allocation

between the D2D user plays an important role on the total number of subcarriers allocated to one D2D user. To satisfy the minimum rate requirements of the D2D users, closely located D2D users require less number of subcarriers compared to the distantly located D2D users. Fig. 4.7 depicts the scenario where D2D users located within 20 meters need three subcarriers to satisfy the minimum rate requirement whereas D2D users located within 70 to 80 meters range need five subcarriers to satisfy the minimum rate requirement.

In Fig. 4.8, we plotted the transmission rate of D2D users versus the interference threshold introduced to the PUs band for different schemes. As we see, the transmission rate for all the schemes increases as the interference threshold increases. Also the transmission rate achieved by the proposed scheme outperforms other three existing schemes. The reason is that the proposed scheme maintains both the power and interference constraints at all stages of the operation. The transmission rate of the uniform power loading scheme is significantly lower than the other schemes due to the violation of both of these constraints.

Fig. 4.9 shows the transmission rate achieved by the D2D users versus the number of subcarriers for the different schemes. It is obvious that as the number of subcarriers increases, the proposed scheme provides better transmission rate for D2D users than the other existing
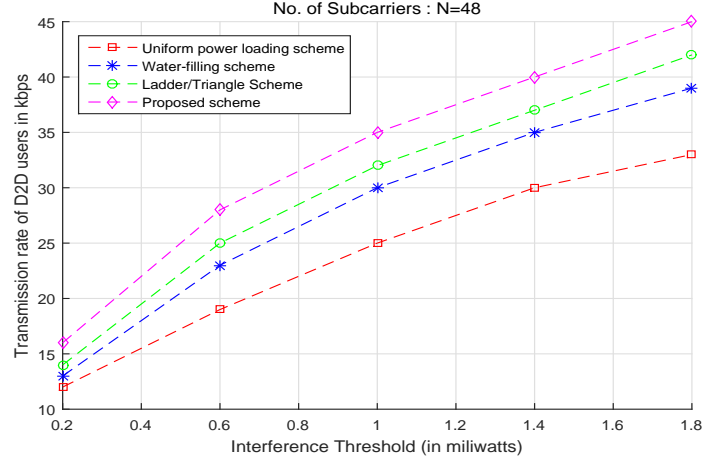
Figure 4.8: Transmission rate of D2D users versus interference threshold to the PUs for different schemes
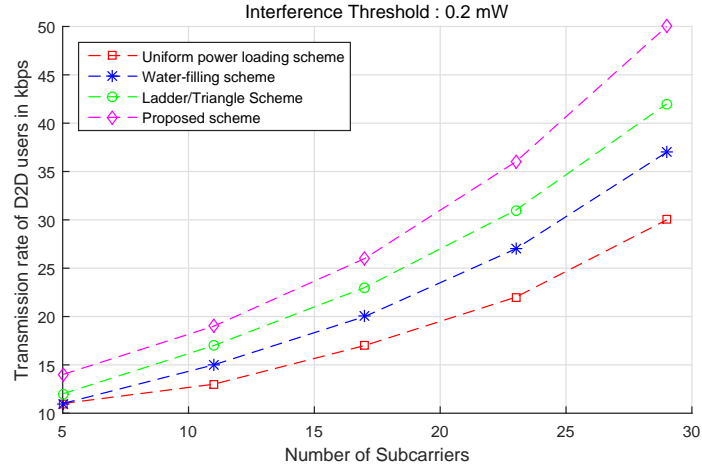
Figure 4.9: Transmission rate of D2D users versus number of subcarriers with fixed interference threshold for different schemes

methods. The reason is that our proposed ASA scheme is adaptive in nature due to the three different parts in the used metric.
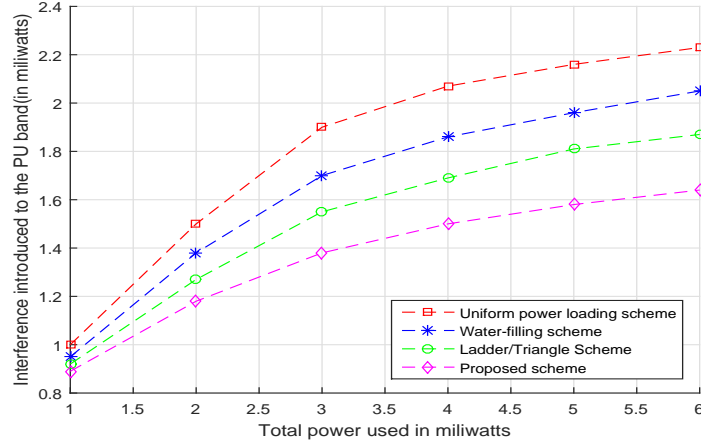
Figure 4.10: Total power budget versus interference introduced to the PU band for different schemes.

Fig. 4.10 presents the interference introduced to the PU band versus total power budget for different schemes. As the total power budget increases, the interference generated to the PU band by the uniform power loading and water-filling schemes are severe due to not taking the interference constraints into account. On the other hand, our proposed scheme is able to load power into multi-D2D users providing increased transmission rate while always keeping the interference introduced to the PU band below a specified threshold.

Fig. 4.11 illustrates the scenario of the total transmission rate versus the number of D2D users for the different schemes. It can be observed that as we increase the number of D2D users, the total transmission rate of our proposed scheme outperforms the other existing schemes while maintaining different constraints. When the number of D2D users remain small, the total transmission rate graph for all the schemes follow the linear pattern with a larger slope. However, for large number of D2D users, the total transmission rate graph for all the schemes become little flat with a smaller slope. This is obvious that as we increase the number of D2D users, the interference constraint become dominant in this region and
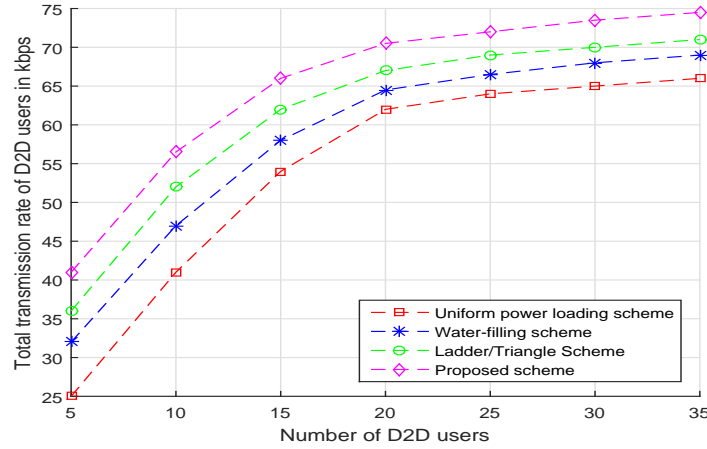
Figure 4.11: Total transmission rate versus number of D2D users for the different schemes

the total transmission rate does not increase as the number of D2D users increase. However, in both region (linear or little flat), our proposed scheme provides superior performance than the other schemes.
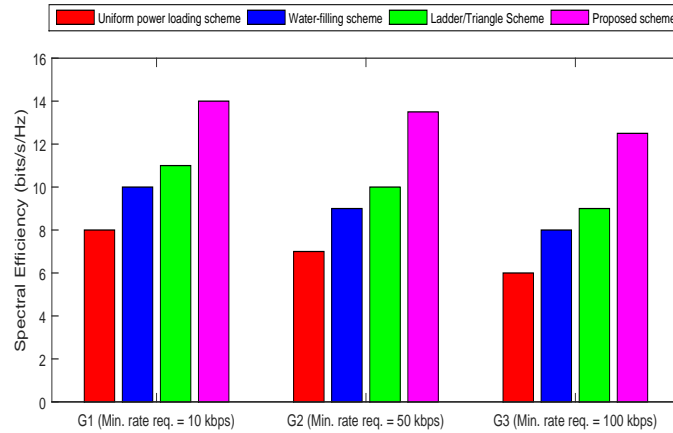
Figure 4.12: Performance of different schemes for different minimum rate requirements

Fig. 4.12 investigates the performance of different algorithms for different minimum rate requirements. Here, three different groups (e. g. G1, G2 and G3) are categorized for three different minimum rate requirement values (e. g. 10 kbps, 50 kbps and 100 kbps) to evaluate the algorithms performance in terms of spectral efficiency. Spectral efficiency is defined as the

total transmission rate divided by the bandwidth of the spectrum dedicated to the D2D user with unit bits/s/Hz. The comparison result presents that due to an increase in the minimum rate requirement, for the same constraints, the spectral efficiency decreases. This is because less number of D2D users are admitted due to high rate requirement threshold and stringent power and interference constraints. However, still the proposed scheme outperforms the other schemes. From Fig. 4.12, the improvement (in %) of the proposed scheme on spectral efficiency compared to the other schemes for different minimum rate requirements has been calculated which is well depicted in Table 4.4.

Table 4.4: Improvement (in %) of the proposed scheme on spectral efficiency compared to other schemes.

Groups	Other schemes	Improvement
G1 (Min. rate req. 10kbps)	Uniform power loading	43%
	Water-filling	29%
	Ladder/Triangle	22%
G2 (Min. rate req. 50kbps)	Uniform power loading	48%
	Water-filling	33%
	Ladder/Triangle	26%
G3 (Min. rate req. 100kbps)	Uniform power loading	52%
	Water-filling	36%
	Ladder/Triangle	28%

4.6 Chapter Summary

This Chapter provides the system model to jointly employ CR technology and D2D communication in cellular networks and construct the RA problem considering five constraints. Describes a two-stage approach where a new ASA scheme is designed first and then, a novel PA scheme is developed utilizing geometric water-filling (GWF) approach. Present simulation results that validate the proposed solutions than the existing schemes.

Chapter 5

Energy Efficient Power Allocation in Underlay and Overlay Cognitive Device-to-Device Communications

5.1 Introduction

There have been several research efforts found in the literature [119–121] on the energy efficient RA schemes for CRNs. The paper [119] presents a subchannel and power allocation protocol that maximizes the energy efficiency (EE) of transmissions from a cognitive base station operating in the TV white spaces. The proposed two-step solution to the EE maximization problem satisfies users minimum rate requirements and keeps the interference to the PUs in the neighboring areas below a specified threshold. The energy-efficient RA is studied in [120] in the orthogonal frequency division multiplexing (OFDM)-based CR networks under channel uncertainty including fairness issue. In [121], the authors proposed two energy efficient RA schemes that utilize the sensing information.

On the other hand, due to the benefit of D2D communication, International Mobile Telecommunications (IMT)- advanced standard systems, such as long term evolution (LTE) and WiMax, allow D2D communication sharing the same radio resources with the cellular network to increase the spectral efficiency [19]. D2D communication is, in fact integrated into LTE-Advanced networks in [100].

RRA for D2D communication underlaying cellular networks are currently extensively investigated by researchers in terms of energy efficiency [122–127]. The paper [122] demonstrates how the integration of D2D communication in cellular systems operating under dynamic time division duplex (TDD) can improve energy efficiency. In this paper, the authors perform joint optimization of mode selection, uplink/downlink transmission period, and power allocation to minimize the transmission energy consumption while satisfying the traffic requirement. In [123], the authors have investigated the energy-efficient power control for D2D communications with underlaying cellular networks, where both the total EE and individual EE have been considered. Another energy-efficient RA problem is studied in [124] for D2D communication with underlaying cellular networks, which aims to maximize the minimum weighted energy efficiency of D2D links while guaranteeing minimum data rates for cellular links. On the other hand, joint RA and power control scheme has been derived

in [125] to maximize the EE of D2D communications. In [126], the average EE and spectral efficiency of multihop D2D communications have been analyzed under orthogonal sharing mode. Joint channel and power allocation scheme for D2D communication has been studied in [127] in order to optimize the expected data during battery lifetime of user equipments (UEs), instead of the traditional EE.

From the literature survey, it is found that, most recent works focus on exploiting D2D communication in cellular networks under different constraints. Only a few efforts [19, 110–113] have been incorporated D2D communication with CR technology to jointly maximize the spectrum efficiency, not to mention the EE. Very few efforts [128, 129] have been observed in the literature addressing the EE. The paper [128] has developed energy-efficien RA algorithms for both underlay and overlay communications, in the presence of co-existing multiple-input single-output (MISO) primary link with a multiple-input multiple-output (MIMO) secondary link. Authors of this paper have solved the RA problem by maximizing the SUs EE subject to a minimum rate requirement of the PU and tackled it by fractional programming. In [129], the energy optimization problem for cognitive D2D communications has been investigated considering mutual preferences and satisfactions of users and proposed an EE stable matching algorithm based on game and matching theories.

5.2   System Model

Let us consider the downlink of a single cell cognitive D2D system where K cellular users (PUs) coexists with M D2D users (SUs) as shown in Fig. 5.1. It is assumed that K active PUs occupy a total of N orthogonal channels and there is no co-channel interference among the PUs. Usually, the number of PUs is much higher than the number of D2D users. Hence we assume $K >> M$ and a PU can share an orthogonal channel with only one D2D user. In the following, the index sets of active PUs, D2D users and orthogonal channels are denoted as $\mathcal{K} = \{1, ..., k, ..., K\}$, $\mathcal{M} = \{1, ..., m, ..., M\}$ and $\mathcal{N} = \{1, ..., n, ..., N\}$ respectively. In
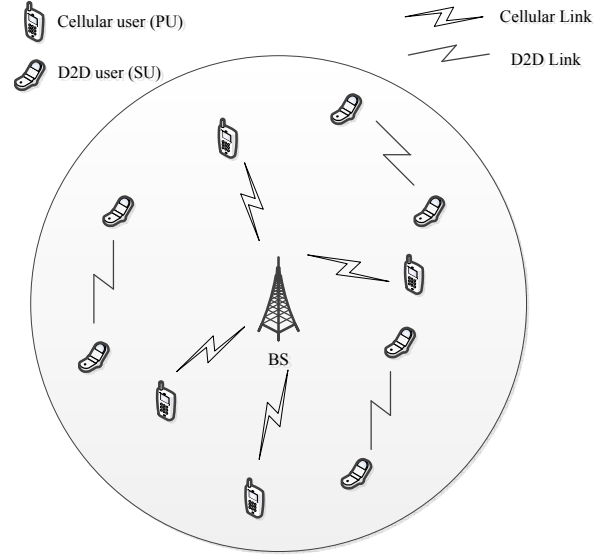
Figure 5.1: A D2D enabled cognitive radio system.

addition, it is assumed that both PUs and D2D pairs meet their minimum QoS requirements in terms of SINR, and the base station (BS) has the perfect CSI information of all the links.

Besides the distance based pathloss model, both the fast fading due to multi-path propagation and slow fading due to shadowing are also considered in this channel model. Thus, the channel gain between the kth PU transmitter and the mth D2D user receiver on the nth channel can be expressed as [129]

$$g_{k,m}^n = \eta \beta_{k,m}^n \zeta_{k,m}^n \mathcal{D}_{k,m}^{-\alpha}, \tag{5.1}$$

where, η is the pathloss constant determined by system parameters, $\beta_{k,m}^n$ is fast fading gain with an exponential distribution, $\zeta_{k,m}^n$ is the slow fading gain with a log-normal distribution, α is the pathloss exponent, and $\mathcal{D}_{k,m}$ is the transmission distance between the kth PU and the mth D2D user receiver. Similarly, we can denote the channel gain between the mth D2D user transmitter and the kth PU receiver on the nth channel as $g_{m,k}^n$. Also, the channel gain of the kth PU transmitter and receiver on the nth channel as g_{kk}^n and the mth D2D user transmitter and receiver on the nth channel as g_{mm}^n.

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In this work, two approaches are considered to manage the coexistence among the primary and secondary system: the underlay and the overlay approach. In the underlay approach, a secondary system may reuse the primary resource as long as the primary rate remains above the threshold T_1 set by the primary system. The underlay protocol popular in cognitive radio systems [130–132], has observed application in D2D systems that operate in the reuse mode recently [133]. In this underlay D2D mode, a pair of neighbouring devices can autonomously set up a D2D connection reusing resource presently used by a cellular user (PU), granted that the cellular link is still able to preserve its required communication rate.

On the other hand, the overlay approach regards a different situation. An underlying assumption in the underlay approach is that the transmission rate of the primary link (without the presence of the secondary link) is larger than the required communication rate T_1. Therefore, the secondary system may reuse the primary system resources as long as its interference does not affect the primary transmission rate to drop below T_1. However, if the primary system faces poor propagation conditions, or if it wanted to preserve energy transmitting at a lower power, it might occur that even without any interference from the secondary system, the transmission rate of the primary link might be already below T_1. A solution for this problem is that the primary system may get the assistance of a secondary (D2D) transmitter, that is probably located in a more suitable position with better channel condition. In these situations, the secondary (D2D) system becomes a relay for the primary message, and in exchange can reuse the primary resource to transmit its own message [46].

Therefore, the underlay and overlay approaches can be exploited in complementary fashion. If the primary system enjoys good condition and able to have much higher than the required communication rate, then the underlay approach should be utilized, because it is simpler, need no coordination between the primary and D2D systems. If instead, the transmission rate of the primary link is below the required communication rate, then the overlay approach can be applied to raise the primary system transmission rate. In many practical scenarios, the resulting rate increase is large enough to allow the primary system to guarantee

the required communication rate [128, 134–136].

In this paper, we consider the following power consumption model. It captures not only the transmission power of the D2D users but also the power consumption along the entire circuitry including mixer, analog-to-digital converter (ADC), digital-to-analog converter (DAC), filters, and digital signal processing (DSP) blocks. The circuit power consumption can be divided into the static background power consumption P_{back} and the dynamic power consumption εR that is dependent on the communication transmission rate R and the power consumption per unit rate ε. Therefore, the circuit power consumption can be expressed as,

$$p_{\text{cir}} = \varepsilon R + P_{\text{back}}. \tag{5.2}$$

Now, the total power consumption by the D2D users can be written as,

$$p_{\text{t}} = \sum_{m \in \mathcal{M}, n \in \mathcal{N}} \frac{1}{\theta} P_{m,n} + 2p_{\text{cir}} \tag{5.3}$$

where p_{t} is composed of the transmission power over all of the channels, and the circuit power of both the D2D transmitter and receiver, i.e., $2p_{\text{cir}}$. θ is the power amplifier efficiency, i.e., $0 < \theta < 1$.

5.2.1 Underlay Approach

In the underlay mode D2D users share the resources with the PUs. This is possible since D2D communication links are usually short-range so that interference to PUs is rather low. In addition, extensive researches [137] have shown that the inter-cell interference can be kept very low by power control and proper radio resource management. Thus in this work, we confine our focus to the intra-cell interference between the PU and the D2D users only. By fully utilizing the knowledge of the CSI, power allocation can be executed to attain efficient spectral usage and power saving in cellular networks.

We suppose that x_1 and x_2 be the transmitted signal from the PU and the D2D users

respectively. Then the received signals at the PU and D2D user receivers at a given time
instant can be written as,

$$y_1 = \sqrt{P_{k,n}} g_{kk}^n x_1 + \sqrt{P_{m,n}} g_{m,k}^n x_2 + \sigma_1 \tag{5.4}$$

$$y_2 = \sqrt{P_{m,n}} g_{mm}^n x_2 + \sqrt{P_{k,n}} g_{k,m}^n x_1 + \sigma_2 \tag{5.5}$$

respectively. Here, $P_{k,n}$ and $P_{m,n}$ indicate the transmission power of the kth PU and the mth
D2D user on the nth channel respectively. Furthermore, $\sigma_1 \sim \mathcal{CN}(0, \sigma_p^2)$ and $\sigma_2 \sim \mathcal{CN}(0, \sigma_d^2)$
model the additive white Gaussian noise (AWGN) for the PU and the D2D user receiver,
respectively.

The channel gain to noise ratio of the kth PU and the mth D2D user on the nth channel
can be expressed as,

$$\Gamma_{k,n} = \frac{|g_{kk}^n|^2}{P_{m,n}|g_{m,k}^n|^2 + \sigma_1} \tag{5.6}$$

$$\Gamma_{m,n} = \frac{|g_{mm}^n|^2}{P_{k,n}|g_{k,m}^n|^2 + \sigma_2} \tag{5.7}$$

respectively.

Now, the achievable rate in b/s/Hz (i.e., normalized with respect to the channel band-
width) of the kth PU and the mth D2D user on the nth channel can be written as

$$R_{k,n} = \log_2(1 + \Gamma_{k,n} P_{k,n}) \tag{5.8}$$

$$R_{m,n} = \log_2(1 + \Gamma_{m,n} P_{m,n}) \tag{5.9}$$

respectively.

5.2.2 Overlay Approach

In the overlay approach, the D2D transmitter assists the PU by relaying the primary message and, in exchange enjoys the privilege to use the primary spectrum. Any of the relaying techniques can be employed in the D2D system. Here, half-duplex amplify-and-forward (AF) relaying technique is considered. Unlike decode-and-forward (DF), the use of AF does not require any decoding operation at the D2D transmitter, which results in a lower complexity, lower-delay, and lower-feedback requirement, and a simpler design [138]. The considered digital implementation of AF has been explicitly proposed for the LTE-A standard [139]. Moreover, time division duplex mode is utilized to split the incoming signal from the forwarded signal. In the first phase, the PU employs maximum ratio transmission to transmit its signal x_1 , as in the underlay approach. During this phase, the signal x_1 is also received by the D2D transmitter, which, in the second phase precodes and then transmits this amplified signal together with its own message. The superposition of these two signals is labeled z_2 .

Now, the received signals at the PU receiver and at the D2D user transmitter in the first phase are expressed as,

$$y_1^{(1)} = \sqrt{P_{k,n}} g_{kk}^n x_1 + \sigma_1^{(1)} \tag{5.10}$$

$$y_{d_t} = \sqrt{P_{m,n}} g_{k,m_t}^n x_1 + \sigma_{d_t} \tag{5.11}$$

where, g_{k,m_t}^n is the channel gain the PU and the D2D user transmitter on the nth channels, $\sigma_1^{(1)} \sim \mathcal{CN}(0, \sigma_p^2)$ and $\sigma_{d_t} \sim \mathcal{CN}(0, \sigma_{d_t}^2)$ model the AWGN at the PU receiver and D2D user transmitter, respectively.

Similarly, the received signals at the PU and the D2D receivers in the second phase are expressed as,

$$y_1^{(2)} = \sqrt{P_{m,n}} g_{m,k}^n z_2 + \sigma_1^{(2)} \tag{5.12}$$

$$y_2^{(2)} = \sqrt{P_{m,n}} g_{mm}^n z_2 + \sigma_2^{(2)} \tag{5.13}$$

where, $\sigma_1^{(2)} \sim \mathcal{CN}(0, \sigma_p^2)$ and $\sigma_2^{(2)} \sim \mathcal{CN}(0, \sigma_d^2)$ model the AWGN at the PU and the D2D user receiver, respectively, and z_2 is given by $z_2 = \gamma y_{d_t} + x_2$, where $\gamma = \sqrt{\frac{P_{m,n}}{g_{k,m_t}^n P_{k,n} + \sigma_{d_t}}}$ is the amplifying factor at the AF relaying system.

Now, the signal received at the PU receiver in the two phases can be written as

$$
\begin{aligned}
y_1 = \sqrt{P_{k,n}} \left\{ g_{kk}^n + \sqrt{P_{m,n}} g_{m,k}^n \gamma g_{k,m_{d_t}}^n \right\} x_1 + \sqrt{P_{m,n}} g_{m,k}^n x_2 + \\
\sqrt{P_{m,n}} g_{m,k} \gamma \sigma_{d_t} + \sigma_1^{(1)} + \sigma_1^{(2)}
\end{aligned}
\tag{5.14}
$$

and the signal received at the D2D receiver can be written as,

$$
\begin{aligned}
y_2 = \sqrt{P_{m,n}} g_{mm} \sqrt{P_{k,n}} \gamma g_{k,m_t}^n x_1 + \sqrt{P_{m,n}} g_{mm}^n x_2 + \\
\sqrt{P_{m,n}} g_{mm} \gamma \sigma_{d_t} + \sigma_2^{(2)}.
\end{aligned}
\tag{5.15}
$$

The channel gain to noise ratio of the kth PU and the mth D2D user on the nth channel can be expressed as

$$
\Gamma_{k,n} = \frac{|g_{kk}^n|^2 + P_{m,n} |g_{m,k}^n|^2 \gamma |g_{k,m_{d_t}}^n|^2}{P_{m,n} |g_{m,k}^n|^2 + P_{m,n} |g_{m,k}^n|^2 \gamma \sigma_{d_t} + \sigma_1^{(1)} + \sigma_1^{(2)}}
\tag{5.16}
$$

$$
\Gamma_{m,n} = \frac{|g_{mm}^n|^2}{|g_{mm}^n|^2 P_{k,n} \gamma |g_{k,m_t}^n|^2 + |g_{mm}^n|^2 \gamma \sigma_{d_t} + \sigma_2^{(2)}}
\tag{5.17}
$$

respectively.

Now, the achievable rate in b/s/Hz (i.e., normalized with respect to the channel bandwidth) of the kth PU and the mth D2D user on the nth channel can be written as

$$
R_{k,n} = \frac{1}{2} \log_2(1 + \Gamma_{k,n} P_{k,n})
\tag{5.18}
$$

$$
R_{m,n} = \frac{1}{2} \log_2(1 + \Gamma_{m,n} P_{m,n})
\tag{5.19}
$$

respectively, where the factor "$\frac{1}{2}$" indicates that the transmission takes only half of the protocol time.

5.3   Power Allocation problem and solution

In this section, we will first formulate the power allocation problem, and then describe the corresponding power allocation algorithms.

5.3.1   Problem Formulation

For both the underlay and overlay approaches, the EE of the D2D users can be defined as follows:

$$EE_d = \frac{\sum\limits_{m \in \mathcal{M}, n \in \mathcal{N}} R_{m,n}}{p_{\mathrm{t}}} \tag{5.20}$$

Then, the EE optimization problem can be formulated as follows:

$$\max_{P_{m,n} \geq 0} EE_d(P_{m,n}) \tag{5.21}$$

subject to:

$$C1: \sum_{k \in \mathcal{K}, n \in \mathcal{N}} R_{k,n} \geq T_1$$

$$C2: \sum_{m \in \mathcal{M}, n \in \mathcal{N}} R_{m,n} \geq T_2$$

$$C3: P_{m,n} \leq P^d_{max} \quad \forall m \in \mathcal{M}, \forall n \in \mathcal{N}$$

where, constraint C1 and C2 ensure that the PU and D2D users' rates remain above the thresholds T_1 and T_2, and constraint C3 is the D2D users' power constraint, with P^d_{max} the D2D user's maximum feasible power.

5.3.2   Solution Approaches

The EE optimization problem in (5.21) is a non-linear fractional optimization problem where, the objective functions have the numerators as non-linear functions and the denominators in a sum power form. Therefore, the fractional objective function in (5.21), which is a nonconvex

function, turns the problem even more complicated and computationally intractable. Due to the fractional form of the EE optimization problem, the Karush-Kuhn-Tucker (KKT) conditions can not directly be utilized to solve it. Hence, existing algorithms seldom directly solve the EE maximization problem, including the widely-utilized Dinkelbach algorithm [140].

(a)

(b)
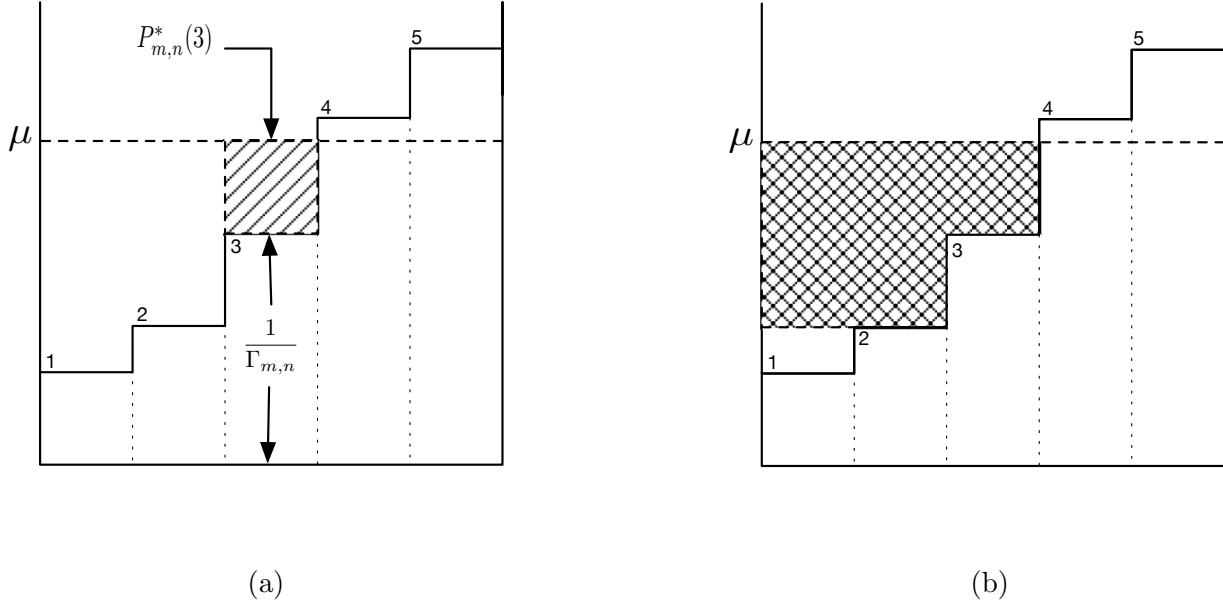
Figure 5.2: Illustration for the GWF algorithm (a) Illustration of water level step $j^* = 3$, allocated power for the third step $P_{m,n}^*(3)$, and step depth is $\frac{1}{\Gamma_{m,n}}$ and (b) Illustration of $P(j)$ (shadowed area, representing the total power above step j) when $j = 2$.

In this section, a proven power allocation algorithm based on GWF approach [141] has been utilized to solve the EE optimization problem. In order to illustrate GWF technique, a water tank with equal width and monotonically increasing N steps/stairs is considered that correspond to the N channels. Fig. 2 gives an illustration of the GWF approach. Let $\lambda_{m,n}$ denotes the "step depth"of the mth D2D user of the nth stair/channel which is the height of the nth step to the bottom of the tank, and is given as:

$$\lambda_{m,n} = \frac{1}{\Gamma_{m,n}}, \ \forall m \in M, \forall n \in N. \tag{5.22}$$

Since the sequence $\Gamma_{m,n}$ is sorted as monotonically decreasing, the step depth of the stairs

indexed as $\{1, ..., N\}$ is monotonically increasing. When water (power) P_T is poured into the tank, a water level μ is obtained. The optimal power allocation to each channel corresponds to the area above the stair up to the water level.

The main idea of the GWF algorithm [78] is summarized as follows. Let j^* denote the index of the highest (in terms of shadow) step under water, then it can be written as:

$$j^* = \max\left\{ j | P(j) > 0, \ 1 \leq j \leq N \right\} \tag{5.23}$$

where, $P(j)$ is the whole water volume above the jth step. Considering the geometrical relationship, $P(j)$ can be written as,

$$P(j) = \left\{ P_T - \sum_{n=1}^{j-1} \left(\frac{1}{\Gamma_{m,j}} - \frac{1}{\Gamma_{m,n}} \right) \right\}^+ , \forall m \in \mathcal{M}, \forall j \in \mathcal{N}. \tag{5.24}$$

Then, the allocated power for the mth D2D user to the j^* step is

$$P_{m,j^*} = \frac{1}{j^*} \ P(j^*), \tag{5.25}$$

and the complete solution is given by

$$P_{m,n} = \begin{cases} P_{m,j^*} + \left(\frac{1}{\Gamma_{m,j^*}} - \frac{1}{\Gamma_{m,n}} \right) & 1 \leq n \leq j^* \\ 0, & j^* < n \leq N. \end{cases} \tag{5.26}$$

The GWF algorithm is denoted by $\text{GWF}(\{\Gamma_{m,n}\}, P_T)$, i.e., the mapping from $\{\{\Gamma_{m,n}\}, P_T\}$ to $\{j^*, P(j^*)\}$.

On the other hand, the P-GWF algorithm [142] has been proposed to compute the sum power minimization problem with the transmission rate requirement constraint. The basic sum power problem can be stated as: given the target transmission rate $T > 0$, a group of

powers $\{P_{m,n}\}$ need to be found to satisfy,

$$\min \sum_{m \in \mathcal{M}, n \in \mathcal{N}} P_{m,n} \tag{5.27}$$

$$\text{subject to: } C1: \ 0 \leq P_{m,n}, \forall m, \forall n;$$

$$C2: \ \sum_{m \in \mathcal{M}, n \in \mathcal{N}} R_{m,n} \geq T.$$

In [142], algorithm P-GWF has been proven to provide the optimal solution to the problem (5.27). Algorithm P-GWF provides the mapping of $(\{\Gamma_{m,n}, T\})$ to the exact solution $\{P_{m,n}\}$ and j^*.

Here, we develop an algorithm denoted by EE-GWF to solve the optimization problem (4.8), based on the GWF approach and P-GWF method. In the first step, GWF algorithm has been used to find the highest water (power) level index that denotes the maximum number of the channels for power allocation. In the second step, P-GWF algorithm has been utilized in two rounds in order to find a group of power levels that has been satisfied by both the minimum rate requirement for the PU and D2D users i. e., T_1 and T_2.

Now, the final step is to find the EE-optimal power allocation for the target problem in (4.8) that satisfies the water-filling like architecture with the water tank model. Thus, a water tank with unit width and monotonically increasing steps is utilized to illustrate the geometric relationship of the variables as in Fig. 5.3. Let, again N denote the total number of the steps that correspond to the N channels in the tank. Assume a certain amount of water is poured into the tank, making water level μ between the Lth and the $(L+1)^{\text{th}}$ step. For the nth step ($n \leq L$), the power allocated is $P_{m,n} = \mu - \lambda_{m,n}$. An auxiliary variable ΔP, shown as the shadowed area in Fig. 5.3, denotes the entire volume of the water (power) above the Lth step. Since each step is assumed to have a unit width, the allocated power for the Lth step is,

$$P_L = \frac{\Delta P}{L}. \tag{5.28}$$
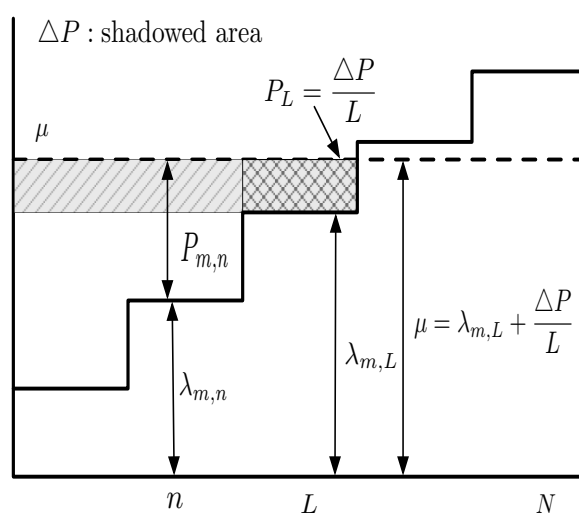
Figure 5.3: Illustration of geometric relation and auxiliary variable ΔP.

From the geometric relationship, ΔP lies between $[\Delta P_{\min}, \Delta P_{\max}]$, where $\Delta P_{\min} = 0$, $\Delta P_{\max} = L(\lambda_{m,L+1} - \lambda_{m,L})$. $\Delta P_{\min}$ occurs when the water level μ is at the Lth step, and $\Delta P_{\max}$ happens when the water level μ reaches the $(L+1)^{\text{th}}$ step.

Then, for a given L, let us introduce a function $F(\Delta P)$, where ΔP is the variable with the geometric meaning shown as in Fig. 5.3,

$$F(\Delta P) = (\Delta P + \lambda_{m,L}.L) \, log\left(\lambda_{m,L} + \frac{\Delta P}{L}\right) - \left(\lambda_{m,L} + \frac{\Delta P}{L}\right)$$
$$\sum_{j=1}^{L} log(\lambda_{m,j}) - P_T, \ \forall m \in \mathcal{M} \tag{5.29}$$

where $P_{m,n}$ is the allocated power for the mth D2D user on the nth channel,

$$P_{m,n} = (\lambda_{m,L} - \lambda_{m,n}) + \frac{\Delta P}{L}, \ \forall 1 \leq n \leq L, \forall m \in \mathcal{M}. \tag{5.30}$$

In [141], it is proven that $F(\Delta P)$ exhibits the desired monotonically increasing property

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in the range of $(\Delta P_{\min}, \Delta P_{\max})$. Hence, the EE-optimal power allocation is equivalent to,

$$\min |F(\Delta P)| \tag{5.31}$$

$$\text{subject to: } 0 \leq \Delta P \leq L(\lambda_{m,L+1} - \lambda_{m,L}).$$

The optimal solution to (5.31) is classified into three cases which are illustrated in Fig. 5.4.
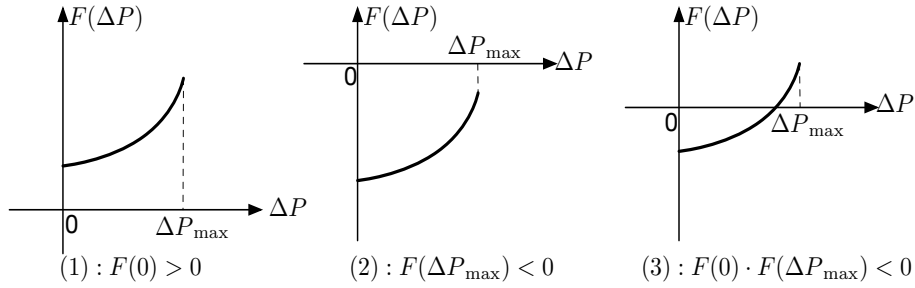
Figure 5.4: Illustration for solving conditions (5.31).

When the optimal solution to (5.31) is not at the boundaries i. e., $F(0) < 0$ and $F(\Delta P_{\max}) > 0$, then ΔP can be calculated through the following iteration,

$$\Delta P_{i+1} = \Delta P_i - \frac{F(\Delta P_i)}{F'(\Delta P_i)}, \ \forall i \in \mathcal{I}^+, \tag{5.32}$$

where, $\mathcal{I}^+$ is the set of non-negative integers. The subscript of ΔP_i is the iteration index. Details of the iteration steps can be found in [141].

Next, the required steps for performing the power allocation in EE-GWF algorithm are described in Fig. 5.5 and the detailed algorithm is well depicted in the Algorithm description.

Algorithm EE-GWF:
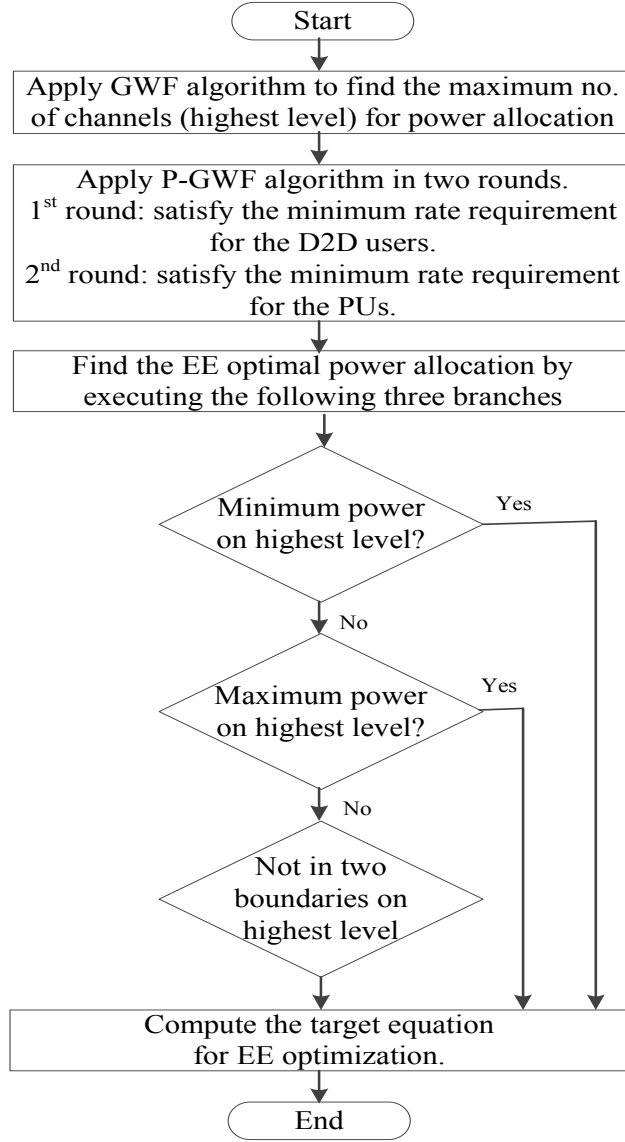
Figure 5.5: Flow chart of EE-GWF algorithm.

1) Pre-processing:

$$
\begin{aligned}
&\{j^*, P(j^*)\} = \text{GWF}(\{\Gamma_{m,n}\}, P_T), \\
&j^* \to W \text{ and } \frac{P(W)}{W} + \frac{1}{\Gamma_W} \to \frac{1}{\Gamma_{W+1}}, \\
&\text{1st round}: \{j^*, \{P_{m,n}\}\} = \text{P-GWF}(\{\Gamma_{m,n}\}, T_2), \\
&\text{2nd round}: \{j^*, \{P_{k,n}\}\} = \text{P-GWF}(\{\Gamma_{k,n}\}, T_1), \\
&\min\{j | P_{m,j^*} + \frac{1}{\Gamma_{m,j^*}} < \frac{1}{\Gamma_{m,j}}, 1 \le j \le N\} - 1 \to \underline{j}. \\
&P_{m,j^*} + \frac{1}{\Gamma_{m,j^*}} \to \lambda_{m,j}, \text{ for } 1 \le j \le \underline{j}; \\
&\text{while } \frac{1}{\Gamma_{m,j}} \to \lambda_{m,j}, \text{ for } \underline{j} < j \le N.
\end{aligned}
\tag{5.33}
$$

where the symbol "$\to$" denotes the assignment operation and a new index $\underline{j}$ is utilized after applying P-GWF to guarantee both the minimum rate requirements constraints.

1) Input: Let $i = \underline{j}$ and assigning a

   $N + 1 - \underline{j} \times N$ matrix $\mathbf{P}$ a null matrix.

2) Loop for i from 1 to W: for each loop, one of the following three branches being executed to update the ith row of the matrix $\mathbf{P}$:

   From now on we are omitting m in the subscript of P in order to reduce notation complexity.

   2.1) If $F(\triangle P_{\min}) = F(0) > 0$,

$$
P_{i,x} = \frac{1}{\Gamma_i} - \frac{1}{\Gamma_x}, \quad x = 1, \cdots, i,
\tag{5.34}
$$

   and then go to Step 3); else

   2.2) if $F(\triangle P_{\max}) = F\left(i\left(\frac{1}{\Gamma_{i+1}} - \frac{1}{\Gamma_i}\right)\right) < 0$,

$$
P_{i,x} = \frac{1}{\Gamma_{i+1}} - \frac{1}{\Gamma_x}, \quad x = 1, \cdots, i,
\tag{5.35}
$$

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and then go to item 3); else

2.3) if

$$F(0) \cdot F\left(i\left(\frac{1}{\Gamma_{i+1}} - \frac{1}{\Gamma_i}\right)\right) < 0, \tag{5.36}$$

then solving $\triangle P$ by using equation (5.32) and

$$P_{i,x} = \frac{\triangle P}{i} + \left(\frac{1}{\Gamma_i} - \frac{1}{\Gamma_x}\right), \quad j = 1, \cdots, i. \tag{5.37}$$

3) If $i = W$, compute

$$i^* = \arg\max_{\{i|1 \le i \le W\}} \left\{\frac{\frac{1}{2}\sum_{n=1}^{N}\log_2(1 + \Gamma_n P_{i,n})}{2p_{\text{cir}} + \sum_{n=1}^{N}\frac{1}{\theta}P_{i,n}}\right\}, \tag{5.38}$$

and then output $\overline{P}_j = P_{i^*,j}, \forall j$; else let $i + 1 \to i$ and go to Step 2).

5.4 Performance Evaluation

5.4.1 Simulation Setup

In order to evaluate the performance of the developed power allocation algorithm, a multiuser single cell system is simulated with radius 500 m. The BS is located in the center of the cell. All cellular users (PUs) and D2D users (SUs) are randomly distributed with uniform distribution within the cell. The distances between D2D pairs vary depending on their relative position in the cell. The cellular link transmits with power at 20 dBm, and requires a minimum rate T_1 set as a percentage T of the PU transmission rate without the presence of the D2D system. All other simulation parameters are considered according to Table I. The simulation results are evaluated over different realization of the PUs and D2D user locations, rate constraints and channel gains. Average EE optimization for both the underlay and overlay approaches are obtained from several independent simulation runs.

Let us first analyze the performance of the developed algorithm for the underlay approach.

Table 5.1: Simulation Parameters

Parameters	Values
Total no. of D2D users	5-35
Total no. of PUs	10-50
Max D2D T_x power	20dBm
Max PU T_x power	10dBm,20dBm
Max D2D transmission distance	10-90 m
Power consumption per unit rate ε	1mW/kbps
Static background power consumption P_{back}	5dBm
Power amplifier efficiency θ	30%
Pathloss exponent α	4
Pathloss constant η	10^{-2}
Shadowing $\zeta_{k,m}^n$ (standard deviation of a log-normal distribution)	8dB
Multi-path fading $\beta_{k,m}^n$ (the mean of an exponential distribution)	1
Noise power σ	-144dBm
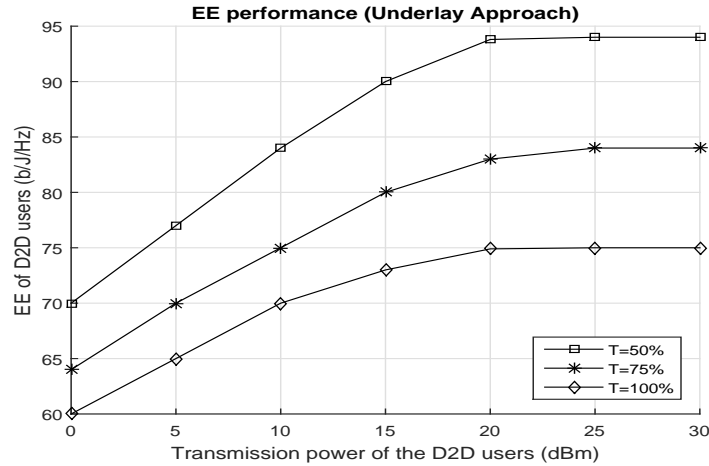
Figure 5.6: Energy Efficiency versus transmission power of the D2D users with underlay approach

In Fig. 5.6, the EE of the developed scheme versus the transmission power of the D2D users is illustrated under different minimum rate requirements (e. g. $T = 50\%, 75\%$ and 100%). As the transmission power of the D2D users increases the EE of the developed scheme also increases almost linearly first and then it becomes saturated. Saturation happens because

it exceeds the maximum transmission power limit of the D2D users. Also, as the minimum rate requirement increases, the EE performance decreases. The reason behind that is less number of D2D users are admitted due to high minimum rate requirement.
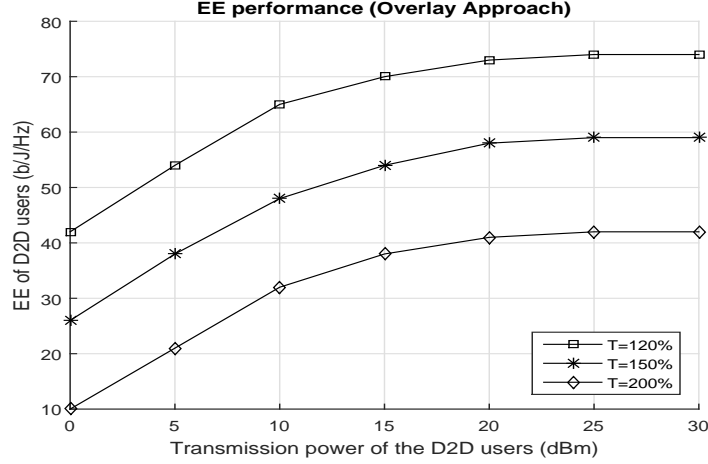
Figure 5.7: Energy Efficiency versus transmission power of the D2D users under overlay approach

Next, let us focus on the overlay approach where the PUs need the help of the D2D transmitter to meet its own minimum rate requirement. Similar simulation parameters have been considered for analysing the overlay performance as in the underlay approach. All the users' positions are randomly generated as earlier. However, the D2D transmitter has been placed closer to the PU receiver than the PU transmitter. Thus, the distance between the D2D transmitter and the PU receiver is kept between 15% and 75% of the distance between the PU transmitter and the PU receiver. All other parameters remain the same except that the PU transmission power is kept at 10 dBm. In Fig. 5.7, the EE of the developed scheme versus the transmission power of the D2D users is illustrated under different minimum rate requirements (e. g. $T = 120\%, 150\%$ and 200%). Similar behaviour holds for the Fig. 5.7 as in underlay case.

Fig. 5.8 depicts the affects of the distance between the D2D pairs on the EE performance of the developed solution. It can be observed that the EE performance decreases in both
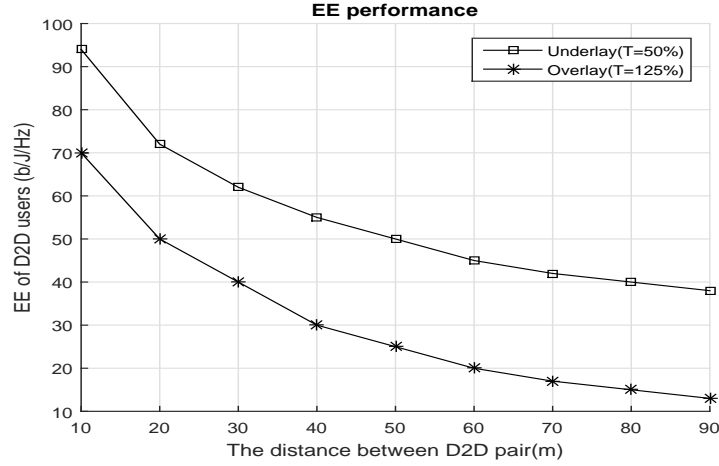
Figure 5.8: Energy Efficiency versus the distance between the D2D pair

the underlay and overlay schemes with the increase of the distance between the D2D pairs. This is because the total fading (path-loss, shadowing and small-scale fading) increases with the distance between the D2D pairs. The effect of the distance on the energy efficiency in overlay case is more than in the underlay case due to the requirement regarding the distance between the D2D transmitter and the PU receiver.
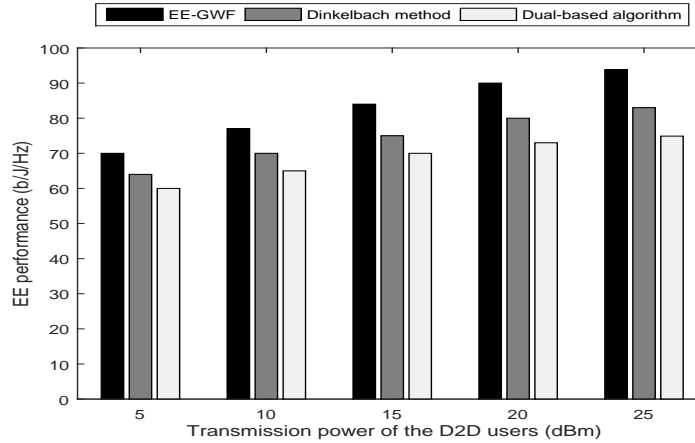
Figure 5.9: EE performance versus the transmission power of the D2D users

Next, in order to evaluate the performance of the developed solution, the EE-GWF algorithm is compared with the widely-adopted Dinkelbach method [125] and the dual-

based method [124] from the existing literature. For EE-GWF algorithm, only the underlay approach is considered since it is well utilized in the literature. Fig. 5.9 presents the EE performance versus the transmission power of the D2D users under different algorithms. It is observed from Fig. 5.9 that as the transmission power of the D2D users increases the EE performance increases for all three algorithms. However, the EE-GWF algorithms outperforms the other two algorithms.
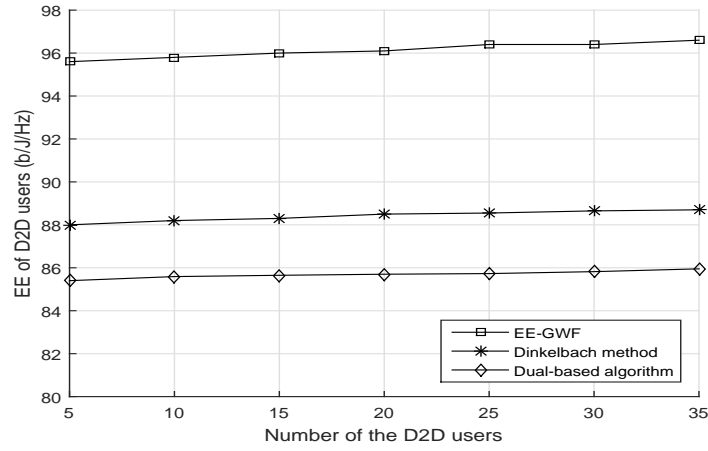
Figure 5.10: EE performance versus the number of the D2D users
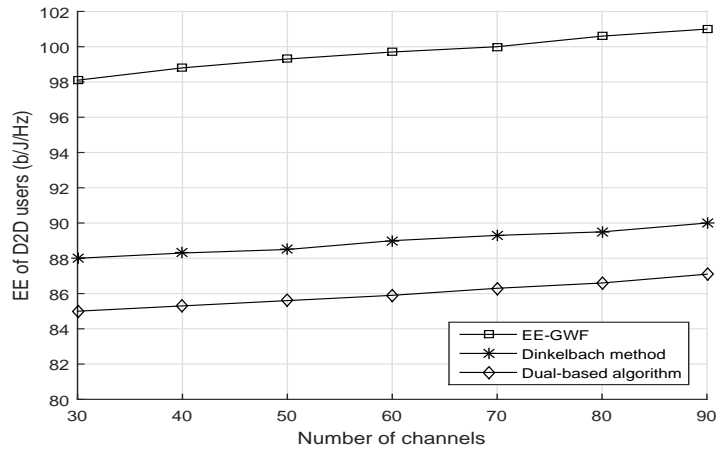
Figure 5.11: EE performance of the D2D users versus the number of the channels

Fig. 5.10 and Fig. 5.11 describe the two scenarios of the EE performance of the D2D users

versus the number of the D2D users and the number of the channels for different algorithms, respectively. In both figures, it is observed that as the number of D2D users or the number of channels increases, the EE performance of the D2D users increases. In Fig. 5.10, the increase in the EE performance of the D2D users is very little as compared to the EE performance in Fig. 5.11. This is because as the number of D2D users increases in Fig. 5.10, they are all utilizing the same fixed channels. On the other hand, in Fig. 5.11, the increase in the EE performance is more because more resources (channels) are available for the fixed number of the D2D users. In Fig. 5.10 and Fig. 5.11, it is also observed that the developed algorithm EE-GWF outperforms the other two schemes. The reason is that in the EE-GWF algorithm only the channels with high channel gains are considered for the power allocation.
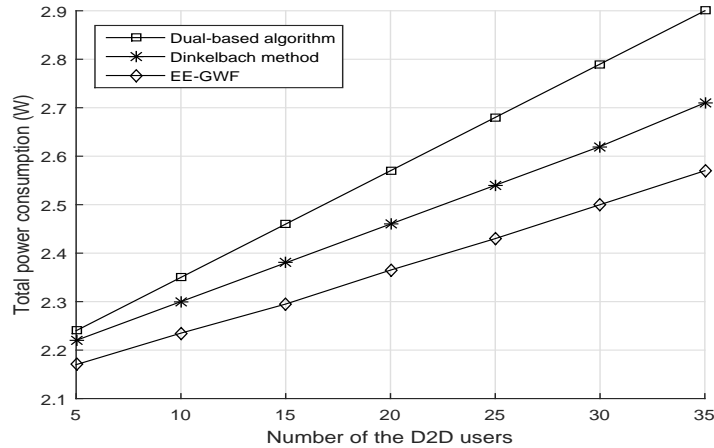
Figure 5.12: Total power consumption versus the number of the D2D users

Fig. 5.12 shows the total power comsumption by differents algorithms versus the number of D2D users for certain EE target. It is observed from Fig. 5.12 that the total power comsumption increases with the increase of the number of the D2D users and the EE-GWF algorithm consumes least amount of power than the other two algorithms. This is because the algorithm EE-GWF allocate more power to the wireless channels that have less fading. Thus, the EE-GWF allows better utilization of the available resources and saves power.

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5.5 Chapter Summary

This chapter investigates the energy-efficient power allocation problem of co-existing D2D and cellular users considering both underlay and overlay CR approaches. In both the (underlay and overlay) spectrum sharing schemes, the optimization problem is formulated as the EE maximization of the D2D users subject to the minimum rate requirement for both the D2D users and the cellular users. A proven power allocation algorithm based on the GWF approach is utilized to solve this EE optimization problem. Contrast to the widely used Dinkelbach method for EE maximization, this algorithm can directly compute the optimal solution by applying the geometry-based approach, with exactness and low-degree polynomial complexity. Simulation results reveal the benefits of the proposed algorithm.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Spectrum crunch escalates as wireless communication solutions, both human and machine centric, being deployed overwhelmingly and require more and more bandwidth. In the realm of such severe spectrum scarcity a sustainable solution for the spectrum crunch is essential. The CRN solution, that enables intelligent spectrum sharing and dynamic spectrum access could provide a serious long term solution. This is further facilitated by the dominance of software control in wireless systems, both at the transceiver level and the network level.

This thesis discusses certain key issues upon which a practical CRN may be built. The texonomy for the RA in CRNs is well researched in this thesis. Finally, the co-existance of the D2D communication in CRNs is investigated in terms of spectral efficiency and energy efficiency.

In detail, Chapter 1 presents an overview of cognitive radio networks and defines overlay, underlay and interweave type CRNs. The basic elements for the operation of CR systems and the main functions of those elements to support intelligent and efficient utilization of frequency spectrum are also envisioned here. This chapter also discusses about the D2D communication as a promising paradigm for the next generarion wireless networks.

Chapter 2 provides a taxonomy for the centralized and distributed RA process in CRNs for both infrastructure based or ad-hoc type CRNs. The resource allocation is a multivariate optimization problem that is often solved considering the throughput as the objective function and factors like transmission power, maximum transmission delay, allowable interference, QoS and fairness as the constrains. This optimization problem can be solved using classical optimization algorithms or using heuristic approaches.

In chapter 3, more OFDM, that has been widely accepted as the de-facto standard for 5G networks is used as the foundation[1]. Although different optimization strategies are possible, we focus on a modified GWF algorithm applied in general OFDM based cognitive radio

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[1]Although Non Orthogonal Medium Access (NOMA) type algorithms are discussed for 5G networks, their performances are not yet proven and they require a significantly differential power transmission which may not be practical.

systems considering per subchannel power constraint and individual peak power constraint aiming to maximize the throughput.

For this purpose, an efficient power and subcarrier allocation algorithm, named as IGPP is discussed. This algorithm is optimized in such a way to consider both individual subcarrier peak power constraint and per subchannel (group of subcarriers) power constraint. Simulation results are provided to illustrate the effectiveness of the algorithm. The proposed algorithm allows better utilization of the available power resources, thus maximizes the throughput than some other existing algorithms. The algorithm allocates more power to wireless channels that have less fading, hence saving power resources. Also a weight factor is considered for each channel to further fine tune the optimization.

Then in chapter 4, it is studied how efficiently D2D communications can be employed with a CR approach. Here, again an OFDM based cognitive cellular network with D2D communication has been modeled and analyzed using Lagrange formulation. The adaptive subcarrier allocation is optimized in terms of power, interference and transmission rate. The proposed algorithm based on GWF is tested to maximize the total downlink transmission rate of the D2D system under both power and interference constraints along with minimum rate requirements. Our developed scheme outperforms the existing schemes as revealed in the simulation results.

Chapter 5 investigates the EE power allocation problem of co-existing D2D and cellular users considering both underlay and overlay CR approaches. The underlay and overlay approaches are utilized in complementary fashion to support more practical scenarios. In both the (underlay and overlay) spectrum sharing schemes, the optimization problem is formulated as the maximization of the D2D users EE subject to the minimum rate requirement for both the D2D users and the cellular users. This leads to a nonconvex fractional optimization problem which is more complicated and computationally intractable. Alternatively, we utilize the proven GWF power allocation algorithm to solve this optimization problem. Contrast to the widely used Dinkelbach method for EE maximization, this algorithm can directly

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compute the optimal solution by applying the geometry-based approach, with exactness and low-degree polynomial complexity.

In a nutshell, we brought the awareness on the key issues in designing a reliable high performance cognitive D2D communication networks. The need for optimal RA is discussed and few algorithms proposed by the authors are used to perform an optimal RA for CRNs that co-exist with D2D communication.

6.2 Future Research Directions

In this section, the challenges in RA methods are discussed and the future research directions and opportunities are outlined.

6.2.1 Spectrum Sensing Issues

The existing RA schemes are developed under the assumption of having perfect spectrum sensing. However, this assumption may not be true and there may be errors in spectrum sensing which may direct to inefficient RA and interference with PUs. Therefore, discovery process of spectrum need to be carried out more carefully because it is influenced by three main issues:

- The hidden transmitter

- The exposed transmitter and

- The hidden receiver.

The hidden transmitter issue has been resolved by carrying out sensing operation at both transmitter and receiver ends, but there are still no satisfactory solutions for the latter issues. A CR user should be capable of discovering the existence of a neighboring primary receiver to resolve these issues. Hence, feasible solutions for this purpose are yet to be investigated.

Furthermore, spectrum sensing performance is limited by hardware and physical constraints. For instance, SUs with a single transceiver cannot transmit and sense simultaneously. Moreover, users usually only observe a partial state of the network to limit sensing overhead. There is a fundamental trade-off between the undesired overhead and spectrum holes detection effectiveness: the more bands are sensed, the higher the number and quality of the available resource. Thus this problem needs to be further investigated to improve spectrum sensing effectiveness. Lastly, sensing errors due to false detection and miss detection in PU signal sensing are ignored in many cases in the literature. Accurate models that take both false alarm and mis-detection probabilities into account, need to be devised. Therefore, the simplified ON/OFF model for PU traffic may not be a proper choice for practical environment where PUs may be cellular or wireless sensors. To improve the probability of detection with less sensing errors, cooperative techniques have been proposed [143]. However, many aspects of cooperative sensing need to be still investigated for better solutions [144]. Future RA schemes have to incorporate more complex considerations such as the impact of correlation among sensing channels, imperfectness of reporting channels etc. to develop more efficient cooperative sensing schemes [145]. Furthermore, trade-off between sensing action and throughput as well as other applications such as multimedia application over CRNs needs to be further investigated.

6.2.2 Channel Models

The majority of the proposed RA algorithms have adopted a Rayleigh fading channel model. Few works considered Nakagami-m channel model [146]. However, it is suggested to test the existing algorithms and propose new algorithms for different channel models. Particularly, the environment where the CR entities communicate whether urban, sub-urban, rural, indoor, or outdoor will affect the wireless channel characteristics. For example, the deployment of a secondary network in a rural area with low building density increases the line-of-sight probability, and thus Rician fading channels would be more appropriate. Alter-

ing the adopted channel model will definitely affect the analytical performance results and also could have an effect on the algorithms optimality. Furthermore, more efforts considering non-i.i.d channels is encouraged [147].

6.2.3 Cross-layer Design Approaches and Security Issues

In CRNs, superior interaction is needed between different layers of protocol stacks in order to attain desired goals and performance in terms of radio resource management, QoS provisioning, security and other network objectives. The idea behind the Cross-layer design [148] approach refers to devise the protocol stack by exploiting the information exchange and reliance between different protocol layers to acquire superior performance. But at the same time, it will also be susceptible to cross-layer attacks which may happen due to malevolent operations executed at one layer that could cause security violations at another layer [88]. CRNs inherently require greater interaction between different layers of the protocol stack. Therefore, cross-layer attacks and security related issues [149] including jamming attack and mitigation, selfish behavior in collaborative sensing and misbehavior in detection, physical layer and MAC layer in security, and the modeling and detection of insider attacks should be given special attention. A cross-layer security mechanism that incorporates recent advances on security threats/attacks and countermeasures, need to be investigated in RA design in order to permit a reliable and secure environment for CRNs [150]. Finally, the application of artificial intelligence (AI) techniques can be included to tackle security challenges for dynamic spectrum access [151].

6.2.4 Spectrum Mobility Issues

Spectrum mobility is also an essential issue in RA design aspect. Studies in the literature incorporate several design issues such as PU detection, handoff decision, target channel selection and spectrum handoff strategy [152]. Spectrum sensing speed and precision that greatly influence PU detection event, can be increased by cooperative sensing [153]. Handoff decision

is another important issue which can cause harmful interference to PU. This can be greatly improved by using proper handoff algorithm e. g. fuzzy logic based algorithm [154]. Appropriate target channel selection approaches in the literature include having a backup channel, target channel availability prediction under partial sensing scheme and selection utilizing historical data. PU traffic modeling taking PU mobility [155] into account needs careful attention in order to intelligently select the target channel by SUs. Several prediction and estimation schemes [156], like hidden Markov models [157], neural networks [158], Bayesian inference [159] and, autoregressive model [160] can be adopted for better realization of PU activity. Proper spectrum handoff strategies need to be chosen that are adaptive in nature according to PU traffic. In order to minimize delay in handoff event, simultaneous data transmission in multi-channel CRNs need to be performed. Effective contention resolution for multiple SUs during handoff need to be carried out for successful handoff. Cross-layer approach for link maintenance is necessary to effectively address mobility issues in physical, MAC and network layers. Finally an integrated handoff management process [161] is necessary to improve network performance.

6.2.5 Multi-hop Scenario

Dynamic spectrum access in multi-hop domain incorporates several challenges in RA schemes. Several studies [162], [163] in the literature tried to bring up research issues regarding RA design for multi-hop CRNs which can be summarized as:

1. Control channel establishment and management scheme without a predefined dedicated control channel,

2. Transceiver synchronization,

3. CTS timeout and problems in decoding CTS,

4. Multi-channel hidden terminal problem,

5. Hidden incumbent node problem,

6. Number of transceivers,

7. Coordination of spectrum sensing and accessing decision making,

8. Radio frequency heterogeneity,

9. Group communication, and

10. MAC layer authentication.

Some other attributes like the effect of channel state information in spectrum access, QoS guarantee, concern in fairness aspect, PU protection also need careful attention and further investigation in multi-hop environment.

6.2.6   QoS Management in CR Environment

Spectrum utilization and network capacity of CRNs can be increased by dynamic spectrum supervision. However, this imposes several challenges in QoS management [164]. Users can exploit available spectrum successfully captured by a CR but accurate information needs to be forwarded to the application to amend traffic features and user requirements. Once the available frequency bands are characterized, the most suitable spectrum bands can be selected by taking into account the spectrum characteristics and QoS criteria. However, spectrum characteristics can alter due to the dynamic nature of PU traffic and network parameters. Thus, appropriate spectrum decisions and necessary interactions among application streams, need to be performed to meet the QoS provisioning. Several QoS supportive RA schemes are reported in the literature. Most of the approaches assumed that PU traffic characteristics are known by SUs. However, this may not be true in general. Hence, PU traffic parameter estimation needs to be done often [165]. Such accurate estimation is necessary to guarantee QoS criteria in terms of disruption caused to the PUs. Overall, further

investigations are needed to design QoS supportive RA schemes for CRN based on different criteria.

6.2.7 Cognitive Heterogeneous Networks (HetNets)

Cognitive heterogeneous networks (HetNets) are an attractive solutions for expanding network capacity to multiple spectrum access technologies, network structures and communication protocols. Some applications such as tactical applications in military communications [166], medical applications in CR-based wireless body area networks [167], are few interesting recent applications of cognitive HetNets. A thorough study of RA schemes with the capability of cognitive HetNets is still an open area of research. However, only a few works address the issues in a coexistent heterogeneous CRNs scenario [168]. Since the system characteristics of these cognitive HetNets, are different in several categories such as spectrum sensing aspects, PU detection ability, hardware capacity, fairness issue, all these categories need to be explored while designing MAC structure. A scenario of coexistent heterogeneous CRNs with collision-based PUs and fairness issue are discussed in [169]. Further research towards opportunistic 3G/4G/5G spectrum sharing involve precise evaluation of the scenario conditions, in terms of terminal confinement, link maintenance, and user preferences, and will also need to consider face side aspects such as security supervision and privacy preservation. The rising requirement of wireless data traffic and the scarceness of accessible radio spectrum, will extend 3GPP's LTE (Release 8) and LTE-Advanced (Release 10) to unlicensed bands (5 GHz). Thus dynamic spectrum management for LTE [170] and LTE-Advanced [171], [172] mobile communication network as a CR-ready technology, become challenging and provide an active area for research.

Appendix 1

Acronyms

AF	Amplify-and-Forward
AWGN	Additive White Gaussian Noise
CSI	Channel State Information
CCI	Co-Channel Interference (CCI)
CXI	Cross-Channel Interference (XCI)
CR	Cognitive Radio
CRN	Cognitive Radio Network
CRP	CR Pair
CWF	Conventional Water-Filling
DFT	Discrete Fourier Transform
DSL	Digital Subscriber Lines
DVB	Digital Video Broadcasting
D2D	Device-to-Device
FFT	Fast Fourier Transform
GWF	Geometric Water-Filling
GWFPP	Geometric Water-Filling with Individual Peak Power Constraints
ISI	Inter-Symbol Interference
IPWF	Iterative Partitioned Water-Filling
IGPP	Iterative Partitioned Weighted Geometric Water-Filling with Individual Peak Power Constrai
LTE	Long Term Evaluation
LWF	Linear Water-Filling
MAC	Medium Access Control
MIMO	Multiple Input, Multiple Outout
OFDM	Orthogonal Frequency Division Multiplexing
PDF	Probability Density Function
PHY	Physical Layer
PU	Primary User
PUP	PU Pair
QoS	Quality of Service
RF	Radio Frequency
RRA	Radio Resource Allocation
SDR	Software-Defined Radio
SU	Secondary User
SNR	Signal-to-Noise Ratio
WRAN	Wireless Regional Area Network

Appendix 2

Derivation of $P^*_{m,n}$

In order to find the solution of the optimization problem depicted in (4.9), Lagrange multipliers $(\alpha, \beta, \gamma, \delta, \psi)$ are used corresponding to the five constraints. The Lagrange can be formed as

$$
\begin{aligned}
L(\mathbf{X},\mathbf{T},\alpha,\beta,\gamma,\delta,\psi) = \Delta B \sum_{m=1}^{M}\sum_{n=1}^{N} x_{m,n} \log\left(1 + \frac{t_{m,n}}{x_{m,n}}\Gamma_{m,n}\right) - \sum_{m=1}^{M}\sum_{n\epsilon\mathcal{N}_m} \alpha_n \left(\sum_{m=1}^{M}\sum_{n=1}^{N} t_{m,n} - P_T\right) \\
- \sum_{m=1}^{M}\beta_m\left(\sum_{n=1}^{N} t_{m,n} - P_{m,max}\right) - \sum_{m=1}^{M}\sum_{n\epsilon\mathcal{N}_m}\gamma_n\left(t_{m,n} - \bar{P}_{m,n}\right) - \sum_{k=1}^{K}\delta_k\left(\sum_{m=1}^{M}\sum_{n=1}^{N} t_{m,n}I_{m,n}^{(k)} - I_{th}\right) \\
- \sum_{m=1}^{M}\psi_m\left(\Re_{m,min} - \sum_{n=1}^{N} x_{m,n}\Re_{m,n}\right)
\end{aligned}
$$

$$(2.1)$$

The Lagrangian dual problem can be rewritten as follows:

$$D(\alpha, \beta, \gamma, \delta, \psi) = \max_{\mathbf{X}, \mathbf{T}} \sum_{m=1}^{M} \sum_{n=1}^{N} \left\{ (1 + \psi_m) \, x_{m,n} \log \left(1 + \frac{t_{m,n}}{x_{m,n}} \Gamma_{m,n} \right) - \left(\alpha_n + \beta_m + \gamma_n + \sum_{k=1}^{K} \delta_k \right. \right.$$

$$\left. \left. I_{m,n}^{(k)} \right) t_{m,n} \right\} + \sum_{m=1}^{M} \sum_{n \epsilon \mathcal{N}_m} \alpha_n P_T + \sum_{m=1}^{M} \beta_m P_{m,max} + \sum_{m=1}^{M} \sum_{n \epsilon \mathcal{N}_m} \gamma_n \bar{P}_{m,n} + \sum_{k=1}^{K} \delta_k I_{th} - \sum_{m=1}^{M} \psi_m \Re_{m,min}$$

$$= \max_{\mathbf{X}} \sum_{m=1}^{M} \sum_{n=1}^{N} \max_{\mathbf{P}} \left[x_{m,n} \left\{ (1 + \psi_m) \log \left(1 + P_{m,n} \Gamma_{m,n} \right) - \left(\alpha_n + \beta_m + \gamma_n + \sum_{k=1}^{K} \delta_m I_{m,n}^{(k)} \right) P_{m,n} \right\} \right]$$

$$+ \sum_{m=1}^{M} \sum_{n \epsilon \mathcal{N}_m} \alpha_n P_T + \sum_{m=1}^{M} \beta_m P_{m,max} + \sum_{m=1}^{M} \sum_{n \epsilon \mathcal{N}_m} \gamma_n \bar{P}_{m,n} + \sum_{k=1}^{K} \delta_k I_{th} - \sum_{m=1}^{M} \psi_m \Re_{m,min}$$

$$= \max_{\mathbf{X}} \sum_{m=1}^{M} \sum_{n=1}^{N} \max_{\mathbf{P}} \left\{ x_{m,n} \Psi(P_{m,n}) \right\} + \sum_{m=1}^{M} \sum_{n \epsilon \mathcal{N}_m} \alpha_n P_T + \sum_{m=1}^{M} \beta_m P_{m,max} + \sum_{m=1}^{M} \sum_{n \epsilon \mathcal{N}_m} \gamma_n \bar{P}_{m,n}$$

$$+ \sum_{k=1}^{K} \delta_k I_{th} - \sum_{m=1}^{M} \psi_m \Re_{m,min}$$

$$(2.2)$$

with $\Psi(P_{m,n})$ being defined as follows:

$$\Psi(P_{m,n}) = (1 + \psi_m) \log \left(1 + P_{m,n} \Gamma_{m,n} \right) - \left(\alpha_n + \beta_m + \gamma_n + \sum_{k=1}^{K} \delta_k I_{m,n}^{(k)} \right) P_{m,n} \qquad (2.3)$$

To maximize (2.2) for any given $x_{m,n}$, (2.3) is differentiated with respect to $P_{m,n}$ and set the result to 0. This yields

$$P_{m,n}^* = \left[\frac{1 + \psi_m}{\ln \left(\alpha_n + \beta_m + \gamma_n + \sum_{k=1}^{K} \delta_k I_{m,n}^{(k)} \right)} - \frac{1}{\Gamma_{m,n}} \right]^+ \qquad (2.4)$$

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