Resource management
for network-assisted D2D communication

DEMIA DELLA PENDA

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Abstract

During the last decade, the widespread use of smart devices and mobile applications has lead to a massive growth of the mobile traffic demand. Efficiency and scalability are therefore key criteria for the development of future cellular systems, in which device-to-device (D2D) communication is recognized as one of the promising technologies. D2D communication allows mobile users in physical proximity to communicate directly, bypassing the base station as in conventional cellular networks.

In this thesis, we investigate some of the possible benefits and challenges brought by the introduction of D2D communication in cellular systems. In particular, we focus on resource management techniques for network-assisted D2D communication using cellular spectrum. Our main contributions lie in the context of mode selection, power control and (frequency/time) resource allocation mechanisms, recognized as key techniques to realize the promises of this technology.

First, we investigate how the integration of D2D communication in cellular systems operating under dynamic Time Division Duplex (TDD) can enhance their energy efficiency. We perform joint optimization of mode selection, uplink/downlink transmission period, and power allocation to minimize the transmission energy consumption. The resource management problems for different scenarios are formulated as mixed-integer nonlinear programming problems. In several cases, we exploit the problems’ structure to design efficient algorithms that achieve optimal solutions in polynomial time. In the remaining cases, we propose a heuristic algorithm that computes near-optimal solutions while respecting practical constraints in terms of execution times and signalling overhead. Our simulations demonstrate that D2D communications in dynamic TDD systems can yield significant energy savings and improved spectral efficiency compared to traditional cellular communication.

Second, we study the performance of various power control strategies applicable to D2D communications in 3GPP LTE networks. We compare them with an utility maximization approach that trades off spectrum efficiency and total transmit power consumption. Our numerical results suggest that the LTE power control scheme is well prepared for network-assisted D2D communications, especially from the cellular user perspective. However, for D2D users, the utility based scheme can provide gains in terms of SINR and power consumption.

Finally, we investigate the subcarrier allocation problem for uplink transmissions in a D2D-enabled network. We focus on maximizing the aggregate transmission rate of the system. In addition to the traditional inter-cell interference, we also account for the intra-cell interference caused by D2D pairs reusing cellular resources. This problem is computationally hard due to its nonconvex and combinatorial nature. However, we show that it can be described as a potential game; hence, we can find a Nash equilibrium using iterative algorithms based on best/better response dynamics.
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Demia
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<th>Abbreviation</th>
<th>Full Form</th>
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<tr>
<td>BS</td>
<td>Base Station</td>
</tr>
<tr>
<td>BW</td>
<td>Bandwidth</td>
</tr>
<tr>
<td>CL</td>
<td>Closed Loop</td>
</tr>
<tr>
<td>CSI</td>
<td>Channel State Information</td>
</tr>
<tr>
<td>D2D</td>
<td>Device-to-Device</td>
</tr>
<tr>
<td>DL</td>
<td>Downlink</td>
</tr>
<tr>
<td>FDD</td>
<td>Frequency-Division Duplex</td>
</tr>
<tr>
<td>FO</td>
<td>Full Orthogonality</td>
</tr>
<tr>
<td>ITU</td>
<td>International Telecommunications Union</td>
</tr>
<tr>
<td>LTE</td>
<td>Long Term Evolution</td>
</tr>
<tr>
<td>MCS</td>
<td>Modulation and Coding Scheme</td>
</tr>
<tr>
<td>NE</td>
<td>Nash Equilibrium</td>
</tr>
<tr>
<td>OFDMA</td>
<td>Orthogonal Frequency Division Multiplexing</td>
</tr>
<tr>
<td>OFPC</td>
<td>Open Loop with Fractional Path Loss Compensation</td>
</tr>
<tr>
<td>OL</td>
<td>Open Loop</td>
</tr>
<tr>
<td>PC</td>
<td>Power Control</td>
</tr>
<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>RB</td>
<td>Resource Block</td>
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<td>RRM</td>
<td>Radio Resource Management</td>
</tr>
<tr>
<td>RS</td>
<td>Resource Sharing</td>
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<tr>
<td>Rx</td>
<td>Receiver</td>
</tr>
<tr>
<td>SINR</td>
<td>Signal-to-Interference-Plus-Noise Ratio</td>
</tr>
<tr>
<td>SRS</td>
<td>Sounding Reference Signal</td>
</tr>
<tr>
<td>TDD</td>
<td>Time-Division Duplex</td>
</tr>
<tr>
<td>Tx</td>
<td>Transmitter</td>
</tr>
<tr>
<td>UE</td>
<td>User Equipment</td>
</tr>
<tr>
<td>UL</td>
<td>Uplink</td>
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The mobile communications sector has experienced an explosive growth during the last decade, both in the number of mobile subscribers and in the data traffic demands. Voice traffic dominated the mobile networks for many years. However, the spread of smart devices and the massive usage of mobile applications made the data traffic increase dramatically. Today, the global monthly data traffic is more than seventeen times the voice traffic, as reported in [1].

Richer web contents, multimedia file sharing, audio and, above all, high-definition video streaming, are factors that will continue raising the amount of traffic in future wireless networks. According to Cisco’s latest Visual Networking Index report, the global mobile data traffic will increase nearly tenfold from 2014 to 2019 (see Figure 1.1), with an average traffic generated by a single smartphone close to 4.0 GB per month, a fivefold increase compared to the 2014 monthly average of 819 MB [2]. Another contribution to the global mobile traffic growth will be also given by the spread of wireless devices accessing mobile networks for new applications beyond personal communications (e.g., machine-type-communication) [3].

The need to support this traffic explosion is certainly the main challenge of next generation cellular system, referred to as the fifth generation (5G). 5G networks are meant to provide, among other targets, 1000 times larger mobile data volume per area, 10 to 100 times higher user data rate, and to serve 10 to 100 times more connected devices than current cellular systems [4–6]. Designing wireless networks able to fulfill these ambitious specifications, while taking into account constraints in terms of cost, energy, and radio spectrum, is a challenging goal for both industry and academia.

According to the EU flagship 5G project METIS\(^1\), future systems should meet the new communication requirements by means of the evolution of existing technologies, complemented by new radio concepts [5]. Existing approaches that operators can leverage today in order to further increase the system capacity can be grouped into three main categories: i) increased radio spectrum (e.g., by moving to higher frequencies), ii) improvement in link efficiency by means of advanced communication

\(^1\)Mobile and Wireless Communications Enablers for the Twenty-Twenty Information Society [7]
technologies such as multi-antenna transmissions (MIMO), and iii) densification of the network by increasing the density of base stations (BSs) and reducing the cell size [4, 8, 9].

In particular, the deployment of smaller cells as part of heterogeneous networks is a common solution to enhance capacity in highly populated areas (i.e., business districts, universities, malls, etc.). This because smaller cells manage higher-quality links and allow for increased spatial reuse [10, 11]. However, extreme densification needs appropriate interference management and can lead to large infrastructure costs and operating expenses. Besides cell shrinking, another approach to the network densification for future 5G systems is represented by device-to-device (D2D) communication: a radio technology which allows users in close proximity to establish a direct local link, bypassing the base station.

D2D communication in a cellular networks brings several benefits to both the mobile users and the network operators. For this reason, it is drawing a growing attention by 3GPP LTE\(^2\) standard. First, mobile users can experience high data rates and low latency, saving power and energy because of the direct short-range communication and its potentially favourable propagation condition. Second, the cell coverage can be extended and the capacity per area improved without increasing the infrastructure cost. In fact, cell-edge users, usually experiencing poor performance, can communicate directly or by means of a relay. In the latter case, both a D2D communication and a connection to the cellular infrastructure is established. Third, by allowing spectrum reuse between traditional cellular communications and direct D2D communications, spectrum efficiency can be enhanced, accommodating a larger number of concurrent transmissions [13–15]. Finally, since D2D communication offers

\(^2\)3rd Generation Partnership Project Long Term Evolution [12].
the opportunity for local management of short-distance transmissions, it allows for data offloading from the base station, which alleviates network congestion and traffic management effort at the central network nodes [16, 17].

Apart from all these promising advantages, the integration of D2D communication in future wireless networks opens up also new challenges, as it will be described later in this chapter. The objective of this thesis consists in proposing resource management techniques for D2D-enabled networks, aiming at tackling some of the challenges and at validating the potential of this technology.

1.1 Opportunities for device-to-device communication

We point out some examples where D2D communication is foreseen to both improve the performance of existing proximity-based services and to open up new uses.

Social and commercial services. The use of direct communication between nearby devices is promoted by the increasing popularity of proximity-based services [18], for which conventional uplink/downlink transmissions might be inefficient. An example is given by local information sharing in crowded places (e.g., in a stadium or at a concert), where many users request for the same popular content; or when groups of people in the same area (e.g., in a shopping center or in a campus) want to communicate with each other. Another application is mobile multiplayer gaming, for which high speed, low-latency and battery lifetime are important constraints.

D2D communication is also foreseen as a potential new channel for local promotions or advertisement from stores and restaurants to nearby users, and for local broadcast of information about public transportation services, such as train schedules in a subway station or flight updates in airports [19–21].

Although all these proximity-services can be implemented on existing technologies (e.g. Bluetooth), they generally cannot provide large range of operation, high security and quality of service guarantee, as cellular networks can.

Public safety. D2D communication represents an attractive option for public safety organisations\(^3\), such as police, fire and rescue services that are demanded to intervene after a natural disaster (e.g., earthquake or hurricane) or during crowded events (e.g., Olympic Games) [23, 24]. In these situations, the cellular network might fail because of the damage of the infrastructures or because of the high congestion and overload due to the intense communication [25]. Thereupon, D2D-enabled devices represent a solution to convey important information over reliable short-range communications between first responders, who must always be connected with each other and with the local and remote command centers to receive and send timely information. Additionally, D2D communication can be used by people in

\(^3\)The US government has already expressed its interest to move to LTE for future public safety communications, and 3GPP LTE standards aim at meeting the public safety application requirements also by means of D2D communication [22].
an emergency status to notify nearby responders and/or next of kin about their whereabouts and condition.

**Traffic safety and D2D relay.** Vehicle-to-vehicle (V2V) communication is a technology supporting cooperation between vehicles in close proximity, in order to avoid accidents and to improve the traffic management. Due to its strict requirements in terms of reliability and latency of the communication, it turns out that D2D communication naturally fits the purpose [26].

Another emerging technology for wireless cellular networks is the so-called Machine-to-Machine (M2M) communication, which allows a large number of devices to attach to the cellular network for applications like large scale environment sensing, health monitoring, etc. [27]. Such devices are usually low-powered; therefore, a reliable D2D link between them and a smart device can be used as a relay to the cellular infrastructure. This example shows the possibility to extend the D2D concept to mobile relaying, which may be employed for supporting the communication of devices located in areas with poor cellular coverage [28].

Figure 1.2 illustrates the main conceptual use-cases foreseen for D2D communications. More use-cases descriptions can be found in [29].

**Figure 1.2:** Representative use-cases of D2D communication in cellular networks.

### 1.2 D2D technology

D2D communication can be implemented as either *self-organized D2D communication* or *network-assisted D2D communication*, depending on the involvement of the cellular infrastructure in the direct communication set-up.

Self-organized D2D communication is similar to the traditional ad-hoc networks and exploits the unlicensed spectrum. This approach is usually motivated by its
1.2. D2D technology

D2D technology is characterized by limited overhead and easy deployment. Therefore, it finds application when the cellular infrastructure is not operative, such as in case of natural disaster.

Network-assisted D2D communication, on the other hand, represents the case when the BS assists the D2D communication by means of control signaling and resource management. As a consequence, the network can coordinate D2D and cellular communications and mitigate the mutual interference. However, the coordination might require high signaling overhead and complex centralized resource management. For this reason, different levels of network support can be assumed, with the goal of achieving a good trade-off between complexity/signaling overhead and guaranteed performance. For example, D2D users can be supported by the network during the discovery phase, and then they manage the radio resources and schedule their transmission autonomously [30].

Based on how users access the spectrum, D2D communications can be further divided in the following categories (see Figure 1.3 for illustration):

- **In-band D2D**: D2D users exploit the licensed spectrum allocated to the cellular operator, experiencing a high control from the BS, and hence with more guarantees on the communication performance. In-band D2D communication branches out into two subcategories:
  
  - **Underlay in-band D2D** (shared mode): Most of the works in literature suggest to use the same cellular spectrum for both D2D and cellular users in order to increase the spectrum efficiency. In this case, the interference among concurrent transmissions must be carefully managed.
  
  - **Overlay in-band D2D** (dedicated mode): To eliminate intra-cell interference between cellular and D2D communications, the licensed spectrum can be divided into two non-overlapping parts; one part is used for cellular communications, while the other is assigned to the D2D users.

- **Out-band D2D**: In this case direct communications use unlicensed spectrum, avoiding interference with cellular links.

In this thesis, we focus on in-band network-assisted D2D communication, which we believe being the most innovative concept in the context of short distance wireless communications. Out-band and self-organized D2D communication, in fact, has already been exploited by technologies such as, for example, Bluetooth and Wi-Fi Direct. Both these technologies work in the unlicensed Industrial, Scientific and Medical (ISM) bands, which can be subject to unexpected interference and, therefore, to poor communication performance, especially when the usage density is high. Differing from these conventional approaches, network-assisted D2D in-band communication utilizes licensed spectrum with quality of service guarantees, thanks to the interference management of the cellular spectrum. Moreover, network-assisted D2D devices can take advantage of the synchronization of the network during the discovery process, which means that the devices do not need to constantly
scan for available access points or other Bluetooth users nearby. This is especially advantageous in reducing the power consumption and prolonging the battery lifetime of the mobile equipment. D2D communication also allows for a larger device coverage and discovery area than existing technologies, due to the possibility to transmit with higher power (up to 250 mW for D2D communication, compared to around 100 mW for Bluetooth communication). Finally, we recall that one of the main benefits of D2D communication in cellular networks is the offloading of the local traffic from the BS in crowded areas. In Bluetooth and Wi-Fi, this direct pairing is established by the end users. In network-assisted D2D communication, instead, this operation may be transparent to the users and activated directly by the network when it is needed (and possible). A brief comparison of the main features of Bluetooth, Wi-Fi Direct and in-band D2D is listed in Table 1.1.

**Table 1.1:** Comparison of D2D technologies

<table>
<thead>
<tr>
<th>Feature</th>
<th>In-band D2D</th>
<th>Wi-Fi Direct</th>
<th>Bluetooth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standardization</td>
<td>3GPP LTE</td>
<td>IEEE 802.11</td>
<td>Bluetooth SIG(^a)</td>
</tr>
<tr>
<td>Frequency band</td>
<td>Licensed band for LTE-A</td>
<td>Unlicensed ISM band</td>
<td>Unlicensed ISM band</td>
</tr>
<tr>
<td>Interference control</td>
<td>yes</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Max transmission distance</td>
<td>1000 m</td>
<td>200 m</td>
<td>10-100 m</td>
</tr>
<tr>
<td>Max data rate</td>
<td>1 Gbps</td>
<td>250 Mbps</td>
<td>24 Mbps</td>
</tr>
</tbody>
</table>

\(^a\)Special Interest Group.
1.3 Challenges of D2D-enabled networks

The integration of D2D capabilities in cellular networks poses new technical challenges and design problems. In the following we give a brief overview of the most evident ones.

Mode selection. A natural question in the context of D2D communication is under which condition two users should communicate through a direct link rather than via the BS. For in-band D2D it also involves the decision on whether D2D users should be in shared mode or in dedicated mode.

Design issues related to the mode selection problem include the decision on: the performance measure that one wishes to optimize; what algorithms should be used; what measurements are available; and the frequency of the measurements and mode selection updates. Furthermore, to realize the full potential of D2D communication, especially for underlay D2D communication where the interference becomes an issue, the mode selection should be done jointly with other radio resource management decisions, such as power and subcarrier allocation. However, the joint optimization generally leads to challenging problem formulations, as it will be discussed in Chapter 2.

Spectrum use and interference management. Since obtaining more licensed bandwidth is a significant and costly challenge for the operators, an efficient use of the available spectrum is required, especially by means of appropriate coordination of the interference.

Interference management is a challenging issue especially in underlay D2D communication. In that case, in fact, there is not only the inter-cell multiple-access interference due to frequency reuse between neighbour cells, but also intra-cell interference due to the presence of D2D connections. Such an effect can become severe due to the random positions of the D2D transmitters and receivers. In classical cellular systems, interfering users are located at a distance that amounts to at least the cell radius. By introducing D2D links, interfering transmissions can operate at any distance, potentially jeopardizing the system performance.

Balancing performance, computational complexity and signaling overhead. Designing optimal resource allocation algorithms that operate with both limited computational complexity and limited signaling overhead is a challenging target. In many cases, in fact, algorithms for resource allocation policies require to solve optimization problems that are nonconvex, combinatorial, mixed integer nonlinear, etc. This can be highly time consuming, not scalable, and thus not manageable in real systems. Additionally, optimal solutions often leverage on the full channel status information of all involved links and/or on the exchange of information among the nodes. This might be also impractical due to the corresponding signaling. Therefore, the main challenge consists in finding a good trade-off between optimality and
applicability, choosing among separate versus joint optimization and centralized versus distributed approaches.

**Peer discovery and synchronization.** Peer discovery consists in searching for potential users nearby to communicate with.

For self-organized D2D communication, the discovery can be done by the existing procedures for ad-hoc networks, e.g., [31]. Users searching for a peer can broadcast their identity periodically so that other users in proximity can identify their presence and decide to set up a D2D communication. However, due to the lack of synchronization, the receiver should always monitor the channel to not miss the discovery signals from other transmitters. This becomes an important issue in terms of time and energy efficiency, because the listening phase can significantly drain the battery of the mobile devices [19].

For in-band network-assisted D2D communication, instead, the synchronization given by the cellular infrastructure can help the discovery phase. However, there is no standardized signaling exchange between the mobile users, which indeed needs to be properly designed.

There is an on-going research effort in tackling these and other challenges in the context of D2D networks. This thesis is part of this effort, focusing on the first three aforementioned aspects.

### 1.4 Outline and contributions

This thesis investigates on how to improve the performance of D2D-enabled systems by means of proper design and coordination of radio resource management techniques. Specifically, we recognize the importance of *mode selection, power control* and *resource (time/frequency) allocation* to realize the promises of D2D communication.

The outline of the thesis, together with the publications supporting the contributions, is as follows. In Chapter 2 we present an overview on resource management techniques for network-assisted D2D communication, referring to related works in literature. Chapter 3 describes the general network model and motivates the main design choices used in the thesis. Chapter 4 presents a mode selection and resource (time and power) allocation algorithm for energy efficient D2D networks. It is based on:

- Demia Della Penda, Liqun Fu and Mikael Johansson, “Mode selection for energy efficient D2D communications in dynamic TDD systems,” in *IEEE International Conference on Communications (ICC)*, 2015.

- Demia Della Penda, Liqun Fu and Mikael Johansson, “Energy efficient D2D communications in dynamic TDD systems,” *submitted to IEEE Transactions on Communications (under review)*.
Chapter 5 examines the performance of the legacy LTE power control tool-box and benchmarks it against an utility optimal iterative scheme. This chapter includes part of the material in:


Chapter 6 considers the subcarrier allocation problem for uplink transmissions in a multi-cell network, based on:


Finally, in Chapter 7 we conclude the thesis with a summary of the main contributions and a discussion on potential directions for future work.
Chapter 2

Related work on RRM techniques for D2D-enabled networks

The introduction of D2D communication in legacy cellular systems creates a need for revisiting the existing radio resource management (RRM) techniques to make the best possible use of the technology. RRM for D2D communication in cellular networks consists of three key decisions: mode selection, that is, deciding if a user equipment (UE) should communicate directly or via the base station (BS); power control, namely, setting the transmit power; and (time/frequency) resource allocation, i.e., assigning the physical resource blocks (RBs) to the users. These three resource management techniques are not independent. For example, if we want to minimize the energy consumption, the optimal mode selection is affected by the assigned transmit powers, and by the ability to allocate physical resources with limited interference. In general, choosing the communication mode for a user pair involves the decision on whether the D2D candidate pair should share the physical resources with other communications. This decision naturally leads to the following questions: i) Which links should share the same resources and thus interfere with each other? ii) Which power level should be assigned to the transmitters in order to limit the mutual interference? Fig. 2.1 illustrates the interplay of the mode selection, power, and resource allocation in a simple example. It is clear from this example that the RRM decisions should be taken jointly to guarantee an optimal performance. However, the joint optimization formulation usually turns to be computationally difficult, and it might require a system knowledge that is very costly to acquire. Thus, many papers in the literature consider the three problems separately or only partially jointly; see Fig. 2.2.

The aim of this chapter is to describe the mode selection, power control and resource allocation problems for D2D-enabled cellular networks, and to give a brief overview on the solution approaches proposed in literature.
Figure 2.1: Illustrative example of the interplay of mode selection, power control and time/frequency resource allocation. In the considered example, mode selection needs to be performed for the transmitter indicated by UE3, assuming that cellular users UE1 and UE2 are already assigned to RB1 and RB2, respectively. The mode selection decision assigns to UE3 one of the three possible modes: cellular mode, D2D mode with dedicated resource or D2D mode with shared resource. In the latter case, proper resource allocation and power control algorithms are needed to select the RB and the transmit power that limits the mutual interference between the D2D and cellular communications on the same RB.

Figure 2.2: The three main RRM problems for D2D communication in cellular networks and some of the related solutions in literature.

2.1 Mode selection

Mode selection is the problem of choosing whether two users should communicate through a direct link, using dedicated or shared resources, rather than via the BS.
The optimal mode selection depends on the performance measure to optimize (e.g., sum rate, transmit power, energy consumption and system capacity), and on the state information available when making the decision (e.g., physical distance, channel quality of the links, interference level).

The simplest and most intuitive mode selection algorithms base their decision on the path loss, which is directly related to the physical distance between the nodes. In [40], for example, the D2D mode is activated if the path loss of the users forming the D2D pair is smaller than a given threshold. A mode selection approach that accounts for both D2D link distance \( r_d \) and cellular distance \( r_c \) is proposed in [55]. Here, D2D mode is selected if \( T_d r_d^{-\alpha} \geq r_c^{-\alpha} \), where \( \alpha \) is the path loss exponent and \( T_d \) is a bias factor to control the traffic offloading from the cellular infrastructure to the D2D communication. By selecting large values of \( T_d \), in fact, more user pairs are forced to communicate in D2D mode. Another example of distance-dependent mode selection can be found in [33], for a slightly different scenario, where several fixed relay nodes are considered to help cellular communication, and the mode selection for the D2D pair is among underlay or overlay D2D communication. Different spectrum sharing methods for the D2D mode, and different uplink servers for the cellular users (BS or relay nodes) bring various combinations of communication modes. The proposed algorithm picks the mode with the highest sum rate.

Mode selection based on channel quality rather than only link distance is proposed in [46]. The algorithm takes into account both the quality of the involved links and the different interference levels occurring when the D2D pair shares the uplink or downlink resource with a cellular transmission. The objective of this scheme is to maximize the sum rate while satisfying SINR constraints on active cellular links. The authors also investigate the extension of their method to the multi-cell scenario, where the interference from other cells might affect the decision. However, the signaling load of the scheme increases significantly.

Several works on mode selection assume single antenna system and constraints that give priority to the cellular users [32, 46]. Differently, the authors of [36] take into account the effect of multiple antennas at the BS and give the same priority to all users, regardless of their communication mode. They consider two different approaches to optimize the mode selection: maximizing the rate for a given transmit power and the dual problem of minimizing the power to maintain a given rate. They derive closed-form solutions and show that even if the two problems are tightly connected, they behave differently in terms of selected communication mode.

Most of the analysis in the literature focus on the simplified scenario of an isolated cell [32, 33, 36, 46], assuming that inter-cell interference is mitigated by other interference management mechanism in order to deal with more tractable problems. In a multi-cell system, in fact, the mode selection problem becomes more complex not only for the additional interference, but because it might also involve the BS-user association. The joint problem of mode selection and BS association has recently been considered in [37]. In this work, the author aims at maximizing the perceived SINR at the receivers, limiting the max number of users that each BS can support. The integer programming problem is solved to optimality by means of
a graph-based approach.

It is worth mentioning that around the mode selection problem there are several design issues to consider: how often the communication mode should be updated, what channel state information is needed, and at which frequency this information should be reported. The timescale for the mode selection, in fact, cannot be too coarse because the wireless channel might change rapidly, and, on the other hand, the necessary signaling overhead should be minimal.

2.2 Power control

Power control is used in cellular networks to assign transmit powers to the users, such that a desired data rate is supported. In the third generations of mobile telecommunications technology (3G), power control was a critical component, especially for the uplink transmission to handle the near-far problem. This is because concurrent communications to the BS are nonorthogonal and high power transmitted by users close to the BS (typically at the cell center) can overwhelm the weak transmissions from the cell edge. In 4G systems, intra-cell interference is not an issue because uplink transmissions use orthogonal resources. Therefore, the power control mechanism mainly compensates for path loss and shadowing on a slow basis. Fast scheduling procedures, on the other hand, are taking over the (primary) role of the power control mechanism to increase the user data rate [12, 56].

However, the introduction of D2D communication in future 5G system, reusing cellular spectrum, might reinstate the importance of the power control. This is because of its potential to handle the new intra-cell interference scenarios, and to reduce the power consumption of short-link communications.

In D2D-enabled networks, cellular users are often considered as those with the highest priority to whom a certain communication quality must be always guaranteed. The most intuitive way to reduce the interference from D2D communications to cellular communications consists in limiting the transmit power of D2D users. The authors of [38] analyze this problem for the single cell scenario. The idea is to set the power of the transmitting D2D user such that the SINR degradation of the cellular user from the SNR (i.e., without interference) is limited to 3 dB. The authors of [39] also mitigate the interference from the D2D transmissions on uplink cellular resources reducing the power of the D2D transmitter by means of a back-off parameter. Since a low D2D transmit power translates into a small range of the D2D link, the power of the cellular users is also increased by to compensate for the interference and thus limit this drawback.

Different LTE power control schemes for the hybrid cellular and D2D system are evaluated in [40]. The study is mainly based on simulations but shows good insights into the impact of the different approaches. For example, the fixed transmit power scheme is very simple, but it does not work well in the context of D2D communication due to the possible large dynamic range of the D2D SINR (i.e., it might provide too good performance for some users, meanwhile too bad performance
for some other users). On the other hand, when considering the fixed SNR target scheme, the selection of the SNR target value affects both the allocated transmit power and the final SINR of the interfering transmissions. Agreeing upon the fact that the mode selection criterion is crucial, authors conclude that the closed loop LTE power control with a dynamic tuning step can be a suitable for D2D users. Nevertheless, the standalone power control scheme is not an efficient solution to avoid the strong mutual interference between different types of communication, hence it needs to be complemented by mode selection, resource scheduling and link adaptation.

Joint mode selection and power allocation formulations can be found in [44, 45]. The algorithm proposed in [44] maximizes the power efficiency of the system, which is defined as the ratio between the sum rate and the sum transmit power of all users, for all possible modes. Then, it selects the mode with the highest values. The drawback of this algorithm is that it is based on an exhaustive search over all possible mode combinations of the users. A joint admission control, mode selection and power control is proposed in [45], which attempts to maximize the total throughput and number of admitted users in the system. The problem is formulated as a mixed integer nonlinear problem. Due to its combinatorial nature, the solution complexity increases exponentially with the number of user pairs. However, the authors exploit the problem structure to apply a linearization technique that gives guaranteed $\epsilon$-optimal results.

2.3 Time/frequency resource allocation

Assigning particular time/frequency resources to the users in the system is important not only for taking advantage of the possible frequency diversity among channels, but also for increasing the spectrum efficiency and the system capacity through intelligent resource reuse.

Frequency resource allocation strategies based on distance-constraints between possible interfering users (cellular and D2D) are proposed in [41] and [42], where the main idea is to avoid the coexistence on the same resource of cellular and D2D users when they are too close to each other.

Considering the spectrum reuse problem from an optimization perspective usually leads to nonconvex and mixed integer formulations, where an optimal solution is in general very hard to achieve, even for small-sized networks. Optimal results are obtained in very special situations, as, for example, in [32]. Here, a simplified model of only one cellular user and one D2D pair is considered for the joint power and resource allocation that maximizes the throughput.

Other works limit the resource allocation analysis to a single cell case, considering different objectives with different system constraints. The sum rate maximization problem is considered in [47] and [43]. The authors of [47] design a resource sharing strategy such that a single D2D pair can utilize all possible cellular resources without jeopardize the cellular communications. The resource allocation problem
is formulated as a power control problem. Even though the problem is originally nonconvex, the authors show that it can be transformed into a convex one, and solved to optimality. The resource allocation problem in [43], instead, is formulated as a mixed integer nonlinear programming problem. Since it is hard to solve it within the fast scheduling period required by current systems (such as LTE), the authors also propose an alternative heuristic algorithm. This algorithm simply selects the resources to be shared in uplink or downlink as those with the lowest cross gain between the interfering users.

Recent works on the joint resource and power allocation problem for energy efficient D2D communication can be found in [48, 49]. Specifically, in [48], the objective is to maximize the minimum weighted energy efficiency of D2D links, where the weights are employed to control the relative priorities among the D2D links. Each D2D link can share resources with multiple cellular users. However, each cellular resource can be reused at most by one D2D link to limit the interference towards the cellular communications. The problem is solved by separating the goals: authors first characterize the optimal power allocation of the cellular links, and then transform the original resource allocation problem into the joint resource and power allocation problem for D2D links only. The resource allocation problem is a mixed integer nonlinear programming problem, for which branch-and-bound approach is applied to achieve the optimal solution. However, alternative solutions with lower complexity and limited message exchange are also provided. The energy-efficient resource allocation problem formulated in [49] is a nonconvex combinatorial programming problem, with constraints on the resources reuse similar to those in [48]. However, by exploiting the proprieties of fractional programming, the authors obtain a tractable solution with an iterative approach. Moreover, they also propose a two-layer iterative solution approach, in which the original joint formulation of power and resource allocation is transformed into two separate optimization problems in each iteration.

Finally, the resource allocation problem in multi-cell networks is seldom addressed in literature. Instead, most works assume that an advanced inter-cell interference mitigation scheme works on top of the per-cell resource allocation algorithms. Some exceptions are [57, 58]. In [57], the authors apply fractional frequency reuse approach, where cellular and D2D users use different downlink frequency resources depending on their locations within the cell area. The procedure proposed in [58] is also based on the position of the users, together with a significant exchange of information between the users and the BSs, and between the BSs.

2.4 Joint RRM

As introduced at the beginning of this chapter, and as supported by the above literature overview, the best system performance is obtained by joint solution to the mode selection, power control and resource allocation problems. Example of such joint formulations are given in [50–54]. These works are mainly developing
mixed-integer programming models. In some cases they are solved off-line with the purpose of obtaining benchmark results and insight into the potential gains of D2D communication [50]. Alternative proposed solutions are: to decompose the joint problem into separated subproblems [52]; to resort to more practical heuristics [50–53], or to consider game-theoretic approaches [54]. However, numerical simulations in [50, 52] show that the proper design of heuristics can give a performance close to the optimal solutions.

2.5 Summary

The use of D2D communication in cellular networks can be enabled by smart RRM techniques, such as mode selection, power control, and time/frequency resource allocation. The most intuitive and simplest way to select the communication mode for a pair, and to mitigate the interference, is to consider the path loss gain (and therefore the physical distance) between the involved users. This approach is useful to give a geometric interpretation of the solution. However, distance-based solutions do not account for the effective quality of the links, affected, for example, by shadowing and interference. Therefore, CSI and perceived SINR are preferred as decision metric in the context of RRM strategies. Solutions based on optimization formulations lead to better system performance. However, they are often less practical due to their complexity and required signaling overhead. This aspect is even more pronounced for the joint solution of the three RRM problems. For this reason, the existing work focuses mainly on solving the problems individually, or on proposing practical heuristic alternatives.
In this chapter, we present the general system model and motivate the design choices shared by the remaining chapters of the thesis.

The system model and the analysis approach to the radio resource management problems can be broadly classified into two groups: instantaneous analysis and statistical analysis [55]. The former approach considers objective functions based on instantaneous system information (e.g., channel gains and link distances), and the model is used to derive instantaneous optimal decisions. In this case, the possible rapid variation of the system parameters might affect the decisions, which therefore need to be updated accordingly. The statistical approach, on the other hand, is based on statistical information about the system (e.g., the distributions of the users locations and channel gains), which are stable over a relative longer period of time. Hence, decisions made under this assumption may not be the best solutions in a particular point of time, but they can be optimal over a longer time horizon.

This thesis is based on the instantaneous analysis, with the aim of investigating the potential limits and gains of the considered scenarios.

3.1 System model

We consider a cellular network consisting of a set $B$ of base stations (BSs). Each BS is placed in the center of an hexagonal cell and serves mobile users randomly placed within its cell area. We assume a set $L$ of L transmitter-receiver pairs, each constituting a logical link that we label with an integer $1, 2, \ldots, L$. A logical link can be a pair of cellular users transmitting data through the serving BS, or a D2D pair communicating through a direct link. We refer to the users in pair-$l$ as transmitter-$l$ (Tx-$l$) and receiver-$l$ (Rx-$l$), respectively. See Fig. 3.1 for illustration.

Taking LTE as a reference system, we assume orthogonal frequency division multiplexing (OFDM) [12]. The available system bandwidth is divided into a number
of physical Resource Blocks (RBs) of size $W$ Hz, and time duration of $T$ seconds\(^1\). We assume that each BS manages a set $\mathcal{F}$ of $F$ time-frequency RBs to be assigned to the logical links within its own cell area.

We assume that all nodes are equipped with omnidirectional antennas, and consider a full-buffer traffic model where transmitters always have unlimited amount of data to send to their intended receivers. We denote by $P_{lm}^f$ the transmit power level used by Tx-$l$ towards Rx-$m$ on RB-$f$. Note that the BS can act both as transmitter and receiver, depending on whether it is involved in a downlink (DL) or uplink (UL) transmission, respectively. We consider per-link peak-power constraints in the form

$$0 \leq P_{lm}^f \leq P_{l}^{\text{max}},$$  \hspace{1cm} (3.1)

where $P_{l}^{\text{max}}$ is the maximum allowable transmit power for Tx-$l$. Communication links are assumed as Gaussian channels, where each receiver treats multi-user interference, due to the possible subcarrier reuse, as additive noise. The maximum achievable rate (link capacity) of the data transmission from Tx-$l$ to Rx-$m$ using RB-$f$ is given by the Shannon capacity formula

$$r_{lm}^f = W \log\left(1 + \frac{P_{lm}^f G_{lm}^f}{\sigma^2 + I_{lm}^f}\right).$$  \hspace{1cm} (3.2)

\(^1\)In an LTE system, a RB consists of 12 consecutive subcarriers with a spacing of 15 kHz, thus occupying a total of 180 kHz, for a time slot duration of 0.5 ms (normal cyclic prefix case) [12].
Here, $W$ is the bandwidth, $G_{lm}^f$ is the channel gain between Tx-$l$ and Rx-$m$ on RB-$f$, and $\sigma^2$ is the thermal noise power at the receiver, assumed equal for all RBs. We indicate with

$$\gamma_{lm}^f = \frac{P_{lm}^f G_{lm}^f}{\sigma^2 + I_m^f}$$

the signal-to-interference-plus-noise (SINR) perceived at Rx-$m$ from transmission on RB-$f$ by Tx-$l$, where the term

$$I_m^f = \sum_{j \neq l} P_{jj}^f G_{jm}^f,$$

represents the interference due to concurrent transmissions on RB-$f$. In the definition of the interference $I_m^f$ we are assuming that the summation runs over all the users in the network, in all cells.

### 3.2 Problem formulation and performance metrics

In this thesis, we pose radio resource management tasks as utility maximization problems. The decision variables depend on the specific scenario, and include the communication mode (cellular or D2D) assigned to each transmitter-receiver pair, the assignment of RBs to user pairs, the transmission power allocation for each user pair, and the time duration of each communication.

To formally describe this generic formulation, we introduce:

- the mode selection vector $m \in \{0, 1\}^{L \times 1}$, with $m_l = 0$ if pair-$l$ is assigned to cellular mode and $m_l = 1$ if in D2D mode;

- the transmit power matrix $P \in \mathbb{R}^{L \times 2F}$, defined as a concatenation of matrices $P_c \in \mathbb{R}^{L \times F}$ and $P_d \in \mathbb{R}^{L \times F}$, whose elements $P_{lf}^c$ and $P_{lf}^d$ represent, respectively, the power level used by transmitter-$l$ when in cellular mode and in D2D mode. When mode selection decision has been made, the matrix $P$ reduces its dimensions to $L \times F$. In this case, the element $P_{lf}^f$ of $P$ represents the power allocated to transmitter-$l$ on RB-$f$;

- the RB assignment matrix $X \in \{0, 1\}^{L \times F}$, whose entry $x_{lf}^f$ is 1 if transmitter-$l$ is assigned to RB-$f$, 0 otherwise;

- and the vector $t \in \mathbb{R}^{L \times 1}$, with $t_l$ being the time duration assigned to the communication of pair-$l$. 
With this notation, the general problem formulation can be written as the following mixed-integer problem:

\[
\begin{align*}
\text{maximize} & \quad f(m, P, X, t) \\
\text{subject to} & \quad h_i(P, X, m, t) = 0, \quad i \in \mathcal{E} \\
& \quad g_j(P, X, m, t) \leq 0, \quad j \in \mathcal{I} \\
& \quad m \in \{0, 1\}^{L\times 1}, \quad t \in \mathbb{R}^{L\times 1} \\
& \quad P \in \mathbb{R}^{L \times F}, \quad X \in \{0, 1\}^{L \times F}.
\end{align*}
\] (3.3)

The objective function and constraints vary depending on the scenario that we consider. For example, inequality constraints can represent the power limitation of the devices, the minimum rate or SINR of the transmissions, etc. The equality constraints might be used, for example, as a constraint on the number of RBs assigned to the users.

The definition of the objective function \(f(\cdot)\) in (3.3) depends on the network performance we wish to optimize. In order to explore and exploit the different advantages derived by introducing D2D communication in cellular networks, in this thesis we consider different performance metrics.

**Energy consumption.** The growing energy bills of operators, limited battery lifetime of mobile devices and environmental concerns led our interest towards the problem addressed in Chapter 4, where we investigate how D2D communication can be integrated in cellular systems to minimize the transmission energy consumption. We leverage on the observation that the energy required for sending a fixed amount of data is a convex and decreasing function of the transmission duration. To guarantee a certain QoS to the communication of pair-\(l\) on RB-\(f\), we can define a traffic requirement of \(b_l\) nats per time frame. Let \(t_l(m_l)\), or for short \(t_l\), be the transmission time assigned to Tx-\(l\), which depends on the communication mode. Then, the minimum transmission energy required can be expressed as a function of the time duration

\[
E^f_l(t_l, m_l, X) = \left(\exp\left(\frac{b_l}{W_{t_l}}\right) - 1\right) \frac{\sigma^2 + f^f_l(X)}{G^f_{ll}} t_l.
\]

As shown in Chapter 4, the energy consumption does not depend only on the transmission duration and the communication mode, but also on the RB allocation policy (which affects the perceived interference). Therefore, the objective function in problem (3.3) becomes

\[
f(t, m, X) = - \sum_{f \in F} \sum_{l \in \mathcal{L}} E^f_l(t_l, m_l, X).
\]

**Aggregate utility.** In Chapter 5, we jointly consider two of the main gains of D2D communication: increased *spectrum efficiency* and reduced *power consumption.*
3.3 Assumptions

In doing so, we consider an aggregate utility function that takes into account both the satisfaction level of the users when transmitting at a certain rate, and the total power consumption \[59\]. The satisfaction level of user pair-\(l\) is represented by the individual utility \(u_l(\cdot)\), which is increasing and strictly concave in the transmission rate of pair-\(l\), referred to as \(s^f_l\) and upperbounded by the link capacity. We indicate with \(\mathcal{L}_f\) the set of links sharing RB-\(f\). The objective function is then

\[
f(P, s) = \sum_{f \in \mathcal{F}} U^f(P, s),
\]

where the per-RB utility function is defined as

\[
U^f(P, s) = \sum_{l \in \mathcal{L}_f} u_l(s^f_l) - \omega \sum_{l \in \mathcal{L}_f} P^f_l, \quad \forall f \in \mathcal{F},
\]

where \(\omega \geq 0\) is a parameter that allows to set the desired tradeoff between the two objectives.

**Sum rate.** The optimization problem presented in Chapter 6, aims at maximizing the aggregate transmission rate when D2D reuse the cellular resources. By assuming that mode selection and power allocation are already been performed, the objective function becomes

\[
f(X) = \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} \log \left( 1 + \frac{P^f_l G^f_{ll} \sigma^2}{\sigma^2 + I^f_l(X)} \right).
\]

Fig.3.2 summarized the performance metrics optimized in this thesis.

![Figure 3.2: Performance metrics considered in this thesis.](image)

### 3.3 Assumptions

**Spectrum access.** For communications in cellular mode, we consider the channel allocation policy of legacy LTE systems, that is, cellular communications within the same cell are assigned to orthogonal RBs so to not interfere with each other. For D2D communications, on the other hand, we investigate different allocation strategies: in Chapter 4 we consider the case where D2D communication occurs on
different orthogonal frequency channels than those used for cellular communications (overlay in-band D2D communication), while in Chapters 5 and 6 we consider the case where D2D transmitters are allowed to use the RBs occupied by cellular users (underlay in-band D2D communication); see Table 3.2.

Duplexing is an integral part of the communication design. LTE system supports both Frequency-Division Duplex (FDD) and Time-Division Duplex (TDD) to separate UL and DL traffic. FDD implies that DL and UL transmission take place in different, sufficiently separated, frequency bands, whereas TDD implies that DL and UL transmissions take place in different, non-overlapping time slots. Legacy networks employed static and symmetric resource utilization, where the UL and DL were often separated in the frequency domain. However, dynamic TDD technology is recently gaining popularity for 5G networks [60–62], mainly because of its capacity to better accommodate DL/UL traffic asymmetry in dense, heterogeneous networks. Additionally, the TDD scheme also allows to simplify the access to the channel state information (CSI) by exploiting channel reciprocity and thus reducing the feedback overhead. Other possible advantages of TDD over FDD can be found in [63]. In Chapter 4, following the trend of employing dynamic TDD for future networks, we investigate the possible advantages of integrating D2D communication in such systems.

**Channel model.** The channel gain $G_{lm}^f$ in Eq. (3.2) captures the phenomenon of signal attenuation over the wireless channel, which is caused by i) the distance between transmitter and receiver (path loss), ii) the presence of large obstacles between transmitter and receiver (shadowing), and iii) the reception of multiple copies, attenuated and phase-shifted, of the transmitted signal (multi-path fading) [64].

Another aspect of the propagation model is frequency-selective fading, which occurs when different frequency components of the signal experience different fading.

There is currently no standardized channel model for D2D communication. Although the problem formulations and the resource allocation algorithms presented in this thesis are independent of the channel model, simulation results will depend on the specific propagation model used. In this thesis, we have used several different channel models, depending on the purpose of our studies.

Specifically, in Chapter 4, we are interested, among other things, in obtaining a geometrical interpretation of the optimal mode selection policy. For this reason we assume that the channel gains follow the simple path-loss model $G_{lm}^f = G_0 D_{lm}^{-\alpha}$, where $D_{lm}$ is the physical distance between Tx-$l$ and Rx-$m$, $G_0$ is the path gain at a reference distance of 1 m, and $\alpha$ is the path-loss exponent. This choice is also motivated by the fact that mode selection decision for D2D communication is usually based on slow scale fading (distance dependent path loss and shadowing) measurements, to reduce the frequency of updates of the CSI.

In Chapter 5, for the sake of comparison between different D2D power control schemes, we use the propagation model described in [40], which is based on the micro urban channel models from the International Telecommunication Union (ITU) [65].
3.3. Assumptions

Finally, in Chapter 6, to exploit the robustness to fading of OFDM systems through adaptive user-to-subcarrier assignment, we consider a frequency selective channel, with log-normal shadowing and fast Rayleigh fading in addition to the path-loss².

Table 3.1 summarizes the different channel models considered in this thesis.

<table>
<thead>
<tr>
<th>Chapter</th>
<th>Path loss</th>
<th>Shadowing</th>
<th>Fading</th>
<th>Frequency-selective fading</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chapter 4</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Chapter 5</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Chapter 6</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**Interference scenarios** When employing in-band underlay D2D communication, intra-cell orthogonality is lost and the characteristics of the interference in the cellular network change.

D2D links can access either the UL or DL cellular resource, or both. When a D2D link is active on a radio resource used by a cellular UL transmission, interference is induced from the UL transmitting user to the D2D receiver, and from the D2D transmitter to the BS. Similarly, when the D2D link utilizes DL resources, interference is induced from the cellular BS to the D2D receiver, and from the D2D transmitter to the cellular user. Additionally, interference among multiple D2D links sharing the same resource must be also taken into account, since it can deteriorate the quality of the direct transmissions. This effect is especially strong in crowded areas where transmitters and receivers of different D2D links are close to each other.

With the exception of Chapter 4, this thesis focuses on underlay D2D communication in the UL scenarios. This choice is very common in the literature. Apart from regulatory requirements in some countries, the use of UL resources is motivated by the asymmetric traffic load in the UL and DL directions and by the fact that the BS has a much better capability to handle interference than mobile devices [21, 67–69].

In Chapter 4, we assume dynamic TDD system and we show the advantage of allocating the full frame duration (i.e., both UL and DL resources) to the D2D link.

A disadvantage of underlay D2D communication in such system is that the receiver of the D2D link will perceive a rapid change of the interference power when the cellular communication switches between UL and DL. It is difficult to compensate for this effect without resorting to complex interference management algorithms that require detailed cross-gain knowledge and have high signalling load; this reason motivated the choice of overlay D2D communication.

²Channel gains are obtained on the basis of the model used in RUdimentary NEtwork (RUNE) simulator, a MATLAB-based software tool for performance analysis in wireless networks, originally developed at Ericsson [66].
The complexity of the interference management further increases in the multi-cell scenario, where there is not only the *intra-cell interference* due to the presence of D2D connections, but also the *inter-cell interference* due to frequency reuse between cells. The intra- and inter-cell interference in underlay D2D communication using UL resources is illustrated in Fig. 3.3 for a simple two-cell network.

**Figure 3.3:** Example of both inter-cell and intra-cell interference in the UL transmissions of cellular network with D2D communications. For illustration purposes, we show only the interference caused by transmissions in Cell-1.

Table 3.2 summarizes the different interference scenarios considered in this thesis.

**Table 3.2:** Spectrum access and interference cases considered in this thesis.

<table>
<thead>
<tr>
<th>Chapter</th>
<th>UL/DL Resource</th>
<th>Underlay/Overlay D2D</th>
<th>Single-/Multi-cell</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chapter 4</td>
<td>UL &amp; DL</td>
<td>Overlay</td>
<td>Single-cell</td>
</tr>
<tr>
<td>Chapter 5</td>
<td>UL</td>
<td>Underlay</td>
<td>Multi-cell</td>
</tr>
<tr>
<td>Chapter 6</td>
<td>UL</td>
<td>Underlay</td>
<td>Multi-cell</td>
</tr>
</tbody>
</table>
In this chapter, we investigate how the integration of D2D communication in cellular systems operating under dynamic TDD can enhance their energy efficiency. Performance improvement that can be obtained by integrating D2D communications in cellular systems with flexible TDD have only recently gained attention in literature. Frameworks for D2D enhanced TDD networks are proposed in [70–72]. However, they do not account for the mode selection and focus mainly on the adaptive UL/DL slot allocation to D2D pairs, so as to balance the traffic load, coordinate the interference, improve coverage probability and sum-rate. Recently, the authors of [73] have extended the resource allocation problem introduced in [70] to include mode selection. Yet, the mode selection decision is based on the instantaneous SINR, and not in joint consideration with the power and transmission time allocation.

In this work, we jointly optimize mode selection, power allocation and UL/DL transmission period, to minimize the transmission energy consumption (from both a system and a device perspective), while satisfying a certain rate requirement. The RRM problem for the different scenarios of interest, are formulated as MINLP. Although they are known to be NP-hard in general, we exploit the problem structure to design efficient algorithms that solve several problem classes to optimality in polynomial (and sometimes even linear) time. For the remaining cases, we propose a heuristic algorithm that computes near-optimal solutions while respecting practical constraints in terms of execution times and signalling overhead.

4.1 System model and assumptions

We consider a single-cell network populated by $L$ logical links, each denoted by an integer $1, 2, \ldots, L$, while the BS is indexed as 0. In-cell users can communicate either in cellular mode or in D2D mode. The mode selection policy divides the set of all user pairs $\mathcal{L}$ into two subsets: $\mathcal{D}$ is the set of user pairs that should communicate in D2D mode, and $\mathcal{C} = \mathcal{L} \setminus \mathcal{D}$ the set of user pairs that should communicate in cellular
mode.

Communication in cellular mode. We assume that the system adopts a dynamic TDD mode, where the UL and DL transmissions for a user pair occur on the same frequency channel but alternate in time. The portioning of resources for UL and DL can be reconfigured in each time frame, but it is assumed to be the same for all communications within the same cell. This intra-cell UL/DL synchronization, in fact, is of critical importance to reduce the complexity of the inter-cell interference management in multi-cell networks with dynamic TDD [60, 74, 75]. Furthermore, to prevent intra-cell interference between concurrent transmissions in cellular mode, the BS follows the channel allocation policy of legacy LTE systems and assigns a separate channel to each cellular user pair (see Fig. 4.1).

We denote by $t_{ul}$ and $t_{dl}$ the portion of the time frame allocated to the UL and DL transmissions, respectively.

Communication in D2D mode. In D2D mode, each pair can use the full frame duration for its single-hop transmission. A large body of work considers underlay in-band D2D communication, where D2D transmitters opportunistically access the radio resources occupied by cellular users. A disadvantage of underlay D2D communication in TDD systems is that the receiver of the D2D link perceives a rapid change of the interference power in one time frame when the cellular pair switches between UL and DL transmission. It is difficult to compensate for this effect without resorting to complex interference management algorithms that require detailed cross-gain knowledge and have high signalling load. In this paper, we therefore focus on overlay in-band D2D communication, where D2D communications and cellular communications are allocated different frequency channels so that they do not cause interference to each other (Fig. 4.1). Nevertheless, resource reuse among D2D communications has been investigated in our studies. In particular, we consider two channel allocation strategies for D2D pairs:

- **Full Orthogonality (FO):** All D2D communications are assigned orthogonal frequency channels. Hence, no receiver is interfered by other transmissions within the cell (Fig. 4.1(a)).

- **D2D Resource Sharing (RS):** All D2D communications are assigned to the same frequency channel, hence interfere with each other (Fig. 4.1(b)).

We denote with $t_l \leq T$ the active time of pair-$l$ in D2D mode. In this work we do not consider frequency-selective fading. Therefore, for the sake of notation, we disregard the index related to the RBs (as in Chapter 3) and define the instantaneous rates $r_{l0}$, $r_{0l}$ and $r_{ll}$ achieved in UL, DL and in D2D mode, respectively, as follows:

$$r_{l0} = W \log\left(1 + \frac{P_{l0}G_{l0}}{\sigma^2}\right), \quad r_{0l} = W \log\left(1 + \frac{P_{0l}G_{0l}}{\sigma^2}\right), \quad r_{ll} = W \log\left(1 + \frac{P_{ll}G_{ll}}{\sigma^2 + I_l}\right).$$

(4.1)
4.1. System model and assumptions

Figure 4.1: Frequency-time resources configuration: D2D links can use the full frame duration $T$, either on orthogonal subcarriers (FO) (a), or sharing the same subcarrier (RS) (b). UL and DL duration for cellular communications can be reconfigured at each time frame.

Since we are ensuring intra-cell orthogonality among cellular communications, the UL and DL transmission rates are not affected by any interference. Hence, their maximum values correspond to maximum power transmissions, and are denoted by $r^{\text{max}}_{0l}$ and $r^{\text{max}}_{0l}$, respectively. On the other hand, the maximum instantaneous rate of the D2D transmission, denoted by $r^{\text{max}}_{ll}$, also depends on the current interference level.

Rate constraint, power feasibility and energy cost. To guarantee a certain QoS, each pair-$l$ has a traffic requirement of $b_l$ nats per time frame, irrespective of the communication mode. This QoS requirement can be translated into a session rate requirement of $b_l/T$ nats per second. Specifically, if pair-$l$ is in cellular mode, the transmission times for UL and DL, along with the corresponding instantaneous transmission rates, must satisfy

$$r_{l0}t_{ul} \geq b_l \quad \text{and} \quad r_{0l}t_{dl} \geq b_l. \quad (4.2)$$

Similarly, if pair-$l$ is in D2D mode, $t_l$ and $r_{ll}$ must satisfy

$$r_{ll}t_l \geq b_l. \quad (4.3)$$

The limitation on the transmission power levels, together with the session rate requirements above, entail the need to verify under which conditions the communication of a pair can be supported by the network. To this end, we introduce the concept of power-feasibility:

Definition 4.1.1 (Power feasibility). We say that the communication of user pair-$l$ is power-feasible.
(a) in D2D mode if \( r_{ll}^{\text{max}} T \geq b_l; \)

(b) in cellular mode if there exists a time allocation \((t_{ul}, t_{dl})\) such that

\[
\begin{align*}
    t_{dl} & \geq \frac{b_l}{r_{dl}^{\text{max}}} \\
    t_{ul} & \geq \frac{b_l}{r_{ul}^{\text{max}}} \\
    t_{ul} + t_{dl} & \leq T.
\end{align*}
\] (4.4)

**Assumption 4.1.2.** There exists a time allocation \((t_{ul}, t_{dl})\) which can support the communication of all users in cellular mode.

**Remark 4.1.3.** The power-feasibility condition (4.4) implies that \( t_{ul} \) must satisfy

\[
\frac{b_l}{r_{ul}^{\text{max}}} \leq t_{ul} \leq T - \frac{b_l}{r_{ul}^{\text{max}}}. 
\] (4.5)

Thus, under Assumption 4.1.1, it must hold that \( \max_l \{ \frac{b_l}{r_{ul}^{\text{max}}} \} \leq \min_l \{ T - \frac{b_l}{r_{ul}^{\text{max}}} \} \).

By rewriting the power-rate relations (4.1), we find the transmission energy necessary to satisfy the session rate requirement \( b_l \) of pair-\( l \), for a given time allocation \((t_{ul}, t_{dl})\)

\[
\begin{align*}
    E_{l0}(t_{ul}) &= P_{l0} t_{ul} = \left( \exp \left( \frac{b_l}{W t_{ul}} \right) - 1 \right) \frac{\sigma^2}{G_{l0}} t_{ul}, & \text{UL, cellular mode;} \\
    E_{0l}(t_{dl}) &= P_{0l} t_{dl} = \left( \exp \left( \frac{b_l}{W t_{dl}} \right) - 1 \right) \frac{\sigma^2}{G_{0l}} t_{dl}, & \text{DL, cellular mode;} \\
    E_{ll}^{\text{D2D}}(t_t, I_l) &= P_{ll} t_t = \left( \exp \left( \frac{b_l}{W t_{ll}} \right) - 1 \right) \frac{\sigma^2 + I_l}{G_{ll}} t_{ll}, & \text{D2D mode.}
\end{align*}
\] (4.6)

These functions are convex and monotonically decreasing in their arguments (see [76] and references therein). This observation leads to the following result:

**Lemma 4.1.4.** When minimizing the transmission energy, optimal solution must allocate the full frame duration for communication. For the D2D mode, this implies that

\[
\min_{t_t, I_l} E_{ll}^{\text{D2D}}(t_t, I_l) = \min_{I_l} E_{ll}^{\text{D2D}}(T, I_l).
\]

For cellular mode, where the energy consumption is given by the sum \( E_{l0}(t_{ul}) + E_{0l}(t_{dl}) \), it must hold that \( t_{ul} + t_{dl} = T \).

The transmission energy cost for communicating in cellular mode includes both the energy cost of the transmitting mobile device and that of the BS. However, the BS often has access to cheap and abundant energy in comparison with the user equipment, in which case it is relevant to only focus on the device energy, aiming at prolonging its battery life. To this end, we consider the following two definitions of energy consumption for a generic user pair-\( l \) in cellular mode:
4.2 Problem statement

- The **System Energy consumption (SE)**: is the energy consumed by both Tx-$l$ in UL and the BS in DL. By Lemma 4.1.4, the minimum energy cost is obtained by minimizing

\[ E_{ll}^{\text{CELL}}(t_{ul}) = E_{l0}(t_{ul}) + E_{0l}(T - t_{ul}), \]  

which is a convex function of $t_{ul}$.

- The **User Energy consumption (UE)**: is the energy consumed by Tx-$l$ in UL transmission, disregarding the energy spent by the BS in DL, that is

\[ E_{ll}^{\text{CELL}}(t_{ul}) = E_{l0}(t_{ul}), \]  

which is a convex and monotonically decreasing function of $t_{ul}$.

### 4.2 Problem statement

We consider the problem of minimizing the transmission energy consumption of a D2D-enabled cellular network with dynamic TDD system, by jointly optimizing:

i) the communication mode of each user pair, ii) the UL/DL time configuration, and iii) the powers allocated to all transmitters. Since we are interested in two possible energy cost functions (SE and UE) and two channel allocation strategies for D2D communications (FO and RS), we obtain four variations of the energy minimization problem, which all can be formulated as MINLPs. Table 4.1 summarizes the main results for these four cases, with the section number for easy reference.

<table>
<thead>
<tr>
<th></th>
<th>UE</th>
<th>SE</th>
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<tr>
<td>FO</td>
<td>Optimal solution in linear time (§ 4.3)</td>
<td>Optimal solution in polynomial time (§ 4.3)</td>
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<tr>
<td>RS</td>
<td>Optimal solution with B&amp;B (§ 4.4.1), Suboptimal solution with heuristic (§ 4.4.1)</td>
<td>Optimal solution with B&amp;B (§ 4.4.1)</td>
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</table>

### 4.3 Minimizing the energy consumption with Full Orthogonality

In this section, we show how the jointly optimal mode selection and resource (time and power) allocation with FO can be found in polynomial time, even though the overall problem is not convex. For ease of exposition, we first derive the optimal solution for a single user pair, and then extend the results to multiple user pairs.

#### 4.3.1 Single user pair

We first characterize the minimum energy cost for a pair to fulfil the rate requirement when in cellular and when in D2D mode. We show that the minimal SE cost can be
found by solving a simple convex optimization problem, while the minimal UE cost admits an explicit expression.

**Minimum energy cost for communication in cellular mode.** In cellular mode, the UL/DL time allocation is chosen to minimize one of the following two objectives:

- **Minimizing SE:** The minimum amount of energy of pair-$l$ in cellular mode can be determined by solving the following single-variable convex optimization problem:

  \[
  \text{minimize} \quad E_{l0}(t_{ul}) + E_{0l}(T - t_{ul}) \quad \text{(4.9a)}
  \]

  subject to \( \frac{b_l}{r_{l0}^{\text{max}}} \leq t_{ul} \leq T - \frac{b_l}{r_{0l}^{\text{max}}} \), \( \text{(4.9b)} \)

  where constraint (4.9b) ensures power feasibility in the sense of Definition 4.1.1. Problem (4.9) can be solved efficiently using a wide variety of methods, e.g., bisection search [77]. Let \( t_{ul}^* \) denote the optimal solution to (4.9). The energy cost of pair-$l$ in cellular mode is then

  \[
  E_{ll}^{\text{CELL}}(t_{ul}^*) = E_{l0}(t_{ul}^*) + E_{0l}(T - t_{ul}^*). \quad \text{(4.10)}
  \]

- **Minimizing UE:** Here, the only difference from the problem formulation in (4.9) is that the objective function reduces to \( E_{l0}(t_{ul}) \). By monotonicity of the objective function, the optimal solution is attained by \( t_{ul}^* = T - \frac{b_l}{r_{0l}^{\text{max}}} \), with the corresponding optimal energy cost

  \[
  E_{ll}^{\text{CELL}}(t_{ul}^*) = E_{l0}(T - \frac{b_l}{r_{0l}^{\text{max}}}). \quad \text{(4.11)}
  \]

**Minimum energy cost for communication in D2D mode.** In the D2D mode, no traffic is forwarded through the BS and only the user equipment consumes energy for the connection. The minimum energy cost follows from Lemma 4.1.4, with \( I_l = 0 \):

\[
E_{ll}^{\text{D2D}} = \left( \exp \left( \frac{b_l}{WT} \right) - 1 \right) \frac{\sigma^2}{G_{ll}} T. \quad \text{(4.12)}
\]

Equation (4.12) is only valid when the D2D mode is power feasible. Since we have ensured power feasibility only for communications in cellular mode (Assumption 4.1.2), we need to verify that \( r_{ll}^{\text{max}}T \leq b_l \) before applying (4.12). To this end, we consider the extended value function

\[
\bar{E}_{ll}^{\text{D2D}} = \left\{ \begin{array}{ll}
(\exp \left( \frac{b_l}{WT} \right) - 1) & \frac{\sigma^2}{G_{ll}} T \quad \text{if} \quad r_{ll}^{\text{max}}T \leq b_l \\
+\infty & \text{otherwise}.
\end{array} \right. \quad \text{(4.13)}
\]
4.3. Minimizing the energy consumption with Full Orthogonality

Optimal mode selection policy and resource allocation. The optimal mode selection policy for the single user pair case, consists in first solving the convex optimization problem to estimate the minimum energy cost for cellular mode (either for the UE or for the SE case), and then comparing it with the energy cost for D2D mode. The optimal communication mode is simply the one that requires the least amount of energy.

Once the optimal communication mode and the optimal transmission time has been selected, the corresponding optimal powers are easily derived as

\[ P_{l0} = \left( \exp\left( \frac{b_l}{W t_{ul}^*} \right) - 1 \right) \frac{\sigma^2}{G_{l0}}, \quad \text{UL, cellular mode;} \]
\[ P_{0l} = \left( \exp\left( \frac{b_l}{W(T - t_{ul}^*)} \right) - 1 \right) \frac{\sigma^2}{G_{0l}}, \quad \text{DL, cellular mode;} \]
\[ P_{ll} = \left( \exp\left( \frac{b_l}{W T} \right) - 1 \right) \frac{\sigma^2}{G_{ll}}, \quad \text{D2D mode.} \]

It is possible to interpret the mode selection policy in terms of the channel gain (and, so, the physical distance) between the two communicating devices. We will explore this geometrical interpretation in § 4.5 to characterize regions in the cell where D2D communication is preferable.

4.3.2 Multiple user pairs

The main challenge with multiple user pairs in fully orthogonal operation is that all cellular connections must use a common UL/DL time allocation. To formulate the joint mode selection and time allocation problem for multiple pairs under full orthogonality, we introduce the mode selection vector \( \mathbf{m} \in \{0, 1\}^L \) whose entries satisfy

\[ m_l = \begin{cases} 
0 & \text{if pair-}l \text{ is in cellular mode,} \\
1 & \text{if pair-}l \text{ is in D2D mode,}
\end{cases} \]  

and consider the following MINLP problem

\[
\begin{align*}
\text{minimize} & \quad \sum_{l=1}^L E_{l0}^{2D} m_l + E_{ll}^{CEL}(t_{ul})(1 - m_l) \\
\text{subject to} & \quad \frac{b_l}{r_{l0}^{\max}} - T m_l \leq t_{ul} \leq T - \frac{b_l}{r_{0l}^{\max}} + T m_l, \quad \forall l, \\
& \quad t_{ul} \in [0, T], \quad m_l \in \{0, 1\}, \quad \forall l.
\end{align*}
\]

The objective function in (4.16) is the total energy consumption of all the \( L \) user pairs, with \( E_{ll}^{CEL}(t_{ul}) \) given by (4.7) or (4.8) under FO-SE or FO-UE, respectively. Here, we assume that D2D pairs do not interfere with each other, and their minimal energy consumption is the same constant value given in (4.13) as in the single user
pair case. Constraints (4.16b) ensure that pair-$l$ can only be assigned to cellular mode if it is power feasible in the sense of Definition 4.1.1.

Since (4.16a) is separable in $m_l$, we can express the objective in terms of the transmission energy for each device when operating in its optimal mode. In other words, we rewrite (4.16) as

$$\text{minimize}_{t_{ul} \in [0,T]} F(t_{ul}), \quad (4.17)$$

where $F(t_{ul}) = \sum_{l=1}^{L} E_l(t_{ul})$, and $E_l(t_{ul})$ denotes the minimum energy-cost for the single pair-$l$ when the UL time is fixed to $t_{ul}$, that is

$$E_l(t_{ul}) = \begin{cases} \min\{E_{ll}^{D2D}, E_{ll}^{CELL}(t_{ul})\} & \text{if } t_{ul} \in \left[\frac{b_l}{r_{l0}^{\max}}, T - \frac{b_l}{r_{l0}^{\max}}\right] \\ E_{ll}^{D2D} & \text{otherwise.} \end{cases} \quad (4.18)$$

Equation (4.18) reveals the piecewise nature of $E_l(t_{ul})$. For $t_{ul} < \frac{b_l}{r_{l0}^{\max}}$ and $t_{ul} > T - \frac{b_l}{r_{l0}^{\max}}$, we have $E_l(t_{ul}) = E_{ll}^{D2D}$, which is a finite constant if user pair-$l$ is power feasible in D2D mode, and $+\infty$ otherwise. In the interval $[\frac{b_l}{r_{l0}^{\max}}, T - \frac{b_l}{r_{l0}^{\max}}]$, $E_l(t_{ul})$ is either equal to the constant $E_{ll}^{D2D}$, or given by $E_{ll}^{CELL}(t_{ul})$, depending on whether and at which points the graphs of $E_{ll}^{CELL}(t_{ul})$ and $E_{ll}^{D2D}$ intersect. Note that the two graphs can intersect only once if $E_{ll}^{CELL}(t_{ul})$ is monotonically decreasing (i.e. when minimizing UE) or twice if it is convex (i.e. when minimizing SE). To better describe the piecewise nature of $E_l(t_{ul})$, we introduce $\Delta_l = [\tau_l^{\min}, \tau_l^{\max}]$ as the interval of $t_{ul}$ during which $E_l(t_{ul}) = E_{ll}^{CELL}(t_{ul})$. If, for a pair-$l$, such an interval does not exist (i.e., $\Delta_l = \emptyset$), this means that it is always more efficient for the pair to operate in D2D mode. See Fig. 4.2 for an illustration.

Figures 4.3 and 4.4 show the minimum energy-cost of three user pairs (obtained as in Fig. 4.2), and the corresponding $F(t_{ul})$, under FO-UE and FO-SE, respectively. Note that function $F(t_{ul})$ is non-convex on the interval $[0,T]$. However, the following lemma establishes a key property of $F(t_{ul})$, useful later to solve Problem (4.17).

**Lemma 4.3.1.** (a) In the FO-SE scenario, $F(t_{ul})$ is a piecewise convex function.

(b) In the FO-UE scenario, $F(t_{ul})$ is a piecewise decreasing function.

**Proof.** For each pair-$l$, if $\Delta_l = \emptyset$, by its definition, $E_{ll}^{CELL}(t_{ul})$ is a constant value on $[0,T]$. Otherwise, $E_{ll}^{CELL}(t_{ul})$ is a constant value or $+\infty$ in the two intervals $[0, \tau_l^{\min})$ and $(\tau_l^{\max}, T]$. During the interval $[\tau_l^{\min}, \tau_l^{\max}]$, in the FO-SE case $E_{ll}^{CELL}(t_{ul})$ is a convex function of $t_{ul}$ (given by (4.7)); in the FO-UE case, $E_{ll}^{CELL}(t_{ul})$ is a monotonically decreasing function in $t_{ul}$ (given by (4.8)). The function $F(t_{ul})$ is obtained as the sum of $E_{ll}^{CELL}(t_{ul})$ of all $L$ pairs. Hence, the whole interval $[0,T]$ is divided into $J \leq 2L + 1$ adjacent intervals.

In the FO-UE case, $F(t_{ul})$ is the sum of constants and convex functions in each interval, which makes $F(t_{ul})$ piecewise convex. In the FO-UE case, on the other hand, $F(t_{ul})$ is the sum of constants and monotonically decreasing functions in each interval, which makes $F(t_{ul})$ piecewise decreasing. \qed
4.3. Minimizing the energy consumption with Full Orthogonality

Figure 4.2: Deriving \( E_l(t_{ul}) \) under both the FO-UE case (a), and the FO-SE case (b), with frame duration \( T = 1 \) time unit. The time interval \( \Delta_t = [\tau_{\text{min}}^{l1}, \tau_{\text{max}}^{l1}] \) is the intersection of the the interval \( [\frac{t_{ul}}{r_{l0}}, T - \frac{t_{ul}}{r_{l0}}] \) for power feasibility in cellular mode, with the interval bounded by the intersection points of the graphs of \( E^{CELL}_{ll}(t_{ul}) \) and \( \bar{E}^{D2D}_{ll} \). In particular, if the two curves never intersect. \( \Delta_t = \emptyset \).

\begin{align*}
\tau_{\text{min}}^{l1} & \leq t_{ul} \leq \tau_{\text{max}}^{l1} \\
\tau_{\text{min}}^{l2} & \leq t_{ul} \leq \tau_{\text{max}}^{l2}
\end{align*}

(a) FO-UE single link case  
(b) FO-SE single link case

Figure 4.3: FO-UE problem with the time frame duration \( T = 1 \): minimum energy-cost functions of three transmitter-receiver pairs (a), and their sum \( F(t_{ul}) \) (b).

Based on Lemma 4.3.1, the optimal solution to (4.17) can be computed efficiently, leveraging on the following results:

**Proposition 4.3.2.** (a) In the FO-SE case, let \( \cup_{j=1}^J \Gamma_j \) be a partition of \( [0, T] \)
induced by the points \( \{ \tau_1^{\text{min}}, \tau_1^{\text{max}}, \ldots, \tau_L^{\text{min}}, \tau_L^{\text{max}} \} \). Then, the optimal UL time allocation \( t_{ul}^* \) can be found by solving at most \( 2L - 1 \) single-variable convex optimization problems of the form

\[
\min_{t_{ul} \in \Gamma_j} \sum_{l \in \mathcal{L}} E_l(t_{ul})
\]

(b) In the FO-UE case, the optimal UL time allocation \( t_{ul}^* \in \{ \tau_1^{\text{max}}, \tau_2^{\text{max}}, \ldots, \tau_L^{\text{max}} \} \). Moreover, if \( \max_l \{ \tau_l^{\text{min}} \} \leq \min_l \{ \tau_l^{\text{max}} \} \), then \( t_{ul}^* = \min_l \{ \tau_l^{\text{max}} \} = \min \{ T - \frac{b_{ul}}{\bar{z}} \} \).

Proof. Since for each user pair-\( l \), \( E_l^{\text{CELL}}(t_{ul}) \) reaches its maximum value during the two intervals \( [0, \tau_i^{\text{min}}] \) and \( (\tau_l^{\text{max}}, T] \), \( F(t_{ul}) \) achieves its maximum value in the two intervals \( \Gamma_1 = [0, \min_l \{ \tau_l^{\text{min}} \}] \) and \( \Gamma_J = [\max_l \{ \tau_l^{\text{max}} \}, T] \). Hence, \( t_{ul}^* \) is not in \( \Gamma_1 \) and \( \Gamma_J \), but must be found in one of the remaining (at most) \( 2L - 1 \) intervals. By Lemma 4.3.1, in the FO-SE case, \( F(t_{ul}) \) is piecewise convex. Hence, its global minimum can be found among its \( 2L - 1 \) local minima in each interval. In the FO-UE case we know that, from Lemma 4.3.1, \( F(t_{ul}) \) is piecewise decreasing. Thus, its global minimum can be found in the set \( \bigcup_{l \in \mathcal{L}} \{ \tau_l^{\text{min}}, \tau_l^{\text{max}} \} \). However, for each \( \tau_l^{\text{min}} \), there is at least one component \( E_l(t_{ul}) \) in the sum defining \( F(t_{ul}) \), that decreases for \( t_{ul} \geq \tau_l^{\text{min}} \). Therefore, the global minimum can only be found in the set \( \{ \tau_l^{\text{max}}, l \in \mathcal{L} \} \). Furthermore, if \( \max_l \{ \tau_l^{\text{min}} \} \leq \min_l \{ \tau_l^{\text{max}} \} \), then \( t_{ul}^* = \min \{ \tau_l^{\text{max}} \} \).

Given the optimal solution \( t_{ul}^* \) to problem (4.17), the optimal mode selection vector \( \mathbf{m}^* \) of Problem (4.16) is then given by setting, \( \forall l \in \mathcal{L} \):

\[
m_l^* = \begin{cases} 0 & \text{if } E_{lul}^{\text{CELL}}(t_{ul}^*) \leq E_{lul}^{\text{D2D}} \\ 1 & \text{otherwise,} \end{cases}
\]
while the corresponding optimal transmission powers are derived as in (4.14).

4.4 Minimizing the energy consumption with D2D Resource Sharing

To increase the cell capacity and the spectral efficiency of the system, we now consider the D2D resource sharing strategy, where all communications in D2D mode are assigned the same channel resource. Due to the cross interference among multiple D2D pairs, the optimal solutions for this scenario are more complicated to compute. Nevertheless, we develop a combinatorial optimization algorithm that is guaranteed to find the optimal solution, and often does so very quickly. This off-line algorithm is complemented by a heuristic, suitable for real-time implementation under practical signaling constraints.

4.4.1 Optimal solution via MINLP

The effect of the interference on the energy consumption for D2D communication appears explicitly in (4.6). Due to the fixed time allocation $T$ (see Lemma 4.1.4), minimizing the energy consumption of D2D communications is equivalent to minimizing the transmission powers. To meet the minimum rate requirement in (4.3), the transmission power of any pair-$l$ in D2D mode must be such that

$$P_{ll} \geq \left[ \exp \left( \frac{b_l}{WT} \right) - 1 \right] \frac{\sigma^2 + I_l}{G_{ll}}. \quad (4.19)$$

Introducing $\gamma_{l}^{tgt} = \left[ \exp \left( \frac{b_l}{WT} \right) - 1 \right]$ as the target SINR required to satisfy the session rate requirement of pair-$l$, and the terms $\eta_l = \frac{\gamma_{l}^{tgt} \sigma^2}{G_{ll}}$ and $h_{lj} = \gamma_{l}^{tgt} \frac{G_{jl}}{G_{ll}}$, we can re-write this inequality as

$$P_{ll} \geq \eta_l + \sum_{j \neq l} P_{jj} h_{lj}. \quad (4.19)$$

The joint mode selection and power/time allocation problem can now be formulated as the following MINLP problem:

\[
\begin{align*}
\text{minimize} & \quad \sum_{l=1}^{L} (TP_{ll}) m_l + E_{ll}^{CELL}(t_{ul})(1 - m_l) \\
\text{subject to} & \quad \frac{b_l}{r_{l0}^{\max}} - Tm_l \leq t_{ul} \leq T - \frac{b_l}{r_{l0}^{\max}} + Tm_l, \quad \forall l, \\
& \quad \left[ \eta_l + \sum_{j \neq l} P_{jj} h_{lj} \right] - C(1 - m_l) \leq P_{ll}, \quad \forall l, \\
& \quad P_{ll} \leq P_{l}^{\max} m_l, \quad \forall l \quad (4.20d) \\
& \quad m \in \{0, 1\}^L, \quad t_{ul} \in [0, T], \quad P_{ll} \geq 0. \quad (4.20e)
\end{align*}
\]
Here, \( \mathbf{m} \) is the mode selection vector defined in (4.15). Constraint (4.20b) ensures power feasibility for pairs in cellular mode, while (4.20c) guarantees that the rate requirement is satisfied for each pair in D2D mode. Finally, (4.20c) bounds the transmit power level. The constant \( C \) in (4.20c) is a large number (e.g., \( C = \max_l \{ \eta_l + \sum_l P_{ll}^{\text{max}} \} \)) ensuring that the constraint is only enforced for users in D2D mode. The expression for \( E_{ul}^{\text{CELL}}(t_{ul}) \) in the objective function is either (4.7) or (4.8), depending on whether we are interested in the RS-SE or RS-UE problem, respectively.

Problem (4.20) belongs to the class of mixed boolean-convex problems, where for each fixed \( \mathbf{m} \in \{0, 1\}^L \) the objective function is convex in the continuous variables. In general, MINLPs are NP-hard problems \([78]\), combining the combinatorial difficulty of optimizing over discrete variable sets, with the challenges of handling nonlinear functions. Their solution times grow exponentially with the problem dimension. In particular, if \( L \) in (4.20) is very small (i.e., smaller than 15), the optimization problem can be solved exactly by exhaustive enumeration of the \( 2^L \) possible mode selection vectors. However, realistic cellular networks might consist of a large number of user pairs. For this reason, we develop a customized solver based on B&B (see, e.g., \([79, 80]\)). Special attention is given to developing novel variable selection and branching rules, along with efficient procedures for infeasibility detection and performance bound computations. This solver allows us to find provably optimal solutions much more efficiently than using generic B&B solvers or naive exhaustive search.

In the sequel, we will focus on algorithms that solve the RS-UE problem, considering that the mobile devices are the most energy-sensitive component of the network. However, the same approaches can be applied to the RS-SE case.

### A branch-and-bound approach for finding the optimal solution

Before describing the proposed B&B algorithm, it is convenient to introduce a definition and two useful propositions on the feasibility of the mode selection vector \( \mathbf{m} \). Let \( \mathbf{H} \) be a non-negative matrix with entries \( H_{lj} = h_{lj} \) if \( l \neq j \), and zero otherwise, and let us introduce the vectors \( \mathbf{P} = (P_{ll}, \forall l \in \mathcal{L})^\top \), \( \mathbf{P}^{\text{max}} = (P_l^{\text{max}}, \forall l \in \mathcal{L})^\top \) and \( \boldsymbol{\eta} = (\eta_l, \forall l \in \mathcal{L})^\top \). For each mode selection vector \( \mathbf{m} \), we can define the corresponding set of pairs assigned to D2D mode and to cellular mode as \( \mathcal{D}_m \) and \( \mathcal{C}_m \), respectively. Let \( \mathbf{A}_m \) denote the \( L \times |\mathcal{D}_m| \) incidence matrix, which is formed by removing the \( l \)-th column from the \( L \times L \) identity matrix if \( m_l = 0 \). We define \( \mathbf{H}_m = \mathbf{A}_m^\top \mathbf{H} \mathbf{A}_m \), \( \mathbf{P}_m = \mathbf{A}_m^\top \mathbf{P} \), \( \mathbf{I}_m = \mathbf{A}_m^\top \mathbf{A}_m \), \( \mathbf{P}_m^{\text{max}} = \mathbf{A}_m^\top \mathbf{P}_{\text{max}} \) and \( \boldsymbol{\eta}_m = \mathbf{A}_m^\top \boldsymbol{\eta} \). Constraints (4.20c) and (4.20d) can be written in matrix form as

\[
(\mathbf{I}_m - \mathbf{H}_m)\mathbf{P}_m \geq \boldsymbol{\eta}_m \quad \text{and} \quad \mathbf{P}_m \leq \mathbf{P}_m^{\text{max}}, \quad (4.21)
\]

where the inequalities are component-wise, \( \mathbf{I}_m = \mathbf{A}_m^\top \mathbf{A}_m \), and \( \mathbf{P}_m^{\text{max}} = \mathbf{A}_m^\top \mathbf{P}_{\text{max}} \).

The matrix \( \mathbf{H}_m \) has strictly positive off-diagonal elements, and we can assume that it is irreducible because we do not consider totally isolated groups of pairs that
do not interact with each other. Let $\rho(H_m)$ denote the largest real eigenvalue of $H_m$. From the Perron-Frobenius theorem [81], we have the following proposition:

**Proposition 4.4.1** ([82] Chapter 2). For a given mode selection vector $m$, the necessary and sufficient condition for the existence of a positive $P_m$ to solve inequality $(I_m - H_m)P_m \geq \eta_m$ is that

$$\rho(H_m) < 1.$$  

(4.22)

Moreover, $P^*_m = (I_m - H_m)^{-1}\eta_m$ is its component-wise minimum solution.

Proposition 4.4.1 provides an easy condition to verify if a mode selection vector $m$ is feasible.

**Definition 4.4.2** (Feasible mode selection vector). A mode selection vector $m$ is feasible if both condition (4.22) and $(I_m - H_m)^{-1}\eta_m \leq P^\text{max}_m$ are verified.

**Proposition 4.4.3** ([83]). If $m$ is not feasible, then every other mode selection vector $\hat{m}$ with additional users assigned to D2D mode, i.e. such that \(\{l \in L : m_l = 1\} \subseteq \{l \in L : \hat{m}_l = 1\}\), is not feasible.

We now use the results above to design a B&B algorithm that solves the MINLP problem in (4.20). When using a B&B approach, all possible mode selection vectors $m$ are explored through a binary tree. Each node of the tree (except the root) represents a subproblem where one of the mode selection variables $m_l$ is set to either 0 or 1. Thus, to each node corresponds a partial mode selection vector with some components already defined (fixed) and forming the set $F$, while others are still undetermined and represent the set $U$. Therefore, each branch of the tree corresponds to a subset of the possible mode selection vectors. The main idea of B&B is to only explore branches of the binary tree that have the potential to produce better solutions than the best solution found so far, and disregard (prune) the others. This is done by computing upper and lower bounds on the optimal value at each node. If the lower bound of a node is larger than the current upper bound, then there is no need to explore its branches. To achieve a good performance of B&B, it is essential to select the branching rule and tree exploration strategies carefully, and to have efficient methods for computing good (tight) upper and lower bounds [84].

The flowchart in Fig. 4.5 summarizes the proposed B&B algorithm. It is based on the following four choices: 1) the computation of the initial upper bound (UB), where we assume all pairs in cellular mode; 2) the branching rule that selects the variable to fix at each node as the one that increases the likelihood of finding infeasible mode selection vectors, to exploit Proposition 4.4.3, to exploit Proposition 4.4.3 to prune branches; 3) the tree exploration strategy that assigns the selected branching variable to 1 first (i.e., D2D mode comes first as a choice); and, finally, 4) the computation of the upper and lower bounds (Node-UB and Node-LB) as the sum of the minimum energy cost of the pairs in $F$ plus an upper and lower bound of the energy cost of the pairs in $U$, respectively. We refer to Appendix A for a detailed description and motivation of each such choice.
Once the optimal mode selection vector and the corresponding optimal transmission time have been found, the power levels are obtained as in (4.14) for cellular users, and as in Proposition 4.4.1 for D2D users.

The B&B algorithm is guaranteed to find the optimal solution, and does so much faster than the exhaustive search, as shown in § 4.5.2. However, for large networks it can still have impractical running times. In addition, the optimization formulation assumes that all cross-gains between users are known, which in turn would impose significant communication overhead. We therefore turn our attention to heuristics that can be run in real-time and do not assume centralized knowledge of all the channel gains.

A heuristic approach to achieve a practical sub-optimal solution

In this subsection, we present a heuristic algorithm that achieves a near-optimal solution to (4.20) in a more practical and scalable way than the B&B approach. Again, we focus on the UE case.

The key idea of this algorithm is to first determine an initial mode selection vector, together with the corresponding power and time allocation, and then improve this solution by means of a distributed power control algorithm based only on local measurements. The heuristic algorithm, described in Algorithm 1, consists of the
4.4. Minimizing the energy consumption with D2D Resource Sharing

following three main steps:

**Algorithm 1**: Heuristic approach for RS-UE minimization

- **Input**: $(\gamma_{l}^{tgt}, G_{ll}, G_{0l}, G_{0l}) \forall l \in L, \theta$
- **Output**: $m^*, p^*$

1. $(m^{FO}, t_{ul}(m^{FO}), p(m^{FO})) \leftarrow$ solution to FO-UE problem;
2. each $l \in D_{m^{FO}}$ acquires $E_{CELL}^{ll}(t_{ul}(m^{FO}))$ from the BS;
3. $p^{(0)} \leftarrow p(m^{FO})$, $m^{(0)} \leftarrow m^{FO}$, $k = 0$;
4. each $l \in D_{m^{FO}}$ computes $\gamma_{l}^{(0)}$;
5. convergence $\leftarrow$ False;
6. while $\neg$ convergence do
   7. $m^{(k+1)} \leftarrow m^{(k)}$;
   8. for each $l \in D_{m^{(k)}}$ do
      9. $P_{ll}^{(k+1)} = \frac{\gamma_{l}^{tgt}}{\gamma_{l}^{(k)}} P_{ll}^{(k)}$;
      10. if $P_{ll}^{(k+1)} > \min \{ \frac{\theta}{\gamma_{l}^{tgt}} E_{CELL}^{ll}(t_{ul}(m^{FO})), P_{max}^{ll} \}$ then
         11. $m_{l}^{(k+1)} \leftarrow 0$, $D_{m^{(k+1)}} \leftarrow D_{m^{(k)}} \setminus \{l\}$;
   12. each $l \in D_{m^{(k+1)}}$ computes $\gamma_{l}^{(k+1)}$;
   13. if $\gamma_{l}^{(k+1)} \geq \gamma_{l}^{tgt}, \forall l \in D_{m^{(k+1)}}$ then
      14. convergence $\leftarrow$ True;
15. $p^* \leftarrow p^{(k+1)}$, $m^* \leftarrow m^{(k+1)}$.

1. **Initial phase**: We adopt the optimal solution to the FO-UE problem in Section 4.3 as the initial solution, denoted by $(m^{FO}, t_{ul}(m^{FO}), p(m^{FO}))$. The FO-UE problem is solved by the BS. For each pair $l \in D_{m^{FO}}$ (i.e., assigned to D2D mode), the BS also computes the energy it would consume if in cellular mode, that is $E_{CELL}^{ll}(t_{ul}(m^{FO}))$ from (4.8), and broadcasts $m^{FO}$ and $E_{CELL}^{ll}(t_{ul}(m^{FO}))$ to each Tx-$l \in D_{m^{FO}}$.

The initial mode selection vector $m^{FO}$ is obtained under the assumption of no interference among the D2D pairs. However, under the RS scenario, all the D2D pairs share the same channel, thus $m^{FO}$ can be energy inefficient, or even infeasible, due to the interference. Therefore, a distributed power control algorithm is then executed by the D2D pairs to find a feasible and more energy-efficient solution:

2. **Iterative distributed power control for D2D pairs**: Using the iterative power control method originally proposed by Foschini and Miljanic in [85], each Tx-$l$ in D2D mode can achieve its target SINR $\gamma_{l}^{tgt}$ by updating its transmit power as follows

$$P_{ll}^{(k+1)} = \frac{\gamma_{l}^{tgt}}{\gamma_{l}^{(k)}} P_{ll}^{(k)}, \quad (4.23)$$
44 Mode selection and resource allocation in dynamic TDD system

where $P^{(0)} = P(m^{FO})$ and $\gamma^{(k)}_l$ is the perceived SINR for pair-$l \in D_{m^{FO}}$ in iteration-$k$, defined as $\gamma^{(k)}_l = P^{(k)}_l G_{ll}/(\sigma^2 + \sum_{j \in D_{m^{FO}}, j \neq l} P^{(k)}_j G_{jl})$.

To achieve a feasible mode selection vector and to further reduce the energy cost, some links in D2D mode need to switch to cellular mode. Specifically, pair-$l$ in D2D mode will switch to cellular mode if its transmit power level exceeds its maximum limit or if it is more energy efficient for it to communicate in cellular mode, that is, if

$$P^{(k)}_l > \min \left\{ \frac{\theta}{T} E_{CELL}^{C}(t_{ul}(m^{FO})), P^{\max}_l \right\},$$

(4.24)

where we introduce the design parameter $\theta \geq 1$; see Remark 4.4.1. During the power update (4.23), if Tx-$l$ finds that condition (4.24) is fulfilled, it asks the BS to switch it to cellular mode and to assign it an orthogonal frequency channel. Otherwise, it keeps updating its power according to (4.23). The BS keeps track of the pairs changing communication mode, and updates the mode selection vector. This power control algorithm converges to the minimum power levels that the user pairs remaining in D2D mode need to fulfil the rate requirement.

3. **Final phase:** Once the algorithm converges, the BS recomputes the optimal power/time allocation for the user pairs in cellular mode, broadcasting this information before the data transmissions take place.

**On the selection of parameter $\theta$.** The selection of parameter $\theta$ accounts for the following key aspects of the possible practical implementation of the proposed heuristic algorithm:

- Tradeoff between signaling overhead and energy gain: Communication mode switches incur additional signaling overhead between mobile devices and the BS to coordinate the re-allocation of radio resources. Hence, by setting $\theta > 1$, mode switches will occur only if they result in a significant energy gain.

- Tradeoff between channel reuse and energy consumption: Since moving a user pair from D2D mode to cellular mode requires another orthogonal channel, a large value of $\theta$ can enforce more pairs to communicate in D2D mode and thus increase the channel reuse, even if this comes at the cost of a higher energy consumption due to the interference.

- Accounting for the mis-estimation of the energy cost: D2D pairs base their selection to switch communication mode on an under-estimate of the energy consumption in cellular mode (Eq. (4.24)). Since the optimal UL transmission time computed when Algorithm 1 has converged will be greater or equal to the initial $t_{ul}(m^{FO})$, the actual energy consumption in cellular mode can be larger than expected. Using $\theta > 1$ reserves a margin for mis-estimation so that only connections that truly gain by being in cellular switch to cellular.
4.5 Numerical results

This section presents simulation results that validate our theoretical findings and evaluate our proposed algorithms. We consider a single cell with a BS, equipped with an omnidirectional antenna, positioned in the center. The main simulation parameters are listed in Table 4.2.

![Table 4.2: Simulation parameters](image)

4.5.1 Single link analysis

**Geometrical interpretation.** We begin by developing a geometrical interpretation of the optimal mode selection policy for the single link case, under the assumption that the channel gains follow the conventional path loss model introduced in Chapter 3. The aim is to interpret the solution to the mode selection problem in terms of physical distance between the communicating devices, to characterize regions of the cell where D2D mode is optimal.

To ensure that Assumption 4.1.2 is satisfied, we set $b_l$ to its maximum value that guarantees that the constraint set of Problem (4.9) is never empty, i.e., $b_l = \frac{r_{\text{max}}^l}{r_{\text{max}}^0} T$, where the maximum rates $r_{\text{max}}^l$ and $r_{\text{max}}^0$ are functions of gains $G_{l0} = G_0 T_l^\alpha$ and $G_{0l} = G_0 R_{\text{cell}}^{-\alpha}$, respectively, with $R_{\text{cell}}$ being the cell radius.

We first consider the UE case. D2D communication is energy-optimal when $E_{D2D}^l(T) \leq E_{\text{CELL}}^l(t_{ul}^*)$, where $E_{D2D}^l(T)$ and $E_{\text{CELL}}^l(t_{ul}^*)$ are given by (4.11) and (4.13), respectively. Using the path loss model, we can transform the mode selection policy to the following equivalent condition on the distances between the transmitter, the receiver and the BS:

$$D_{ul} \leq \left( \frac{(e^{b_l/W T} - 1)T}{(e^{b_l/W t_{ul}^*} - 1)t_{ul}^*} \right)^{-1/\alpha} D_{l0} = \kappa(D_{0l}) D_{l0}. \quad (4.25)$$

Note that $\kappa$ is a function of $D_{0l}$, since $D_{0l}$ affects $r_{0l}^\text{max}$ and thereby $t_{ul}^* = T - b_l/r_{0l}^\text{max}$. Thus, even though we are neglecting the energy cost for the DL transmission, $D_{0l}$ still influences the optimal mode selection.

To characterize the region where D2D mode is preferable, we fix the position of Tx-$l$ (and therefore $D_{0l}$). We then vary the position of Rx-$l$ along a circle centred at the BS, thus keeping $D_{0l}$ (and $\kappa(D_{0l})$) constant. Inequality (4.25) now states that
D2D mode is preferable when the distance between the transmitter and receiver of pair-$l$ (i.e., $D_{ll}$) is less than $\kappa(D_{0l})D_{l0}$. In other words, D2D mode is more energy efficient when Tx-$l$ is located in the arc defined by the intersection of the circle of radius $D_{0l}$ centered at the BS, and the disc of radius $\kappa(D_{0l})D_{l0}$ centered at Tx-$l$. The D2D optimal area can be constructed by tracing out these arcs for various distances between Rx-$l$ and the BS, as illustrated in Fig. 4.6. The value of $\kappa(D_{0l})$, and thus the D2D optimal area, decreases as Rx-$l$ gets closer to the BS.

Fig. 4.7 illustrates the $D2D$-optimal area in red, and the $D2D$ power-feasible area in light blue, for two different locations of Tx-$l$. Although (4.25) does not formally describe a disc around Tx-$l$, the D2D-optimal area is close to circular. The reason for this is the power imbalance between the user equipment and the BS ($P_{0l} \gg P_{l0}$), which makes $b_l/t_{ul}^{\max}$ very small, $t_{ul} \approx T$ and $\kappa \approx 1$ practically independently of $D_{0l}$.

![Figure 4.6](image_url)

**Figure 4.6:** Dashed circles centred at the position of Tx-$l$ have radius $\kappa(D_{0l})D_{l0}$ from (4.25), and represent, for each of the two positions of Rx-$l$, the area within which D2D mode is more energy efficient than cellular mode for the UE case.

Similar calculations and arguments can be made for the SE objective. In this case, $E_{UL}^{\text{CELL}}(t_{ul}^{*}t_{ul})$ is given by (4.10) and the condition on the direct distance for optimal D2D mode gets a bit more involved (see [86]). In this case we have

$$D_{ll} \leq \left(\frac{(e^{b_lWT} - 1)(e^{b_lWT} - 1)T}{(e^{b_lWT} - 1)t_{ul}^{*}D_{l0}^\alpha + (e^{b_lWT} - 1)t_{dl}^{*}D_{0l}^\alpha}D_{0l}^\alpha\right)^{-1/\alpha} = \kappa(D_{l0}, D_{0l}).$$

(4.26)

Fig. 4.8 shows representative results for our simulation scenario. We observe that the D2D-optimal area is no longer circular and that the D2D mode is preferable in a large portion of the cell. In particular, we observe that the red arcs (D2D optimality area) enlarge as the receiver moves away from the BS. The reason is as follows. When Rx-$l$ moves towards the cell-edge, the feasible set of Problem (4.9) reduces, becoming a single point when the distance between the BS and Rx-$l$ equals the cell radius. In general, we could observe that there is a certain distance $D_{0l}$ after which the optimal solution $(t_{ul}^{*}, t_{dl}^{*})$ to Problem (4.9) remains the same. As a
4.5. Numerical results

Figure 4.7: D2D optimality area when minimizing the UE consumption. Red area represents the positions of Rx-l for which D2D mode is more energy efficient than cellular mode, while light blue disk represents the area within which Tx-l can fulfil the rate requirement transmitting in D2D mode with a feasible power level.

result, after that point, the threshold on the direct distance $D_{ll}$ for D2D optimality starts depending only on the parameter $D_{0l}$. Since it increases with $D_{0l}$, D2D mode results more preferable for larger arcs.

Figure 4.8: D2D optimality area when minimizing the SE consumption. Red area represents the positions of Rx-l for which D2D mode is more energy efficient than cellular mode, while light blue disk represents the area within which Tx-l can fulfil the rate requirement transmitting in D2D mode with a feasible power level.

4.5.2 Multiple link analysis: energy savings and algorithm performance

The simulation experiments for the multi-link case are set up as follows. We generate random network topologies with given number of user pairs. An example of network with 10 user pairs is given in Fig. 4.9.
Without loss of generality, we assume the same max transmission power level for all mobile devices, and the same traffic requirement for all pairs, indicated with $b$. To ensure Assumption 4.1.2, we set $b = \frac{r_{ul}^{\max} r_{dl}^{\max}}{r_{ul}^{\max} + r_{dl}^{\max}} T$, where $r_{ul}^{\max}$ and $r_{dl}^{\max}$ are the maximum achievable rate in UL and DL, respectively, when transmitter and receiver are both at the cell edge. For a given number of user pairs, we investigate 1000 random networks and present the averaged results.

![Network with 10 user pairs randomly placed in a cell of radius 500 m.](image)

**Figure 4.9:** Network with 10 user pairs randomly placed in a cell of radius 500 m. The red squares represent the transmitters and the green circles represent the receivers. Transmitter and receiver forming a pair are labelled with the same number.

**Energy gain by enabling D2D communications in a FO system.** To quantify the energy savings that can be obtained by exploiting D2D communications, we compare the energy cost of the optimal FO-UE solution with the one when all pairs are forced to communicate in cellular mode. For each random configuration used in our Monte Carlo study, we sort the links in order of increasing energy gain and then average over the 1000 values coming from the different simulations. Fig. 4.10 shows the results for networks with 10 and 30 user pairs.

From Fig. 4.10 we observe that when D2D communication is enabled, the average per user energy saving is $\sim 40\%$. In particular, one third of the pairs have an energy gain larger than 60\%, and half of the transmitters achieve an energy gain larger than 20\%. We highlight that the energy gain is not only a consequence of the proximity of the users, but also stems from the more advantageous full time frame allocation to the *single-hop* D2D connections.

**Performance evaluation of the B&B algorithm for RS-UE.** The difficulty in solving Problem (4.20) lies mainly in the possibly large search space of integer feasible points. Table 4.3 shows the average number of mode selection vectors explored by different strategies, before finding the optimal solution. We compare the B&B algorithm described in Section 4.4.1 (both with the proposed branching rule and with
4.5. Numerical results

(a) Networks with 10 user pairs
(b) Networks with 30 user pairs

Figure 4.10: Energy gain by enabling D2D communications in a FO system. User pairs are sorted in increasing order of the energy gain they achieve by performing mode selection, compared with traditional communication via the BS.

The results clearly show that the customized design of the branching rules have a strong effect in reducing the run time.

Table 4.3: Avg. number of explored integer solutions.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>10 user pairs</th>
<th>15 user pairs</th>
<th>20 user pairs</th>
<th>30 user pairs</th>
<th>40 user pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exhaustive search with Proposition 4.4.3</td>
<td>472.975</td>
<td>7.46 × 10^3</td>
<td>NA^a</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>B&amp;B - Random branching rule</td>
<td>69.472</td>
<td>251.21</td>
<td>915.13</td>
<td>1.3 × 10^4</td>
<td>NA</td>
</tr>
<tr>
<td>B&amp;B - Proposed branching rule</td>
<td>25.57</td>
<td>54.72</td>
<td>120.15</td>
<td>579</td>
<td>3.08 × 10^4</td>
</tr>
</tbody>
</table>

^aNA (not available) denotes the case when the optimal solution was not found within 8 hours on a standard PC.

Performance evaluation of the heuristic mode selection algorithm for RS-UE. In this section, we evaluate the performance of the proposed heuristic algorithm. Fig. 4.11 shows the additional energy cost of the heuristic relative to the optimal solution computed using the B&B solver. For networks with 10 user pairs, the heuristic is within 10% of the optimal solution for almost all network configurations; see Fig. 4.11(a). For networks with 30 user pairs (Fig. 4.11(b)), the performance of the heuristic is slightly worse. This degradation is due to the larger degree of freedom in packing D2D links on the same frequency channel. However, the solutions are still within the 10% suboptimality for most configurations.

Fig. 4.9 is an example of those few network configurations where the heuristic performs much worse than optimal algorithm (indicated with a red circle in Fig. 4.11). Under FO, both pair-9 and pair-4 in Fig. 4.9 would be assigned to D2D mode. When the heuristic initially attempts to assign these links to the same channel, it encounters an infeasible configuration due to the high interference that Rx-4 perceives from
Therefore, only one of the two pairs can be assigned to D2D mode. The optimal decision is to let pair-4 in D2D mode, but the heuristic makes a wrong decision during the first iterations, when a temporarily high interference from Rx-9 leads pair-4 to leave the shared channel and switch to cellular mode.

![Networks with 10 user pairs](image1.png)

![Networks with 30 user pairs](image2.png)

**Figure 4.11**: Performance evaluation for different algorithms. Total energy consumption and number of orthogonal frequency channels needed to accommodate all the communication requests within the cell. Values are averaged over 1000 random configurations.

**Energy and spectral efficiency of D2D in dynamic TDD.** We conclude this section by a comparison of the different mode selection policies proposed in this paper, both in terms of their energy efficiency and their spectral efficiency. Fig. 4.12 shows the energy-channel performance of the proposed algorithms for networks with 10 and 30 user pairs, respectively. We note that FO-UE represents the energy-optimal solution, with significant energy savings compared to the purely cellular solution (labelled FO-cellular mode) and the same spectral efficiency (measured in number of allocated channels). Resource sharing (RS-UE-B&B) yields big improvements in spectral efficiency at the cost of a slight increase in energy consumption when D2D transmitters need to compensate for interference. The reason that the energy increase is so small is that the transmission powers assigned to D2D pairs are generally small, partly because D2D pairs typically have high direct gains (since the transmitter and receiver often are in close proximity of each other), and partly because D2D connections can use the full frame duration (see Eq. (4.6)). These results demonstrate that for some user pairs, communicating in D2D mode and interfering with each other is still more energy efficient than communicating in cellular mode on an exclusive frequency channel. Thus, in dynamic TDD systems, D2D communications have the potential to improve both spectrum and energy efficiency over a traditional cellular solution. Finally, we evaluate the performance of the heuristic method for different values of the threshold $\theta$. As expected, large values of $\theta$ decrease the number of channels used at the expense of a slightly increased...
energy consumption. For this reason, \( \theta \) is an important design parameter for finding a suitable tradeoff between energy consumption and channel use.

![Graph](image_url)

(a) Networks with 10 user pairs.

![Graph](image_url)

(b) Networks with 30 user pairs.

**Figure 4.12:** Performance evaluation for different algorithms. Total energy consumption and number of orthogonal frequency channels needed to accommodate all the communication requests within the cell. Values are averaged over 1000 random configurations.

### 4.6 Summary

We investigated the problem of energy efficient mode selection and resource (power and time) allocation for network-assisted D2D communications in dynamic TDD systems. We analyzed the problem under two frequency channel allocation strategies (with and without interference among D2D pairs) and with two objectives (total user energy and total system energy). For each configuration we derived the optimal solution to the corresponding MINLP formulation. In particular, for the interference free case, we demonstrated how the optimal solution can be obtained in polynomial time. On the other hand, when D2D pairs interfere with each other, finding the optimal solution in an efficient manner in terms of execution time and cross-gains knowledge is much harder. Therefore, a customized branch-and-bound solver was complemented by a more practical low-complexity heuristic.

Through numerical simulations, we demonstrated that significant energy savings can be achieved by exploiting the benefits brought both by the better channel gain of D2D links, and by the adaptive transmission time of the dynamic TDD technology. Moreover, leveraging on the observation that large channel gain and long transmission duration for D2D links lead to a low transmit power (and hence low interference), we showed the potential of D2D communications to improve also the spectrum efficiency over traditional cellular communications. Finally, we presented analytical characterizations of the D2D-optimal areas for a transmitter-receiver pair, showing that these regions can be surprisingly large and not necessarily circular.
Chapter 5

Power control schemes for D2D communication

The purpose of this chapter is to analyze the performance of the 3GPP LTE power control (PC) mechanism for UL transmission, when applied to the hybrid cellular-D2D network. A similar investigation has been proposed in [40]. However, differently from that work, here we compare LTE PC schemes with a distributed PC method based on utility maximization.

Building on the already standardized and widely deployed LTE UL PC schemes facilitates not only a smooth introduction of D2D-enabled user equipments, but would also help to develop inter-operable solutions between different devices and network equipment. However, due to the new interference scenarios, the question naturally arises whether the available LTE PC is suitable for D2D communication integrated in an LTE network.

5.1 LTE uplink power control

In this section we give a brief overview of the LTE PC options that might be applied to D2D communication integrated in cellular systems.

The PC mechanism used in LTE system employs a combination of open-loop and closed-loop control to set the UL transmit power of the user. The open-loop sets a coarse operating point for the transmit power level, which is mainly based on the path loss estimation and should be suitable for a reference modulation and coding scheme (MCS). Power level adaptation can then be applied around this operating point by means of the closed-loop control, which mainly compensates for long-term channel quality variations\(^1\). In LTE, in fact, fluctuations of the channel gain due to fast fading, and variations of the interference level are exploited or compensated by fast scheduling\(^2\) and link adaptation, rather than by varying the transmit power.

\(^1\)The closed-loop in LTE would be expected to operate at no more than a few hundred Hertz [12].
\(^2\)In LTE, fast scheduling of different users is applied at 1 ms intervals [12].
Different combinations of the open-loop and closed-loop control mechanisms provide different modes of operation of the LTE UL PC, which can be selected and used depending on the deployment scenario and operator preference [12, 87].

The general LTE PC scheme sets the transmit power $P_{\text{UE}}$ for the user equipment, up to a maximum level of $P_{\text{max}}$, as follows:

$$P_{\text{UE}} = \min\{P_0 - \rho \cdot PL + \Delta_{\text{TF}} + f(\Delta_{\text{TPC}}) + 10 \cdot \log_{10} M, P_{\text{max}}\} \text{ [dBm]}, \quad (5.1)$$

where $\rho \in [0, 1]$ is the path loss compensation factor, $PL$ is the path gain between the user and the BS, and $M$ is the number of scheduled RBs to the user.

For the open-loop operating point, $P_0$ is a base power level used to control the SNR target $\gamma_{\text{tgt}}$, and it is calculated as [88]:

$$P_0 = \rho \cdot (\gamma_{\text{tgt}} + P_{\text{IN}}) + (1 - \rho) \cdot (P_{\text{max}} - 10 \cdot \log_{10} M), \quad (5.2)$$

where $P_{\text{IN}}$ is the estimated noise and interference power per RB. The term $\rho \cdot PL$ in (5.1) is the path loss compensation component. It is based on the user’s estimate of the downlink path loss $PL$. It represents the degree to which the power is adapted to compensate it, on a scale from no compensation (i.e., $\rho = 0$) to full compensation (i.e., $\rho = 1$). Full path loss compensation maximizes fairness for users at the cell-edge. However, it increases the inter-cell interference, thus reducing the system capacity. Compensation factors around 0.7 - 0.8 give good tradeoff between system capacity and cell-edge data rate. Furthermore, in practice, the typical range of values for the base power $P_0$ is -126 dBm to 24 dBm per RB, while typical values for $\gamma_{\text{tgt}}$ are within the range [-5, 25] dB; see [12, 88].

For the dynamic offset, $\Delta_{\text{TF}}$ is the MCS-dependent component. It allows the power per RB to be adapted according to the MCS which the user has permission to transmit. The MCS can be adjusted by the BS taking into account the instantaneous buffer status, the available power headroom and the QoS requirements of the user. The $f(\Delta_{\text{TPC}})$, on the other hand, represents the explicit transmit PC (TPC) command from the network, which is user-specific and can be accumulative or absolute. When it is accumulative, it signals a power adjustment relative to the previous level. When it is absolute, it indicates a power offset to be applied not to the previous power level, but to the open-loop operating point. Other possible uses for the MCS-dependent component to dynamically adjust the transmit power, and more details on the TPC commands can be found in [12].

### 5.1.1 LTE power control options for D2D communication

Given the general LTE UL PC mechanism described in Section 5.1, we now consider different PC strategies for the D2D-enabled network. These strategies are obtained as different parameter settings in (5.1):

3TF stands for ‘Transport Format’. 

5.2 Power control based on utility maximization

- **Fixed Tx power**: in this case there is no PC, and the transmit power of the transmitters is set to some fixed value $P_{\text{fix}} \leq P_{\text{max}}$. For $M = 1$, this can be obtained by setting $\rho = 0$ and $P_0 = P_{\text{fix}}$ in the open-loop operating point.

- **Fixed SNR target**: this scheme fully utilizes the path loss compensation capability by setting $\rho = 1$ and $P_0 = \gamma_{\text{tgt}} + P_{\text{IN}}$ in the open-loop operating point. Note that the selection of the SNR target will affect the total transmit power and the final SINR.

- **Open-loop** with fractional path loss compensation (OFPC): The OFPC scheme allows users to transmit with variable power levels, depending on their path loss. In contrast to the previous PC cases, the OFPC compensates for the fraction of the path loss by setting $\rho$ to some suitable value within the range $(0, 1)$.

- **Closed-loop**: in this scheme we consider the closed-loop mechanism with the single feedback item $f(\Delta_{\text{TPC}})$ in (5.1). This tuning step is used to compensate the difference between the measured SINR at the receiver ($\gamma$) with the desired SNR target value ($\gamma_{\text{tgt}}$). The tuning step is computed as in [40]:

$$f(\Delta_{\text{TPC}}) = \begin{cases} 
|\gamma_{\text{tgt}} - \gamma|/2 & \text{if } |\gamma_{\text{tgt}} - \gamma| > 2 \text{ dB} \\
1 \text{ dB} & \text{otherwise.}
\end{cases}$$

(5.3)

For users communicating in cellular mode with their respective serving BSs, OFPC provides a well proven alternative, typically used in practice. It avoids the complexity and overhead associated with the dynamic offset of the closed-loop scheme, but makes use of the fractional path loss compensation, thus balancing between overall spectrum efficiency and cell edge performance [87]. For this reason, we assume this scheme as a default PC method for cellular users. For D2D transmitters, on the other hand, we consider the four alternative PC schemes described above. We examine the performance of these four variations and benchmark them against an utility maximizing scheme applied to all transmitters (cellular and D2D). Fig. 5.1 summarizes the different PC options considered in this thesis.

5.2 Power control based on utility maximization

In this section we derive a reference PC scheme for the hybrid cellular-D2D network. The adopted framework has been introduced in [59], and further investigated in the field of flow control and RRM in multi-hop wireless networks in [89, 90]. Without compromising the mathematical soundness, we adopt the framework of [90] to derive a practical algorithm that is appealing to cellular networks with underlay D2D communication. In fact, the algorithm is distributed among the user pairs and does not require any coordination or message flooding scheme between all the users and the BSs.
Power control schemes for D2D communication

- Open Loop
- Utility Maxim.
- Fixed Power
- Fixed SINR target
- Open Loop
- Closed Loop
- Utility Maxim.

**Figure 5.1**: The user communicating in cellular mode with its serving BS uses the standard LTE fractional open-loop PC with path loss compensation (OFPC). For the D2D link, we study various PC strategies that can all be easily deployed using the flexible LTE PC ‘toolkit’. Additionally, for benchmarking purposes, we also consider the case when both D2D and cellular communications are assigned transmit power according to an utility maximization approach.

5.2.1 System model and assumptions

We consider a hybrid cellular-D2D network, where D2D pairs communicate using the cellular UL resources, such as the UL physical RBs in a cellular FDD system or the UL time slots in a TDD system. We assume that the communication mode for each user pair has already been selected, and all links have been already assigned to a specific RB for their communication.

Transmitter-receiver pairs (cellular user-BS and D2D transmitter-receiver, depending on the mode selection decision) are labelled with \( l = 1, \ldots, L \). We indicate with \( L_f \subset L \) the set of pairs assigned to RB-\( f \). To simplify the notation, in this chapter we drop the indices \( m, f \) from Eq. (3.1) and (3.2), and indicate with \( P_l \) the transmit power used by Tx-\( l \) towards its intended receiver on the assigned RB. Similarly, we indicate with \( \gamma_l \) the SINR measured at Rx-\( l \), and with \( r_l \) the capacity of link-\( l \). Both \( \gamma_l \) and \( r_l \) are functions of the power allocation vector \( \mathbf{P} = [P_l] \) related to the set of links sharing the same RB.

Moreover, we denote by \( s_l \) the end-to-end rate for the communication between transmitter and receiver of pair-\( l \). Associated with each link-\( l \) is a function \( u_l(s_l) \), which describes the utility of user pair-\( l \) at the communication rate \( s_l \). The utility function \( u_l \) is assumed to be increasing and strictly-concave. We let \( \mathbf{s} = [s_l] \) and \( \mathbf{r} = [r_l] \) denote the vectors of assigned rates and link capacities, respectively. Obviously, vector \( \mathbf{s} \) must fulfill the following constraints:

\[
\mathbf{s} \leq \mathbf{r}, \quad \mathbf{s} \geq 0.
\]
5.2. Problem statement

It is convenient to look at $s$ as the vector of the rate targets, while the capacity vector $r$ depends on the specific power used by the interfering transmitters.

For each set of links $L_f$ sharing a given RB-\(f\) (and thereby causing interference to one another), we formulate the problem of end-to-end rate setting and power control as:

$$\begin{align*}
\text{maximize} & \quad \sum_{l \in L_f} u_l(s_l) - \omega \sum_{l \in L_f} P_l \\
\text{subject to} & \quad s_l \leq r_l(P), \quad \forall l \in L_f, \\
& \quad s_l \geq 0, \quad P_l \geq 0, \quad \forall l \in L_f.
\end{align*}$$

\(5.4\)

Problem \(5.4\) aims at maximizing the total utility, while taking into account the transmit power consumption (thus reducing the interference and prolonging the lifetime of the devices) by means of a predefined weight $\omega \geq 0$. Constraints of Problem \(5.4\) ensure that the allocated rate does not exceed the capacity of the link, which is optimized through the power allocation. It is worth noting that Problem \(5.4\) is not convex due to the nonconvexity of the link capacities.

5.2.3 Solution based on problem convexification

To render Problem \(5.4\) convex, we invoke the results presented in \([59]\) and \([90]\). In doing so, we transform the nonnegative optimization variables logarithmically, that is $s_l \leftarrow e^{\tilde{s}_l}$ and $P_l \leftarrow e^{\tilde{P}_l}$, \(\forall l \in L_f\), along with a log-transformation of the capacity constraints. The original optimization problem is therefore converted into the following form

$$\begin{align*}
\text{maximize} & \quad \sum_{l \in L_f} u_l(e^{\tilde{s}_l}) - \omega \sum_{l \in L_f} e^{\tilde{P}_l} \\
\text{subject to} & \quad \log(e^{\tilde{s}_l}) \leq \log(r_l(e^{\tilde{P}})), \quad \forall l \in L_f.
\end{align*}$$

\(5.5\)

**Theorem 5.2.1** (\([59]\), Theorem 2). The transformed Problem \(5.5\) is convex if the utility functions $u_l(\cdot)$ are all \((\log, x)\)-concave over their domain.

Under the condition of Theorem 5.2.1, we can solve Problem \(5.5\) to optimality. In particular, we consider $u_l(x) = \log(x)$ \([59]\), and we decompose the problem into two separate problems (namely, **Problem-I** and **Problem-II**) that are executed recursively until convergence. Specifically, Problem-I selects the transmit rate target, while Problem-II selects the transmit power that fulfills the given rate target. This separation of setting the rates target and corresponding power levels is detailed in the next section. For the sake of notation, in the following sections we will omit to specify that the problems are solved for all links assigned to RB-\(f\).

A decomposition approach

We now reformulate Problem \(5.5\) as a problem in the user rates vector $\tilde{s}$, which can be solved for a given power allocation vector $\tilde{P}$. Note that the target rate vector
\( \bar{s} \) can be uniquely mapped to a target SINR vector \( \gamma^{tgt} \), as it will be shown later. We define **Problem-I** as:

\[
\begin{align*}
\text{maximize} & \quad \nu(\bar{s}) \\
\text{subject to} & \quad \bar{s} \in \tilde{S},
\end{align*}
\]

where \( \tilde{S} = \{ \bar{s} | \log(e^{\bar{s}_l}) \leq \log(r_l(e^{\bar{P}})) \}, \forall l \} \) represents the set of feasible rate vectors that, for a given power vector \( \bar{P} \), fulfill the constraints of Problem (5.5). The objective function in (Problem-I) is defined as \( \nu(\bar{s}) = \sum_l u_l(e^{\bar{s}_l}) - \varphi(\bar{s}) \), where \( \varphi(\bar{s}) \) represents the minimum cost in terms of the total transmit power for realizing a given target rate \( \bar{s} \). That is, for a given \( \bar{s} \) vector, \( \varphi(\bar{s}) \) is the solution of **Problem-II**

\[
\begin{align*}
\text{minimize} & \quad \omega \sum_l e^{\bar{P}_l} \\
\text{subject to} & \quad \log(e^{\bar{s}_l}) \leq \log \left( r_l(e^{\bar{P}}) \right), \quad \forall l.
\end{align*}
\]

**Solving the rate allocation problem (Problem-I).** To solve (Problem-I), we disregard the feasibility constraint and we determine the optimal \( \bar{s}^* \) by means of gradient ascent iterations. As shown in [91], (Theorem 4.2.8), by starting with a feasible rate allocation and using a step size \( \epsilon \) small enough, the rate vector remains feasible and approaches to optimum. We consider the gradient ascent iteration

\[
\begin{align*}
\bar{s}_i^{(k+1)} &= \bar{s}_i^{(k)} + \epsilon \nabla_i \nu(\bar{s}^{(k)}), \quad \forall i, \\
\end{align*}
\]

where

\[
\nabla_i \nu(\bar{s}) = \frac{\partial}{\partial \bar{s}_i} \left[ \sum_l u_l(e^{\bar{s}_l}) - \varphi(\bar{s}) \right] = u'_i(e^{\bar{s}_i})e^{\bar{s}_i} - \frac{\partial}{\partial \bar{s}_i} \varphi(\bar{s}).
\]

To compute (5.7), we first need to find \( \varphi(\bar{s}) \) by solving (Problem-II). Since it is convex in \( \bar{P} \), we can use a Lagrangian decomposition approach. Let \( \lambda \) be the Lagrange multipliers for the constraints in (Problem-II) and form the Lagrangian:

\[
L(\lambda, \bar{P}) = \omega \sum_l e^{\bar{P}_l} + \sum_l \lambda_l \left[ \log(e^{\bar{s}_l}) - \log \left( r_l(e^{\bar{P}}) \right) \right].
\]

Then, the dual problem is given by:

\[
\begin{align*}
\text{maximize} & \quad [g(\lambda) = \min_{\bar{P}} L(\lambda, \bar{P})] \\
\text{subject to} & \quad \lambda \geq 0.
\end{align*}
\]

Let us assume that \( (\lambda^*, \bar{P}^*) \) represents the optimum solution of (Problem-II), we can now calculate \( \varphi(\bar{s}) \) from (5.8):

\[
\varphi(\bar{s}) = \sum_l \left[ \omega e^{\bar{P}_l} - \lambda^*_l \log \left( r_l(e^{\bar{P}^*}) \right) \right] + \sum_l \lambda^*_l \log(e^{\bar{s}_l}), \quad \text{and} \quad \frac{\partial}{\partial \bar{s}_i} \varphi(\bar{s}) = \lambda^*_i.
\]
Therefore, recalling (5.7), we have:
\[ \nabla_i \nu(\tilde{s}) = u_i' (e^{\tilde{s}_i}) e^{\tilde{s}_i} - \lambda_i^* = e^{\tilde{s}_i} \left[ u_i' (e^{\tilde{s}_i}) - \frac{\lambda_i^*}{e^{\tilde{s}_i}} \right] = s_i \left[ u_i' (s_i) - \frac{\lambda_i^*}{s_i} \right], \]  
and the final target rate update is:
\[ s_i^{(k+1)} = e^{\tilde{s}_i^{(k+1)}} = s_i^{(k)} \exp \left( \epsilon \nabla_i \nu(\tilde{s}^{(k)}) \right). \]

Finally, combining the result above with (5.7), we can write the rate target setting rule in the following form:
\[ s_i^{(k+1)} = s_i^{(k)} \exp \left( \epsilon s_i^{(k)} \left[ u_i' (s_i^{(k)}) - \frac{\lambda_i^* (s_i^{(k)})}{s_i^{(k)}} \right] \right). \]  
(5.10)

Eq. (5.10) dictates the *outer-loop* iterative mechanism for a certain transmitter-\(i\). Specifically, at any iteration \((k + 1)\), (5.10) determines the rate that should be targeted during the *inner-loop* PC described in the next section.

**Solving the power allocation problem (Problem-II).** Given any \(\tilde{s}^{(k)} \in \tilde{S}\), the constraints in (Problem-II) correspond to require that the SINR-s of the links exceed a target value, i.e.,
\[ \log (e^{\tilde{s}_l^{(k)}}) \leq \log (r_l(e^{\tilde{P}})) \iff \gamma_l(P) \geq \gamma_l^{tgt}(\tilde{s}_l^{(k)}), \quad \forall l, \]

where we recall that \(\gamma_l(P) = \frac{G_{ll} P_l}{\sigma^2 + \sum_{m \neq l} G_{lm} P_m} \), and we define
\[ \gamma_l^{tgt}(\tilde{s}_l^{(k)}) = 2 e^{\tilde{s}_l^{(k)}} W - 1. \]  
(5.11)

Therefore, for a given \(\tilde{s}\), (Problem-II) can be rewritten as:
\[
\begin{align*}
\text{minimize} & \quad \omega \sum_l e^{\tilde{s}_l} \\
\text{subject to} & \quad \gamma_l(e^{\tilde{P}}) \geq \gamma_l^{tgt}(\tilde{s}_l), \quad \forall l,
\end{align*}
\]  
(5.12)
and solved with an iterative PC scheme, as in [92]:
\[ P_l^{(t+1)} = \frac{\gamma_l^{tgt}(\tilde{s}_l)}{\gamma_l(P^{(t)})} P_l^{(t)}. \]  
(5.13)

**Determining the \(\lambda_i^*\)-s.** We can now determine the \(\lambda_i^*\)-s for the outer-loop update (5.10) by exploiting the relationship between the optimal \(P^*\) and the associated Lagrange multipliers \(\lambda_i^*\)-s. To this end, we rewrite the constraints in (5.12) as:
\[ \frac{G_{ll} P_l}{\sigma^2 + \sum_{m \neq l} G_{lm} P_m} - \gamma_l^{tgt} \geq 0 \quad \Rightarrow \quad P_l - \gamma_l^{tgt} \sum_{m \neq l} \frac{G_{lm}}{G_{ll}} P_m - \frac{\gamma_l^{tgt} \sigma^2}{G_{ll}} \geq 0, \quad \forall l. \]  
(5.14)
Let \( H \in \mathbb{R}^{L \times L} \) and \( \eta \in \mathbb{R}^{L} \) be defined as follows:

\[
H = [h_{lm}] = \begin{cases}
-1 & \text{if } l = m \\
\gamma_l G_{lm} G_{ll}^{-1} & \text{if } l \neq m
\end{cases}
\]

\[
\eta = [\eta_l] = \left[ \frac{\gamma_l^{tgt} \sigma^2}{G_{ll}} \right].
\] (5.15)

Using this notation, we can reformulate Problem (5.12) as the following linear programming problem:

\[
\begin{align*}
\text{minimize} & \quad \omega^T P \\
\text{subject to} & \quad HP \preceq -\eta; \quad P \succeq 0,
\end{align*}
\] (5.16)

with the corresponding dual problem

\[
\begin{align*}
\text{maximize} & \quad \eta^T \lambda^{(LP)} \\
\text{subject to} & \quad H^T \lambda^{(LP)} \succeq -\omega 1,
\end{align*}
\] (5.17)

necessary to compute the Lagrange multipliers in Eq. (5.10) for the rate update.

Constraints in Problem (5.17) can be rewritten explicitly as follows:

\[
\frac{\lambda_l^{(LP)}}{\omega} - \sum_{k \neq l} \frac{G_{kl}}{G_{kk}} \gamma_k^{tgt} \frac{\lambda_k^{(LP)}}{\omega} \leq 1, \quad \forall l.
\] (5.18)

Moreover, by defining

\[
\mu_l = \frac{\lambda_l^{(LP)}}{\omega} \gamma_l^{tgt} \frac{\sigma^2}{G_{ll}} = \frac{\lambda_l^{(LP)}}{\omega} \eta_l,
\] (5.19)

Eq. (5.18) can be interpreted as an SINR requirement, i.e.,

\[
\gamma_l^{cc}(\mu) = \frac{\mu_l G_{ll}}{\sigma^2 + \sum_{k \neq l} G_{kl} \sigma_k^2} \mu_k \leq \gamma_l^{tgt}, \quad \forall l.
\] (5.20)

Therefore, Problem (5.17) can be reformulated as:

\[
\begin{align*}
\text{maximize} & \quad \omega^T \mu \\
\text{subject to} & \quad \gamma_l^{cc} \leq \gamma_l^{tgt}, \quad \forall l; \quad \mu \succeq 0.
\end{align*}
\] (5.21)

Similarly to Eq. (5.13), the solution \( \mu \) to (5.21) can be computed according to the following distributed PC scheme:

\[
\mu_l^{(t+1)} = \frac{\gamma_l^{tgt}}{\gamma_l^{cc}(\mu_l^{(t)})} \mu_l^{(t)}, \quad \forall l.
\] (5.22)
5.2. Power control based on utility maximization

Eq. (5.22) can be interpreted as a reverse link PC problem that is executed in the control channel between the receiver and the transmitter of link-\( l \). Specifically, the receiver-\( l \) adapts its transmitting power \( \mu_l \) according to Eq. (5.22), while the transmitter-\( l \) measures the experienced SINR \( \gamma_{lcc}^{\text{cc}} \) in the corresponding control channel. Once the iterative procedure (5.22) converges to the optimum \( \mu^* \), the optimal dual variables \( \lambda^{*(\text{LP})} \) can be retrieved from Eq. (5.19) as

\[
\lambda_l^{*(\text{LP})} = \frac{\omega_l}{\mu_l^{\text{opt}}}, \quad \forall l.
\]  

(5.23)

The original nonlinear PC problem (Problem-II) and the corresponding LP formulation (5.16) are equivalent in the sense that there exists the following specific relation between their optimal solutions (see [90, Theorem 5.1]) \((\tilde{P}^*, \lambda^*)\) and \((P^*, \lambda^{*(\text{LP})})\):

\[
P^*_l = e^{\tilde{P}^*_l}, \quad \forall l,
\]

\[
\lambda_l^* = \log\left(1 + \frac{\gamma_{l_{\text{tgt}}}^*}{\gamma_l^*}P_l^* \log(2)\lambda^{*(\text{LP})}_{l}, \quad \forall l.
\]  

(5.24)

Hence, once both \( P^*_l \) and \( \mu^*_l \) are achieved by link-\( l \) by means of Eq. (5.23) and (5.24), \( \lambda^* \) can be computed as

\[
\lambda_l^* = \log\left(1 + \frac{\gamma_{l_{\text{tgt}}}^*}{\gamma_l^*}P_l^* \log(2)\mu_l^{*} \frac{G_{ll}}{\sigma^2_{l_{\text{tgt}}}}, \quad \forall l.
\]  

(5.25)

Eq. (5.25) is then used to update the user rates in Eq. (5.10).

5.2.4 Summary and implementation guidelines

The previous section developed a dual loop iterative solution approach to the convex optimization problem in (5.5). The basic idea has been to decompose the problem into separate subproblems: one in \( \tilde{s} \) (Problem-I) and one in \( \tilde{P} \) (Problem-II). The solution to (Problem-I) is represented by the outer-loop iterations, it is based on gradient iterations to obtain the SINR targets. The solution to (Problem-II) represents the inner-loop iterations and it is based on a distributed PC algorithm. Specifically, the solution of (Problem-I) at step \( (k) \), i.e., \( \gamma_{l_{\text{tgt}}}^{(k)} \), serves as input to (Problem-II) that is executed until convergence to \( \mu_l^* \) and \( P_l^* \). In turn, (Problem-II) outputs \( \lambda_l^* \), that is used by a new instance of (Problem-I) at step \( (k + 1) \).

The machinery of the distributed utility maximization algorithm is shown in Fig. 5.2, while Fig.5.3 shows the implementation of the inner- and outer-loop mechanism in the network, clarifying which information must be exchanged between the transmitter and receiver of each pair and which computations must be performed by both nodes.
5.3 Mode selection and RB allocation: the MinInterf algorithm

Power control algorithms described in previous sections assume that the mode selection and RB allocation have already been executed. In order to evaluate the performance of the PC schemes, we consider a centralized procedure that assigns the communication mode and the RBs to the transmitter-receiver pairs in the system. This simple algorithm, which we call MinInterf, exploits the proximity
between D2D-candidates for the mode selection, and performs RB allocation that aims at reducing the intra-cell interference by minimizing the sum of the harmful path gains. The MinInterf procedure is single cell based, meaning that interference coordination between neighbouring cells is not considered. Furthermore, it assumes the full knowledge of the path loss measurements between all transmitters and receivers within the cell.

The algorithm involves two steps. First, orthogonal resources are allocated to cellular users employing legacy RB allocation schemes\(^4\). Second, for each D2D-candidate pair-\(l\) in the cell, MinInterf considers two possible cases:

- **D2D transmission with dedicated resource.** If there is an orthogonal resources left, that we indicate with RB-\(f\), it can be assigned to the D2D-candidate so that the D2D transmission does not affect others within the same cell. In this case, mode selection is simply performed as follows: if the direct link gain is greater than the gain towards the BS, then the D2D mode is preferred.

- **D2D transmission with resource reuse.** When there are no unused RBs in the cell, the D2D-candidate pair-\(l\) must communicate in D2D mode and reuse RBs. To reduce this intra-cell interference, for each RB-\(f\), MinInterf considers the sum

\[
S(f) = \sum_{i \in L_f} G_{li}^f + G_{il}^f \quad \text{[dB]} 
\]  
(5.26)

as a measure of the potential interference that assigning the D2D pair-\(l\) to RB-\(f\) causes. Here \(G_{li}^f\) represents the path gain between the D2D transmitter-\(l\) and the receiver of link(s) already allocated to RB-\(f\), which may be the BS and/or other D2D receiver(s). It takes into account the interference that the D2D pair produces transmitting on RB-\(j\). \(G_{il}^f\), on the other hand, is the path gain between the transmitter(s) already allocated to RB-\(f\) (which can be both a cellular-UE and/or other D2D transmitters) and the receiver-\(l\) of the new D2D pair. Therefore, it is related to the interference that the D2D receiver will experience due to the reuse. Once expression (5.26) is computed for each available RB-\(f\), D2D pair-\(l\) is assigned to that RB corresponding to the minimum value.

It is worth noting that the performance of the mode selection and RB allocation achieved by MinInterf are not optimal. Nevertheless, numerical results in Section 5.4.2 show that its interplay with the iterative PC procedure, which takes into account also the inter-cell interference, allows to attain good performance in terms of spectrum and energy efficiency.

\(^4\)Since we are disregarding frequency selective fading, to each user it can randomly pick and assigns an available RB.
5.4 Numerical results

5.4.1 Simulation set-up and parameters setting

We consider the UL transmission of a 7-cell system, in which the number of UL RBs is 4 per cell, and all transmitter-receiver pairs in the system are assigned one RB. In each cell, we drop 2 mobile users transmitting to their respective serving BS, and 4 D2D-candidate pairs, for which a mode selection policy assigns a communication mode between cellular mode, D2D mode with dedicated resource and D2D mode with resource reuse. Since 4 D2D-candidate pairs are dropped in addition to the 2 cellular users, 2 of them are forced to use D2D mode and reuse the resource with either other D2D mode users or with cellular users. This is because we assume 4 RBs per cell accommodating 6 transmitters, and we assume that cellular users and D2D-candidates assigned to cellular mode must remain orthogonal within a cell. To generate the following results we assumed the heuristic mode selection and RB allocation algorithm described in Section 5.3.

We perform Monte Carlo experiments to build some statistics over the used transmit power and achieved SINR by cellular users and D2D pairs, when employing the LTE-based PC algorithms or the distributed optimization-based PC scheme. For the LTE-based scheme, we assume that cellular users operate with OFPC with $\rho = 0.8$, while D2D links use one out of the 4 schemes described in Section 5.1.1. For the utility maximization-based scheme, all transmitters execute the distributed outer and inner loops-based PC, as described in Section 5.2. We consider two different values of $\omega$: $\omega = 0.1$ to consider the power consumption less important than the achieved sum rate, and $\omega = 10$ to simulate low sum power operation of the system.

The main simulation parameters are given in Table 5.1. $P_0$ is set according to Eq. (5.2) to correspond to $\gamma_{tgt} = 12.5$ dB.

Table 5.1: Simulation parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channel Model</td>
<td>Micro Urban [40]</td>
<td>Cell Radius</td>
<td>500 m</td>
</tr>
<tr>
<td>System Bandwidth</td>
<td>10 MHz</td>
<td>$P_{IN} (/\text{MHz})$</td>
<td>-116 dBm</td>
</tr>
<tr>
<td>$P_0$</td>
<td>-78 dBm</td>
<td>$\rho$</td>
<td>0.8</td>
</tr>
<tr>
<td>$P_{\text{max}}$</td>
<td>24 dBm</td>
<td>$\omega$</td>
<td>0.1 and 10</td>
</tr>
<tr>
<td>Number of RB per user</td>
<td>1</td>
<td>Fixed SINR tgt for D2D</td>
<td>15 dB</td>
</tr>
<tr>
<td>Number of outer-loop iterations</td>
<td>200</td>
<td>Fixed Tx Power for D2D</td>
<td>-10 dBm</td>
</tr>
<tr>
<td>Number of inner-loop iterations</td>
<td>10</td>
<td>Distance between cellular user and the BS</td>
<td>300 ± 50 m</td>
</tr>
<tr>
<td>Number of transmitters per cell</td>
<td>6</td>
<td>Distance between D2D pairs</td>
<td>50 ± 25 m</td>
</tr>
</tbody>
</table>

5.4.2 Numerical results

We compare the utility-based algorithm (in the figures indicated as Utility max. PC) applied to all users in the system, to the four different LTE PC schemes presented
in subsection 5.1.1.

Fig. 5.4(a) shows the distribution of the transmit power levels of the cellular users for the OFPC case and for the utility maximizing case. When $\omega = 10$, the utility-based approach results in much lower power consumption. In contrast, when $\omega = 0.1$, the user power consumption is much less penalized and the overall power consumption increases. These results show the propriety of the utility-based scheme to tune through a single parameter ($\omega$) the spectral efficiency - energy efficiency tradeoff by setting the desired system operational point.

While the cellular users power consumption is only affected by the PC algorithm applied to the cellular users (i.e., Utility Max PC or LTE OFPC), the achieved SINR depends also on the PC scheme used by D2D pairs because of the resource reuse. However, Fig. 5.4(b) indicates that the different PC algorithms for D2D communications have similar impact on the cellular layer. This can be explained by the short distance and consequent low power level used by direct links. Having a small impact of the D2D layer on the cellular layer is a key requirement in any system that allows licensed spectrum resources to be used by D2D traffic.

![Figure 5.4: Performance analysis of cellular users.](image)

Fig. 5.5(a) and Fig. 5.5(b) show the distribution of the transmit power and SINR levels of the D2D pairs, respectively. Similarly to the cellular users, the D2D transmit power levels (and achieved SINR) can be tuned by choosing different values of $\omega$. However, for the D2D links, different LTE based schemes perform quite differently both in terms of power consumption and achieved SINR. In Fig. 5.5(a), for the very low power region (< 0 dBm), the LTE-based schemes use less power than the utility-based schemes. However, for higher power D2D transmitters (> 5 dBm), the optimization-based scheme with $\omega = 0.1$ uses less power than any of the LTE-based methods (with the exception of the fixed transmit power case). From a practical point of view, the important region is the one above 5 dBm, since users below this power level do not utilize their available power resources to improve their SINR levels. For users above 10 dBm of transmit power level, the utility-based scheme
with $\omega = 0.1$ and the LTE OFPC schemes perform similarly, while the Fixed SINR target and the Closed Loop scheme set higher transmit power levels. Notice that the Fixed Tx Power setting applies to D2D users that actually use the D2D mode, while D2D-candidate users using cellular mode use the LTE OFPC scheme, which explains the distribution curve for this PC scheme in Fig. 5.5(a).

In terms of SINR, the utility-based PC schemes outperform the LTE-based PC. The SINR gain is especially significant for the high SINR users, where only the fixed transmit power scheme yields higher SINR values than the utility-based approach (with $\omega = 0.1$). However, the fixed transmit power method is clearly unacceptable from a fairness perspective.

![Fig. 5.5: Performance analysis of D2D users.](image)

Finally, to gain some insights into the relation between the used power levels and the resulting SINR values for the PC approaches under study, we consider the scatter plots of Fig. 5.6.

Fig. 5.6(a) represents each dropped user in the Monte Carlo experiments with a dot indicating the transmit power and resulting SINR value for that particular user. Because of the resource reuse between cellular and D2D users, the SINR of the cellular users depend on the PC scheme of the D2D users. Here we can clearly see that the general trend is that the utility-based scheme with $\omega = 10$ uses lower power levels for similar user SINR performance. In other words, similar quality of service level can be maintained by lower user power levels when relying on the dynamic SINR target adjusting algorithm.

Fig. 5.6(b) shows the relation between the D2D transmit power levels and the D2D SINR values. We observe that the utility maximizing scheme tends to allocate higher power levels to lower SINR users, so in that sense it tries to compensate for the performance of the poor users. This is the opposite of the (extreme unfair) fixed Tx power approach (horizontal line) but not as fair as the LTE OFPC scheme in the sense of SINR equalization (close to being ‘horizontal’ in the power-SINR plane).
5.5 Summary

This chapter presented a distributed PC algorithm that maximizes a utility function that takes into account the inherent tradeoff between spectrum and energy efficiency. We used this algorithm as a benchmarking tool with respect to practical PC schemes based on the LTE UL PC ‘toolkit’. For the mode selection and resource allocation, we proposed a heuristic algorithm (MinInterf) that attempts to reduce the intra-cell interference introduced by D2D communications, assuming full path loss knowledge.

Numerical results indicate that the performance of LTE PC gets close to the utility-based scheme (with proper selection of $\omega$), both in terms of used transmit power levels and the resulting SINR values. However, there is a significant gain when employing the optimization-based approach in terms of the SINR obtained by the D2D users. On the other hand, the LTE OFPC scheme, depending on the $\omega$ parameter of the utility-based method, can produce higher SINR values for the cellular users. These results suggest that the flexible LTE PC scheme is well prepared for network-assisted D2D communications, especially for the cellular users perspective. For the D2D pairs, instead, the utility-based scheme shows the possibility of performance improvement. Moreover, its distributed design makes it appealing for a practical implementation, where only the design parameters are controlled by the cellular network.

Figure 5.6: (a) Scatter plot of the used transmit power of the cellular users and the resulting SINR values when using different schemes for the cellular users and the D2D pairs. The clear tendency is that the utility-based scheme gives similar SINR values but typically with much less transmit power. (b) Scatter plot of the used transmit power of the D2D users and the resulting SINR values when using different schemes for the cellular users and the D2D pairs.
In this chapter we assume that mode selection and transmit power allocation have already been performed, and we focus on the subcarrier (also referred to as RBs) allocation problem. We consider a multi-cell network, where D2D communications share the UL resources with traditional cellular users. In this hybrid network, resource management becomes crucial because of the combined inter- and intra-cell interference caused by D2D connections and multi-cell resource reuse. Our objective is to maximize the total rate of the system by taking advantage of frequency diversity among channels and by properly managing the interference level on each RB. Given the nonconvex and combinatorial formulation of the problem, we leverage on the theory of potential games to guarantee convergence to a Nash equilibrium via best and better response dynamics. Potential games have been already shown to be a valid approach for resource allocation problems in multi-cell wireless systems, when maximizing user SINRs and energy efficiency [93], or when minimizing interference [94].

6.1 System model and assumptions

We consider UL transmissions in an LTE-like multi-cell system, where underlay in-band D2D communication is enabled with the assistance of the network. We assume that communication modes and transmit powers are assigned on a slower time-scale than RBs (as in the LTE UL power control [12]). Therefore, we consider the transmit power matrix $P$ to be constant and known, with entries $P_{lf}$ representing the power used by transmitter-$l$ on the assigned RB-$f$.

The set of D2D receivers, denoted by $D$, can be seen as a set of virtual BSs, each serving a single user. We introduce the notation $K = B \cup D$ for the set of receivers in the system. For each receiver-$k \in K$, we let $C_k$ be the set of users served by $k$. Thus, $C_k$ is a singleton if $k \in D$, while it may contain many users if $k \in B$. For each $k \in K$, $X_k$ represents the RB assignment to all users that transmit to receiver-$k$. If
$k \in \mathcal{B}$, $\mathbf{X}_k$ is the RB allocation for all UL transmissions to the BS-$k$. If $k \in \mathcal{D}$, $\mathbf{X}_k$ is the RB allocation for the transmission of D2D pair-$k$. We label each element of $\mathbf{X}_k$ with $x^f_l$, which is 1 if transmitter-$l \in \mathcal{C}_k$ is assigned to RB-$f$, 0 otherwise. Moreover, $\mathbf{X}_{-k}$ represents the set of allocation decisions taken by all receivers except receiver-$k$, and $\mathbf{X} = (\mathbf{X}_k, \mathbf{X}_{-k})$, $\forall k \in \mathcal{K}$ is the overall resource allocation in the system.

The normalized rate (with respect to the bandwidth) in bps/Hz that user-$l \in \mathcal{C}_k$ can achieve on RB-$f$ is

$$R^f_l(\mathbf{X}_{-k}) = \log_2 \left( 1 + \frac{P^f_l G^f_{lk}}{\sigma^2 + I^f_k(\mathbf{X}_{-k})} \right),$$

where $I^f_k(\mathbf{X}_{-k}) = \sum_{q \in \mathcal{K} \backslash \{k\}} \sum_{m \in \mathcal{C}_q} P^f_m G^f_{mk} x^f_m$ is the interference perceived at receiver-$k$ on RB-$f$, which depends on the resource allocation in all cells and D2D pairs, except the one which receiver-$k$ belongs to.

Finally, we denote by $F_l$ the number of RBs to be assigned to transmitter-$l$. We assume that $\sum_{l \in \mathcal{C}_k} F_l \leq F$, $\forall k \in \mathcal{K}$, so that the number of available RBs is sufficient to accommodate all communication requests. This condition can be fulfilled by an admission control algorithm that decides whether to accept or reject a connection request, depending on the number of available resources.

### 6.2 Problem statement

We consider the problem of allocating RBs to users, aiming at maximizing the aggregate system rate, while assigning a given number of RBs to each link and ensuring orthogonality among cellular transmissions within the same cell. This problem can be formally stated as the following integer programming problem

$$\begin{align*}
\text{maximize} & \sum_{f \in \mathcal{F}} \sum_{k \in \mathcal{K}} \sum_{l \in \mathcal{C}_k} R^f_l(\mathbf{X}_{-k}) x^f_l \\
\text{subject to} & \quad \sum_{l \in \mathcal{C}_k} x^f_l \leq 1, \quad \forall f \in \mathcal{F}, \forall k \in \mathcal{K}, \quad (6.2a) \\
& \quad \sum_{f \in \mathcal{F}} x^f_l = F_n, \quad \forall l \in \mathcal{C}_k, \forall k \in \mathcal{K}, \quad (6.2b) \\
& \quad x^f_l \in \{0, 1\}, \quad \forall f \in \mathcal{F}, \forall l \in \mathcal{C}_k, \forall k \in \mathcal{K}, \quad (6.2c)
\end{align*}$$

where (6.2b) are the orthogonality constraints, which are active only for $k \in \mathcal{B}$ because $|\mathcal{C}_k| = 1$ for $k \in \mathcal{D}$; while (6.2c) ensure that each link is assigned the required number of RBs.

### 6.3 Preliminaries on potential games

In this section we briefly introduce the theory of potential games [95], which we will use to design a solution for the multi-cell D2D RB allocation problem formulated in (6.2).
A strategic game can be described by a triplet $\mathcal{G} = [\mathcal{K}, \{\mathcal{X}_k\}, \{U_k\}]$, where $\mathcal{K}$ is the set of players, $\mathcal{X}_k$ is the set of all possible strategies for the $k$th player, and each strategy is represented by $X_k$. The function $U_k(X_k, X_{-k})$ denotes the payoff for player-$k$. It is a scalar function that depends on the strategy taken by all players of the game. Any change in strategy from one player affects all the other players. Therefore, there is a dynamic process where players iteratively update their own strategies as a reaction to the changes in the strategy of other players. Let us recall some useful definitions and results:

**Definition 6.3.1** (Best- and better-response dynamics). The best-response dynamic occurs when each player updates its strategy by selecting the one that produces the highest utility, assuming that the other players do not change their current strategies. That is, given a strategy profile $X = (X_k, X_{-k})$, player-$k$ chooses its new strategy $X_k' \in \mathcal{X}_k$ such that

$$X_k' \in \{X_k \in \mathcal{X}_k : U_k(X_k', X_{-k}) \geq U_k(X_k, X_{-k}), \forall X_k \in \mathcal{X}_k\}. \quad (6.3)$$

In the less demanding better-response dynamics, instead, the strategy update of player-$k$ is defined by replacing condition (6.3) with

$$X_k' \in \{X_k \in \mathcal{X}_k : U_k(X_k', X_{-k}) \geq U_k(X_k, X_{-k})\}. \quad (6.4)$$

which means that the new strategy is only assured to be better than the previous one, but it might not be the best among all possible strategies.

**Definition 6.3.2** (Exact potential game). A strategic game $\mathcal{G} = [\mathcal{K}, \{\mathcal{X}_k\}, \{U_k\}]$ is an exact potential game if there exists a function $\Phi : \mathcal{X}_1 \times \mathcal{X}_2 \times \cdots \times \mathcal{X}_{|\mathcal{K}|} \rightarrow \mathbb{R}$ such that for any $k \in \mathcal{K}$

$$U_k(X_k, X_{-k}) - U_k(X'_k, X_{-k}) = \Phi(X_k, X_{-k}) - \Phi(X'_k, X_{-k}), \quad (6.5)$$

where $X_k$ and $X'_k$ are two different strategies of player-$k$. Any such function $\Phi$ is called the exact potential function of $\mathcal{G}$.

**Definition 6.3.3** (Nash equilibrium (NE)). Given a strategic game $\mathcal{G} = [\mathcal{K}, \{\mathcal{X}_k\}, \{U_k\}]$, the $K$-tuple $(X^*_1, X^*_2, \ldots, X^*_{|\mathcal{K}|}) \in \mathcal{X}_1 \times \mathcal{X}_2 \times \cdots \times \mathcal{X}_{|\mathcal{K}|}$ is a NE if

$$U_k(X^*_k, X^*_{-k}) \geq U_k(X_k, X^*_{-k}), \forall X_k \neq X^*_k, \forall k = 1, \ldots, |\mathcal{K}|.$$ 

Put in words: at the NE no player has an incentive to unilaterally change its strategy.

Potential games possess important properties that relate the optimizers (local optima) of the potential function to pure-strategy NE points of the game.

**Lemma 6.3.4** ([96], Theorem 15). If $\Phi$ is a potential function of the game $\mathcal{G}$ and $X^* \in \text{argmax}_{X} \Phi(X)$ is a maximizer of the potential function, then $X^*$ is a NE of the game.
Another attractive property of potential games, whose potential function is bounded from above, is that the iterative processes based on best and better response dynamics converge to the equilibrium set, as established by the following result:

**Lemma 6.3.5** ([96], Theorem 19). Let \( G \) be a potential game. Then both the best response dynamic and the better response dynamic will converge \( a.s. \) to a NE in a finite number of steps.

### 6.4 Game formulation for the multi-cell D2D RA

In this section we are interested in applying the results from Section 6.3 to the resource allocation problem formulated in (6.2).

#### 6.4.1 Solution based on best response dynamic

We propose a strategic game between all receivers in the set \( K \). The game is described by \( G = [K, \{X_k\}, \{U_k\}] \), where \( X_k \) is the set of all possible allocation decisions for all transmissions to receiver-\( k \in K \), and \( U_k \) is the utility function of the \( k \)th player. The latter is given by the sum of all the achievable bit rates in the system, that is

\[
U_k(X_k, X_{-k}) = \sum_{f \in F} \sum_{k \in K} \sum_{l \in C_k} R_{lf}(X_{-k}) x_{lf}.
\]

(6.6)

Hence, \( U_k \) is a scalar function corresponding to the objective in Problem (6.2). Note that, although each player-\( k \) aims at maximizing \( U_k \) with respect to its own strategy only, all players’ utilities are chosen to be the same. This means that all players aim at maximizing the same utility, thus we can define

\[
\Phi(X) = U_k(X_k, X_{-k}), \quad \forall k \in K.
\]

(6.7)

**Proposition 6.4.1.** The game \( G = [K, \{X_k\}, \{U_k\}] \) is an exact potential game with potential function \( \Phi(X) \) defined in (6.7).

**Proof.** \( G \) is an identical interest game, that is, a game in which the players’ utility functions are chosen to be the same [97]. Moreover, since the potential function is defined as equal to the players’ utility, the change in any player’s utility equals the change in the global utility. This means that condition (6.5) is verified. \( \square \)

Since \( G \) is an exact potential game, the best response dynamic will converge to a NE of the game (Lemma 6.3.5). Thus, given any initial resource allocation for all transmissions in the system, the players take turn to play the game in a sequential

\[1\text{The almost surely (a.s.) convergence comes from the possibility to choose the same node to play the game over and over again. This might cause the algorithm never to converge to a NE. However, in our case this will never happen because the players (receivers in the network) are forced to play in turn.}
manner, choosing their best response strategy. This iterative process terminates
down when no player is willing to change its strategy, that is, when a NE is achieved.

We now turn our attention to deriving the best response of player-$k$. Given $X_{-k}$, player-$k$ updates its strategy by solving the following optimization problem

$$
\begin{align*}
\text{maximize} & \quad U_k(X_k, X_{-k}) \\
\text{subject to} & \quad \sum_{f \in F} x_f^k \leq 1, \quad \forall f \in F, \\
& \quad \sum_{f \in F} x_f^k = F_l, \quad \forall l \in C_k, \\
& \quad x_f^k \in \{0, 1\}, \quad \forall l \in C_k, \forall f \in F.
\end{align*}
$$

(6.8)

The objective function in (6.8) is given in (6.6) and it can be expressed explicitly as function of $X_k$ as

$$
U_k(X_k, X_{-k}) = \sum_{f \in F} \left[ \sum_{l \in C_k} \log_2 \left( 1 + \frac{P_f^i G_{lf}^i}{\sigma^2 + I_f^i(X_{-k})} \right) x_f^l \right] + \sum_{q \in K, q \neq k} \sum_{m \in C_q} \log_2 \left( 1 + \frac{P_m^f G_{mq}^f}{\sigma^2 + I_q^f(X_{-\{q,k\}}) + \sum_{l \in C_k} P_l^f G_{lq}^f x_f^l} \right) x_f^m,
$$

(6.9)

where $I_q^f(X_{-\{q,k\}}) = \sum_{c \in K \setminus \{q,k\}} \sum_{l \in C_c} P_l^f G_{cq}^f x_f^l$ is the interference level at the $q$th receiver. It does not include the effect from the use of RB-$f$ in cell-$k$, which is given by $\sum_{l \in C_k} P_l^f G_{lq}^f x_f^l$, instead.

Problem (6.8) belongs to the family of nonlinear combinatorial optimization problems. Hence, achieving its optimal solution quickly becomes prohibitive when the number of users and/or RBs increases. Another drawback is related to the information that players need to exchange. In fact, to compute $U_k(X_k, X_{-k})$ in (6.9), player-$k$ needs to retrieve from every other player at most $2F$ scalar values, which represent the useful power and the interference level measured on the assigned RB. Then, player-$k$ must be able to remove the contribution from its cell to the global interference at the other receivers (this means that the cross-link gains between transmitters in its own cell and other receivers are known), thus obtaining $I_q^f(X_{-\{q,k\}}) \forall q \in K, q \neq k, \forall f \in F$.

### 6.4.2 Solution based on better response dynamic

The nonlinear nature of the Problem (6.8), together with the amount of information required to be exchanged between the players, encourage us to redefine the utility function of the players.
We consider a reference overall allocation strategy $\bar{X}$. Then, the new utility function for player-$k$ is defined as follows

$$
\tilde{U}_k(X_k, \bar{X}) = \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{C}_k} \left[ R^f_l(X_{-k})x^f_l \right.
\left. + \sum_{q \in \mathcal{K}, \ m \in \mathcal{C}_q} \left( R^f_m(\bar{X}_{-q})\bar{x}^f_m + \frac{\partial R^f_m(\bar{X}_{-q})}{\partial I^f_q(\bar{X}_{-q})} \left( P^f_l G^f_{lq} x^f_l - P^f_l G^f_{lq} \bar{x}^f_l \right) \right) \right],
$$

(6.10)

where

$$
\frac{\partial R^f_m(\bar{X}_{-q})}{\partial I^f_q(\bar{X}_{-q})} = -\frac{P^f_m G^f_{mq}}{(\ln 2)(P^f_m G^f_{mq} + I^f_q(\bar{X}_{-q}) + \sigma^2)(I^f_q(\bar{X}_{-q}) + \sigma^2)}
$$

(6.11)

represents the rate sensitivity to the interference variations, which can be computed at receiver-$q$. $\tilde{U}_k(X_k, \bar{X})$ represents the first-order Taylor approximation of the users’ rate around the interference level given by the reference allocation $\bar{X}$. Since the rate is a convex function of the interference, $\tilde{U}_k(X_k, \bar{X})$ is a lower bound of $U_k(X_k, \bar{X}_{-k})$. Note that this bound represents a tight approximation of the original utility function, under the (reasonable) assumption that the cumulative interference experienced at each receiver is much higher than the potential interference contribution of a single user.

We can further simplify (6.10) by subtracting constant terms that do not depend on the allocation decision of player-$k$, obtaining

$$
\tilde{U}'_k(X_k, \bar{X}) = \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{C}_k} \left[ R^f_l(\bar{X}_{-k}) \right.\left. + \sum_{q \in \mathcal{K}, \ m \in \mathcal{C}_q} \left( \frac{\partial R^f_m(\bar{X}_{-q})}{\partial I^f_q(\bar{X}_{-q})} \right) \left( P^f_l G^f_{lq} \right) \right] x^f_l.
$$

(6.12)

By defining

$$
\tilde{E}^f_l(\bar{X}) = \left[ R^f_l(\bar{X}_{-k}) \right.\left. + \sum_{q \in \mathcal{K}, \ m \in \mathcal{C}_q} \left( \frac{\partial R^f_m(\bar{X}_{-q})}{\partial I^f_q(\bar{X}_{-q})} \right) \left( P^f_l G^f_{lq} \right) \right],
$$

we reformulate Problem (6.8) as follows. Given the current strategy profile $\bar{X}$, player-$k$ updates its strategy by solving

$$
\begin{align*}
\text{maximize} & \quad \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{C}_k} \tilde{E}^f_l(\bar{X}) x^f_l \\
\text{subject to} & \quad \sum_{l \in \mathcal{C}_k} x^f_l \leq 1, \quad \forall f \in \mathcal{F}, \\
& \quad \sum_{l=1}^{F} x^f_l = F_l, \quad \forall l \in \mathcal{C}_k, \\
& \quad x^f_l \in \{0, 1\}, \quad \forall f \in \mathcal{F}, \forall l \in \mathcal{C}_k, k \in \mathcal{B}.
\end{align*}
$$

(6.13)
which is now an integer linear formulation, and thus it is easier to solve than Problem (6.8) [98]. It can be seen that the main difference with (6.8) is that here we consider a given benefit for each user-resource assignment, thus removing the optimization variables from the argument of the logarithm function as in (6.9). Moreover, differently from (6.8), here the objective function depends on at most \( F \) scalar values, to be retrieved from each other player of the game (the rate sensitivity in (6.11) for all assigned RBs).

We now show that, although we have changed the utility function of the game, we can still guarantee convergence to a NE, combining Lemma 6.3.5 with the following result:

**Proposition 6.4.2.** Given any allocation profile \( \bar{X} \), solution \( X^*_k \) to Problem (6.13) is such that \( U_k(X^*_k, \bar{X}_-k) \geq U_k(\bar{X}) \), that is \( X^*_k \) is a better response of player-\( k \) in game \( \mathcal{G} = [\mathcal{K}, \{X_k\}, \{\bar{U}_k\}] \).

**Proof.** Since \( X^*_k = \arg\max_{X_k} \bar{U}_k(X_k, \bar{X}) = \arg\max_{X_k} \bar{U}_k(X_k, \bar{X}) \), then \( \bar{U}_k(X^*_k, \bar{X}) \geq \bar{U}_k(X_k, \bar{X}), \forall X_k \in \mathcal{X}_k \). Moreover, \( \bar{U}_k(X_k, \bar{X}) \leq \bar{U}_k(X_k, \bar{X}_-k), \forall X_k \in \mathcal{X}_k \) because of the linear approximation. By combining the two inequalities above we have \( U_k(X^*_k, \bar{X}_-k) \geq \bar{U}_k(X^*_k, \bar{X}) \geq \bar{U}_k(X_k, \bar{X}) = U_k(X_k, \bar{X}_-k) \).

### 6.5 Implementation guidelines

The iterative better response dynamic requires the players to follow a predetermined order. In this work, we assume that the BSs play in a sequential order, agreed upon before the gameplay. D2D receivers located within a given cell play right after their serving BS in an order decided by the BS itself, and sent to the users as a control command. All players start with a random and feasible RB allocation profile. When player-\( k \) plays, before solving Problem (6.13), it retrieves from each other player-\( q \in \mathcal{F} \), \( m \in \mathcal{C}_q \)

\[
\Delta_q = \left[ \frac{\partial R_{mq}^f(\bar{X}_{-q})}{\partial I_q^f(\bar{X}_{-q})}, f \in \mathcal{F}, m \in \mathcal{C}_q \right].
\]

Its elements represent the rate sensitivity on each RB, estimated after the latest strategy profile’s update. Differently from ad-hoc networks, network-assisted D2D communications are coordinated by the BS. Therefore, we assume that each BS-\( b \in \mathcal{B} \) collects the information related to the rate sensitivity of the D2D pairs under its coverage, and sends it, together with its vector \( \Delta_b \), to the next player (BS). In an LTE network, this communication of the rate sensitivity between the BSs can be naturally mapped onto the X2-Interface [12]; see Fig. 6.1 for illustration. When a D2D transmitter has to play, then its serving BS is in charge of forwarding (on a control channel) the necessary information collected from the other BSs.

It is worth mentioning that the implementation of the better response dynamic requires that each receiver knows the channel gains between its intended transmitters...
and the neighbouring receivers. Channel gains between mobile users and neighbouring BSs are already estimated in cellular networks for handover purposes. However, the presence of D2D communications requires to modify the existing protocols in order to introduce the measurements of the channel gains also between mobile users and neighbouring D2D receivers.

### 6.6 Numerical results

To study the behavior of the proposed resource allocation algorithm based on better response dynamics, we simulate networks consisting of either 7 or 3 hexagonal cells with omnidirectional BSs and randomly placed mobile users. The number of transmissions (UL transmissions and D2D communications) is assumed to be the same in all cells. All transmitters use the same power level and the cellular users are assigned to all resource blocks, i.e., $\sum_{l \in \mathcal{C}_k} F_l = F, \forall k \in \mathcal{B}$. The system parameters used in the simulations are summarized in Table 6.1.

Fig. 6.2 illustrates the convergence of the better response dynamic for a 7-cell network for different number of users. Each curve shows how the total bit rate evolves in a single simulation run. In this figure, one iteration corresponds to the strategy update of one player. The simulations are initialized from a random feasible allocation. As expected, the potential function increases monotonically.
Table 6.1: Simulation parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carrier frequency</td>
<td>1 GHz</td>
<td>Lognormal shadow fading</td>
<td>6 dB</td>
</tr>
<tr>
<td>Cell radius</td>
<td>500 m</td>
<td>No. of RBs assigned to users</td>
<td>1</td>
</tr>
<tr>
<td>Noise power</td>
<td>-174 dBm/Hz</td>
<td>Users’ transmit power</td>
<td>0.25 W</td>
</tr>
<tr>
<td>Path loss coefficient</td>
<td>3.5</td>
<td>Distance between D2D pairs</td>
<td>50-150 m</td>
</tr>
</tbody>
</table>

towards an equilibrium value. The algorithm converges quickly: the most dense network considered has 36 transmissions per cell (24 UL transmissions and 12 direct communications) and converges in less than 4 rounds (that is, in less than 364 player updates).

![Figure 6.2: Convergence behaviour of the better response dynamic for different realizations of a 7-cells network. Each iteration corresponds to the strategy update of one player.](image)

To assess the validity of the proposed scheme, we consider 500 independent simulations, each with the same number of users but placed in different locations and with different channel conditions. We compare the performance of four resource allocation schemes: random resource allocation (R-RA), the proposed game with better response dynamic (Better-RA), the proposed game with best response dynamic (Best-RA), and the globally optimal resource allocation (Opt-RA). The optimal allocation is obtained by exhaustive search, for which the run-time becomes prohibitive for large-size networks. For this reason, we consider a small system with 3 cells, each of them serving 3 cellular users and 2 D2D pairs.

We characterize the efficiency of the NE points achieved using Best-RA and
Better-RA by the relative performance degradation compared with Opt-RA. Fig. 6.3 shows that the Best-RA is within 10% of the optimal solution for almost all network configurations. However, the computation of each best response requires the solution of a combinatorial problem, which leads to runtime limitations for practical network sizes. The Better-RA performs slightly worse, but has faster convergence for all network sizes and is still within 20% of the optimal solution for almost all configurations.

Table 6.2 summarizes the results from the 500 random configurations. As we can see, both the Best- and Better-RA are significantly superior to R-RA, and not so far from the optimum. Moreover, since the set of pure-strategy Nash equilibria achieved with the better and best response dynamics is the set of local maxima of the potential function, playing the game cannot only lead to a performance improvement compared with any initial allocation, but in some cases it can achieve the global optimum (see Table 6.2), which belongs to the set of NE.

**Figure 6.3:** Histogram of the rate loss using the Best-RA and Better-RA with respect to the optimum. Results are obtained considering 500 random independent simulations of a 3-cell network with a total of 15 links.

**Table 6.2:** Simulation results (3-cell network with 15 links)

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Average Utility (bps/Hz)</th>
<th>Percentage of incidences in which optimal solution is obtained</th>
<th>Number of incidences in which the percentage rate loss is within 15%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opt-RA</td>
<td>73.5205</td>
<td>100%</td>
<td>500</td>
</tr>
<tr>
<td>Best-RA</td>
<td>70.5514</td>
<td>19%</td>
<td>491</td>
</tr>
<tr>
<td>Better-RA</td>
<td>65.2594</td>
<td>2%</td>
<td>357</td>
</tr>
<tr>
<td>R-RA</td>
<td>49.8062</td>
<td>0%</td>
<td>11</td>
</tr>
</tbody>
</table>
6.7 Summary

In this chapter we investigated the problem of RBs allocation in a multicellular wireless network, where underlay D2D connections are also enabled. Using a game-theoretic approach, we showed that the challenging non-convex and combinatorial problem of sum-rate maximization can be described by a potential game, for which convergence to a Nash equilibrium can be ensured using best/better response dynamics. We derived a low-complexity iterative algorithm with limited signaling that allocates the RBs to users, exploiting frequency diversity and efficiently managing both the intra- and inter-cell interference. Numerical results showed that the proposed resource allocation mechanism converges quickly to an equilibrium point, even for large networks. Comparisons with alternatives for small networks (for which it is possible to compute the optimal allocation by exhaustive search) show that the achieved performance at the NEs are not too far from the optimum (in most of the cases it is less than 20% from the optimum), and always improved compared to the initial allocation.
Chapter 7

Conclusion and future works

In this chapter, we review the main results of this thesis and outline possible directions for future research.

7.1 Conclusions

D2D communication integrated in cellular networks is a promising technology for enhancing the performance of proximity-based services in future 5G systems. The basic idea of D2D communication is to allow mobile devices in close proximity to communicate directly, bypassing the base station. This leads to several advantages: the traffic load on the cellular system is decreased, the coverage is increased, and performance metrics such as throughput, latency, energy consumption and spectral efficiency are improved. However, the introduction of D2D requires to revisit the resource management techniques used to date for traditional cellular systems.

In this thesis, we investigated some potential gains achievable by proper design and coordination of mode selection, power control and (time/frequency) resource allocation algorithms. Our main focus has been underlay in-band D2D communication, where D2D and cellular transmitters share the available time/frequency resources. Although this approach can improve both the spectral efficiency and the system capacity, it leads to new interference situations for which efficient resource management methods are needed.

Our main contributions can be summarized as follows:

Energy efficient D2D communications in dynamic TDD systems. In Chapter 4, we addressed the problem of joint mode selection, power, and transmission time allocation for energy-optimal operation in a D2D-enabled network with dynamic TDD. Different variations of this joint problem have been formulated as mixed-integer nonlinear programs. Although mixed-integer nonlinear programs are NP-hard in general, we demonstrated that the mathematical structure of the problem in the interfere-free case can be exploited to devise algorithms that find the optimal solution in polynomial time. However, when considering interference
among multiple D2D links, finding the optimal solution remains challenging. In this case, we designed a customized B&B solver, with novel variable selection and branching rules, and efficient procedures for infeasibility detection and performance bound computations. This solver allowed us to find provably optimal solutions much more efficiently than using generic B&B solvers or naive exhaustive search. Furthermore, we proposed a heuristic algorithm for computing near-optimal solutions while respecting practical constraints in terms of execution times and signalling overhead.

Numerical simulations demonstrated that significant energy savings can be achieved by exploiting the benefits brought both by the better channel gain of D2D links, and by the adaptive transmission time of the dynamic TDD technology. By means of an analytical characterizations of the D2D-optimal areas for a transmitter-receiver pair, we also showed that these regions can be surprisingly large and not necessarily circular (as they are when mode selection is based only on distance).

A comparative study of power control schemes for D2D communications. In Chapter 5 we compared the performance of various power control strategies for D2D communications in LTE networks. The main motivation for this examination was to gain an understanding of how well LTE power control schemes perform as compared to an optimization-based approach.

From the numerical results we concluded that the flexible LTE power control scheme is well prepared for network-assisted D2D communications, especially from the cellular user perspective. However, for the D2D pairs, the utility based scheme could provide gains in terms of SINR distribution and total transmit power consumption.

Subcarrier allocation in multi-cell D2D-enabled network. In Chapter 6, we considered the subcarrier allocation problem for a multi-cell network, where D2D communications share the uplink resources with traditional cellular users. We aimed at maximizing the total rate of the system by taking advantage of frequency diversity among the channels, and by properly managing the interference. The nonlinear and combinatorial nature of this resource allocation problem makes the optimal solution hard to find, even in a centralized off-line setting. Our main contribution was to demonstrate how the theory of potential games allows for systematic design of distributed resource allocation schemes. Specifically, we devised low-complexity iterative algorithms based on better response dynamics and showed that these algorithms always attain a Nash equilibrium of the resource allocation game.

Through numerical examples, we demonstrated that the algorithm converges quickly, also for dense networks. Moreover, the achieved solution is not too far from the true optimum (at least not for the small sized networks where we are able to find the truly optimal resource allocation).
7.2 Future works

Our study on energy-efficient D2D communications in dynamic TDD systems considered a single-cell scenario. We thus neglected the impact of the additional interference that is introduced when different cells optimize their individual uplink/downlink time allocation. One interesting extension would be to investigate how the energy efficiency problem can be extended to the multi-cell dynamic TDD scenario without synchronization among the cells. Moreover, we focused on minimizing the transmission energy consumption. Extending this work to account also for circuit and idle power consumption of transmitters is an important challenge.

Regarding the power control schemes evaluated in Chapter 5, it would be interesting to investigate the performance of a hybrid scheme, in which cellular users use the LTE power control, whereas D2D pairs use a distributed utility-based approach. This separation, in fact, might allow for a smoother introduction of D2D communication in LTE systems.

The RB allocation problem considered in Chapter 6 assumed fixed transmit powers. However, combining subcarrier allocation with power control could potentially lead to even better performance. Another interesting future extension could be to design decentralized solutions which are not only distributed among the players (base stations and D2D receivers), but that involve also the transmitters.

Finally, other possible research directions include moving from single to multiple antenna systems, and studying D2D communication in higher frequency bands, such as millimeter wave, which is going to be another key feature of future 5G systems.
Appendix A

The customized design in the B&B method

In the design of our B&B algorithm in Chapter 4, Section 4.4.1, we have made the following choices:

1. **Initial upper bound.** By assumption, letting all pairs communicate in cellular mode (i.e., $m_l = 0 \forall l$) is always feasible. We therefore take the corresponding energy cost as an initial upper bound on the optimal cost, computed by solving

$$
\begin{align*}
\text{minimize}_{t_{ul} \in [0,T]} & \quad \sum_{l \in L} E_{UL}^{CELL}(t_{ul}) \\
\text{subject to} & \quad \max_{l \in L} \{ b_{l0} \} \leq t_{ul} \leq \min_{l \in L} \{ T - \frac{b_{l0}}{r_{0l}} \},
\end{align*}
$$

where $E_{UL}^{CELL}(t_{ul})$ is given by (4.8).

2. **Branching rule.** The branching rule selects the next variable to fix at each node of the tree. The goal is to identify the branching variable that changes the problem the most, either to quickly detect branches that can be cut, or to significantly improve the current solution.

Our branching strategy is based on first solving the FO-UE problem described in Section 4.3. The corresponding optimal mode selection vector $m_{FO}^*$ reveals the set $D_{m_{FO}^*} = \{ l | m_{l_{FO}}^* = 1 \}$ of pairs that prefer to communicate in D2D mode in an interference-free environment. For each link $l \in D_{m_{FO}^*}$, we define a measure of its strength $s_l = \sum_{i \in D_{m_{FO}^*}, i \neq l} G_{li}/G_{ll}$. This measure attempts to account for both the interference that pair-$l$ produces on the shared frequency resource and its own direct gain. The branching rule first selects variables in $D_{m_{FO}^*}$ in order of decreasing $s_l$, and then considers the remaining variables in an arbitrary order. This rule exploits the fact that pairs that prefer to be in cellular mode in FO are also likely to prefer cellular mode in RS. By fixing D2D pairs with high interference strength first, we increase the likelihood of finding infeasible solutions quickly. Once an infeasible mode selection is found, we can make use of Proposition 4.4.3 and discard all branches below the current node in the search tree.
3. **Tree exploration strategy.** Once a branching variable $m_l$ has been selected by the branching rule, the tree exploration strategy determines if the child node to investigate next should be in cellular or D2D mode. We allocate users to D2D mode first (i.e., setting $m_l = 1$ first).

4. **Upper and lower bounds.** When we consider a node, we first verify if the set $F$ forms a feasible mode selection vector in the sense of Proposition 4.4.1. If not, then no bounds are computed and the node and all branches below it can be disregarded by making use of Proposition 4.4.3. Otherwise, upper and lower bounds are calculated. To compute an upper bound, we assign all pairs in $U$ to cellular mode and we solve the problem formulation in (A.1) where $L$ is replaced by the union of $U$ with the subset of $F$ representing users already assigned to cellular mode. To determine a lower bound, we compute the minimal energy cost of the unassigned pairs when they operate in full orthogonality (i.e., we solve the FO-UE problem over only the unassigned pairs. This is a lower bound because the computation is a relaxation of the MINLP, where the UL times of fixed and unassigned pairs are allowed to differ, and where the unassigned links that end up in D2D mode do not suffer interference. Furthermore, we strengthen the lower bound by increasing the noise power of pairs in $U$ by the interference that the transmitters fixed to D2D communication in $F$ incur on them.
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