Network Interference Cancellation for 5G

Liang Zhou
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Abstract

The future fifth generation (5G) mobile communication systems are currently being developed under expectations of fulfilling various technical requirements, which include massive connectivity, high capacity, low latency and ultra-reliability. In order to achieve high capacity, operating at high frequency spectrum such as millimeter wave is considered as an appealing option, which requires more dense allocation of Transmission Reception Points (TRP). With more micro and macro TRPs deployed with small inter-site distance, cell-edge users in 5G networks may encounter strong interference from neighbor transmissions in both uplink and downlink. Successive Interference Cancelation (SIC) receivers, which are applied in 5G with Non-Orthogonal Multiple Access (NOMA), have been presented as a potential solution for heavy interference scenarios, where the performance gain can be further improved by network Interference Cancelation (IC). Motivated by the demands for improving spectral efficiency in different interference environments, this thesis addresses Radio Resource Management (RRM) optimization with network IC in specific 5G uplink and downlink scenarios.

In the uplink, this thesis investigates Device-to-Device (D2D) communications. D2D pairs of transmitters and receivers share the same cellular uplink resource. Situations with and without an uplink cellular user are considered. A centralized RRM optimization algorithm is proposed where the cellular base station maximizes the network utility by adjusting all D2D and cellular users' transmission power, rate and IC configurations. Additionally, distributed RRM algorithms based on strategic games are developed. Simulation results of the centralized and the distribute algorithms show considerable gains in spectral efficiency.

In the downlink, a scenario with only cellular users is considered. Each cellular user may perform SIC on one of the two strongest nearby downlink transmissions. This opens up the possibility that a cell-edge user may be served by the second nearest cell, and cancel the interference from the closest cell. This is called cell-edge inversion in this thesis. The utility of the whole network is maximized by a radio resource optimization method that is distributed among the cells. The simulation results show significant improvement of the rate of cell-edge users.

Keywords Interference cancelation, Radio resource management, D2D, Game theory
It is wonderful to study in the Department of Communications and Networking (Comnet). The rigorous theoretical research, challenging practical projects, academic atmosphere, helpful colleagues and very delicious coffee, I appreciate everything offered by Aalto Comnet during the period of my doctoral studies.

Foremost, I sincerely thank my supervising professor Olav Tirkkonen, who patiently guided me and gave me illuminating advice through my whole doctoral studies. It is my honor and pleasure to study with you. Your enthusiasm on research and attitude to life will encourage me for the rest of my life.

Moreover, I would like to thank Prof. Randall Berry of Northwestern University, for all your irreplaceable support and insightful advice which helps me construct my papers. I also would like to thank Dr. Kalle Ruttik for creative ideas and energetic support when we wrote papers together. I further thank Prof. Walid Saad of Virginia Polytechnic Institute and State University and Prof. Vangelis Angelakis of Linköping University for their respectable work as the pre-examiners of this thesis.

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Helsinki, May 15, 2020,

Liang Zhou
Preface

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This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.


Author’s Contribution

Publication I: “Interference Canceling Power Optimization for Device to Device Communication”

The author of this thesis participated in the planning and algorithm development in this paper, and carried out the simulations as well as the analysis of the results. The author had a leading role in writing the paper.

Publication II: “Interference Canceling Power Control Games in Gaussian Interference Channels”

The author of this thesis participated in the planning of the paper and had a leading role in developing and analyzing the techniques provided in this paper. The author of this thesis carried out the simulations, and had the main role in writing the paper.

Publication III: “Two-player D2D Interference Canceling Games”

The author had a leading role in planning the paper, and in developing and analyzing the techniques provided in this paper. The author of this thesis carried out the simulations and had the main role in writing the paper.

Publication IV: “D2D Networks with Opportunistic Interference Cancellation”

The author had a leading role in planning the paper, and developing the techniques of the paper. The author performed the analysis of the algorithms of the paper, carried out the simulations and wrote the entire paper.
Author's Contribution

**Publication V: “Cell-edge Inversion by Interference Cancellation for Downlink Cellular Systems”**

The author of this thesis participated in planning the paper and had a leading role in developing and analyzing the algorithms. He carried out the simulations, and had a leading role in writing the paper.

**Language check**

The language of my dissertation has been checked by Olav Tirkkonen. I have personally examined and accepted/rejected the results of the language check one by one. This has not affected the scientific content of my dissertation.
## Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>AWGN</td>
<td>Additive White Gaussian Noise</td>
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<tr>
<td>BS</td>
<td>Base Station</td>
</tr>
<tr>
<td>CDF</td>
<td>Cumulative Density Function</td>
</tr>
<tr>
<td>CH</td>
<td>Cognitive Hierarchy</td>
</tr>
<tr>
<td>CoMP</td>
<td>Coordinated Multi-Point</td>
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<tr>
<td>CSI</td>
<td>Channel State Information</td>
</tr>
<tr>
<td>D2D</td>
<td>Device-to-Device</td>
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<tr>
<td>DS-CDMA</td>
<td>Direct-Sequence Code Division Multiple Access</td>
</tr>
<tr>
<td>FM</td>
<td>Frequency Modulation</td>
</tr>
<tr>
<td>GIC</td>
<td>Gaussian Interference Channel</td>
</tr>
<tr>
<td>HHO</td>
<td>Hard HandOver</td>
</tr>
<tr>
<td>IC</td>
<td>Interference Cancelation</td>
</tr>
<tr>
<td>ICIC</td>
<td>Inter-Cell Interference Coordination</td>
</tr>
<tr>
<td>ISD</td>
<td>Inter-Site Distance</td>
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<tr>
<td>LTE</td>
<td>Long-Term Evolution</td>
</tr>
<tr>
<td>LTE-A</td>
<td>LTE-Advanced</td>
</tr>
<tr>
<td>MTC</td>
<td>Machine Type Communications</td>
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<tr>
<td>MIMO</td>
<td>Multiple-Input and Multiple-Output</td>
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<tr>
<td>MISO</td>
<td>Multiple-Input and Single-Output</td>
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<tr>
<td>NE</td>
<td>Nash Equilibrium</td>
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</table>
### Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>NMT</td>
<td>Nordic Mobile Telephone</td>
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<tr>
<td>NOMA</td>
<td>Non-Orthogonal Multiple Access</td>
</tr>
<tr>
<td>NR</td>
<td>New Radio</td>
</tr>
<tr>
<td>NUM</td>
<td>Network Utility Maximization</td>
</tr>
<tr>
<td>PIC</td>
<td>Parallel Interference Cancelation</td>
</tr>
<tr>
<td>PC</td>
<td>Power Control</td>
</tr>
<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>RRM</td>
<td>Radio Resource Management</td>
</tr>
<tr>
<td>SDR</td>
<td>Software-Defined Radio</td>
</tr>
<tr>
<td>SGP</td>
<td>SubGame Perfect</td>
</tr>
<tr>
<td>SHO</td>
<td>Soft HandOver</td>
</tr>
<tr>
<td>SIC</td>
<td>Successive Interference Cancellation</td>
</tr>
<tr>
<td>SIMO</td>
<td>Single-Input and Multiple-Output</td>
</tr>
<tr>
<td>SINR</td>
<td>Signal-to-Interference-plus-Noise-Ratio</td>
</tr>
<tr>
<td>SPO</td>
<td>Subgame Perfect Outcome</td>
</tr>
<tr>
<td>TD-LTE</td>
<td>Time Division Duplex Long-Term Evolution</td>
</tr>
<tr>
<td>TRxP</td>
<td>Transmission Reception Point</td>
</tr>
<tr>
<td>UE</td>
<td>User Equipment</td>
</tr>
<tr>
<td>WLAN</td>
<td>Wireless Local Area Network</td>
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1. Introduction

1.1 Motivation

From analog to digital, from 450 MHz to 2.6 GHz, from Nordic Mobile Telephone (NMT) to Long-Term Evolution (LTE), ever since the invention of mobile communications, the hunger for mobile data speed and connectivity has motivated the mobile communication systems to evolve from first generation (1G) to fourth generation (4G). The fifth generation (5G) cellular systems are currently being developed under expectation of fulfilling various technical requirements [1, 2], which include faster transmission speeds, lower latency, and more reliable connections. The target peak data rates are set to 10/20 gigabits per second (Gbps), together with the target peak spectral efficiency of 15/30 bps/Hz for uplink/downlink [1]. Besides peak spectral efficiency, 5th percentile user spectrum efficiency is also defined as key performance indicator in [1] to guarantee cell-edge users’ experience. With more micro and macro Transmission Reception Points (TRxP) deployed with small Inter-Site Distance (ISD) in 5G networks, cell-edge users may encounter strong interference from neighbor transmissions in both uplink and downlink. From this perspective, 5th percentile user spectral efficiency can be dramatically improved by eliminating the negative impact of interference. Technologies such as Inter-Cell Interference Coordination (ICIC) [3–5], interference alignment [6–8] and Coordinated Multi-Point (CoMP) technique [9–11] have been investigated to avoid or orthogonalize interference. However, applications of such technologies are constrained by system complexity and stringent requirements of coordination between transmitters. As a simple alternative, Successive Interference Cancelation (SIC) receivers have been presented as potential solution which provides considerable gains in wireless communications [12–16]. Further, there are still other potential application scenarios of network IC to investigate in mobile networks.

Device-to Device (D2D) communication underlaying cellular networks has been intensively investigated [17–20], and specified as a part of the 4G LTE-A standard in 3rd Generation Partnership Project (3GPP) Release 12 [21]. Oper-
ating in cellular uplink spectrum supported by LTE networks, underlay D2D communications may be naturally synchronized. It increases spectrum utilization, while posing inevitable challenges such as increased interference and increased network management complexity, especially if multiple D2D users are allowed to use the same resource. Therefore this should be a typical heavy interference scenario where SIC may effectively improve total uplink spectral efficiency for cellular networks. Another typical heavy interference scenario is downlink for cell-edge users.

Motivated by the demands for improving spectral efficiency in different interference environments, this thesis addresses RRM optimization with network IC in the specific uplink and downlink scenarios.

1.2 Scope of the Thesis

The objective of this thesis is to contribute radio resource management methods for cellular & D2D networks enhanced by SIC functionality. We consider application of network IC in the uplink and the downlink scenarios separately.

In uplink, we consider a scenario where D2D devices underlaying a cellular network share the same uplink resource. Situation with and without an uplink cellular user are considered. Such a setting increases spectral efficiency by allowing multiple D2D devices to reuse cellular uplink resources, given that interference is mitigated by applying a SIC receiver. Depending on the different RRM structure, attention is paid to joint optimization of transceiver configuration by a centralized method, and interactive gaming behavior between users for distributed methods.

For downlink, we consider a scenario where cell-edge users may perform SIC on one nearby downlink transmission. This opens up the possibility that a cell-edge user may be served by the neighbouring cell and cancels the interference from the closest cell, which is called cell-edge inversion in this thesis. By optimizing radio resource scheduling for each cell in a distributed manner, better cell utility and spectral efficiency can be achieved.

The goal of this thesis is to investigate feasible RRM methods to improve radio spectral efficiency with IC in cellular & D2D networks. Therefore, to verify the feasibility of practical implementation of IC, experiments are performed on a Software-Defined Radio (SDR) platform built by our research group. The main tool for verification has been Monte Carlo simulations. In order to simulate realistic situations, the propagation parameters are calculated by stochastic geometry location of users, with distance-dependent path loss.
1.3 Contributions and Structure of the Thesis

This work contributes to resource management for SIC-capable cellular/D2D networks. RRM optimization methods are developed for uplink and downlink scenarios.

In uplink, both centralized and distributed RRM optimization algorithms are developed to improve spectral efficiency in an isolated cell. In the centralized algorithm, we optimize network utility for IC configurations by a scheduling approach. Each receiver may or may not decode its strongest interferer, and the scheduling problem of allocating resources to these $2^N$ configurations is solved. We offer an iterative algorithm, iterating between power and scheduling updates, where the transmit power for each configuration is separately optimized. The results demonstrate significant gain in spectral efficiency and give an upper limit in situations with complete centralized CSI. In distributed algorithms, we analyze equilibrium behavior of one-shot game $(P, C, R)$ and several two-stage variants, including games with limited rationality strategies. If a Nash Equilibrium (NE) exists, it indicates that it is possible to realize distributed RRM algorithms that converge. We show that the NEs of these games in a given network state are connected. Game based distributed optimization algorithms are developed and compared to the centralized method. It is observed that applying a strategic game to distributed RRM results in considerable gain with a simple algorithm which does not require massive information exchange.

In a downlink IC scenario, the utility of the whole network is optimized over all cell-edge inversion possibilities, where transmissions from the two best cells are considered for a user. Due to high dimensionality of the resulting convex problem, a distributed algorithm based on resource pricing between cells is devised. Simulation results in a heterogeneous network show significant gains from cell-edge inversion, when proportionally fair network utility is maximized. It is remarkable that almost 70% gains for the rates of the cell-edge users come with a small gain also in the mean data rate of all users. The method opens up significant possibilities for improving resource fairness among users in downlink transmission of heterogeneous networks.

This thesis is organized as follows. Chapter 2 presents an introduction discussing background of network IC applications. The literatures concerning interference cancelation and SIC are first reviewed, followed by discussion of previous study of D2D communication underlaying cellular network. We also review the previous studies of game theory in wireless communications. Chapter 3 demonstrates the general wireless network model applied in this thesis, and the practical verification method of a simple application case of IC. In Chapter 4 and 5, we present our contributions on RRM optimization in the uplink scenario separately with centralized and distributed methods. In Chapter 4, an iterative power and IC configuration optimization algorithm with centralized control is introduced and simulation results are presented. The feasibility of implementing IC on underlaying D2D communication is verified by practical
experiments. In Chapter 5, two-player strategic games are first introduced and analyzed, then the discussion expands to multiplayer cases and limited rationality games. Based on that, distributed algorithms are formulated and evaluated by simulations. A comparison between centralized and distributed methods is also provided. In Chapter 6, distributed RRM optimization applying cell-edge inversion in the downlink scenario is presented. Finally, Chapter 7 summarizes the results and the contributions of this thesis. Directions for future works are also outlined.

1.4 Summary of the Publications

In Publication I, we consider D2D communication underlying cellular uplink communications when SIC receivers are available to improve local service. The interference cancelation configurations and transmission powers are jointly optimized in the network to maximize a network utility. Each receiver may or may not cancel the signal from the dominant interferer. With \( N-1 \) D2D pairs and one cellular transmitter, there are \( 2^N \) possible IC state combinations. A scheduling problem is formulated to allocate resources to these combinations, and network utility is maximized by iterating between scheduling weight and transmit power. The achievable gains in the spectral efficiency are demonstrated by simulation results for different utility functions.

In Publication II, a two-player non-cooperative successive interference canceling and power control (ICPC) game in a Gaussian interference channel is investigated. We characterize the equilibria of this game. As opposed to the pure power control game and the rate splitting game between the same players, we find that in the ICPC game, there exist Nash equilibria where a player voluntarily reduces his power in order to enable interference canceling and to achieve a higher rate.

In Publication III, we investigate a set of non-cooperative two-player radio resource management games in a Gaussian interference channel, where the SIC receivers are equipped. In these games users decide on their transmission power, rate and Interference Canceling (IC) strategy. A set of games, including a one-shot game and its two-stage variants, are considered. We characterize the equilibria of the games and establish a relationship between the equilibria of the one shot and two-stage games. We simulate a 2-pair D2D network where these games are applied as distributed radio resource management methods.

In Publication IV, multiuser uplink RRM games involving underlay D2D communication is studied, where receivers are equipped with SIC. Users greedily decide on their transmission power, rate and Interference Canceling (IC) strategy. We analyze various games and find relationships between the equilibria of these games. Irrespectively of the game setting, there are some network states where no pure strategy equilibria exist. Generically, staging the rate, and possibly IC strategies to a 2nd stage, improves stability. We apply the games to D2D
networks, and find that the two stage games with limited rationality provide good and reliable algorithms for distributed RRM in D2D networks.

In Publication V, a novel method is considered to improve the downlink data rate of cell-edge users in a cellular system by applying SIC on the best two cellular downlink transmissions. Receivers may be served by either the closest cell or a neighboring cell. In the latter case, the receiver cancels the interference from its own cell transmission, and receives the other-cell transmission without this interference. A distributed network utility optimization problem is formulated. Promising results on imposing cell-edge user rate in heterogeneous networks are obtained, accompanied by a moderate gain for the network capacity.
2. Background

2.1 Successive Interference Cancelation as a Trend

Interference limits the capacity of modern wireless communication systems. For example, modern cellular communication systems such as 4G LTE are designed to operate with frequency reuse 1. Allowing for hand-over margins, co-channel interference from neighboring cells may require downlink receivers at cell-edge to operate at Signal-to-Interference-plus-Noise-Ratios (SINRs) as small as -7dB [22].

Much current research attempts to mitigate the cell-edge interference problem. Receivers may be improved by applying interference rejection and cancellation, whereas transmission technologies may be improved by attempting multipoint transmission. Multipoint transmission requires sharing accurate channel information between coordinating base stations and user data sequences may need to be transmitted from multiple points in the network. Consequently, the price of implementing multipoint transmission appears to be rather high.

As an alternative, the receivers may be improved, by using Interference Rejection Combining (IRC) receivers, or more advanced Interference Cancellation (IC) receivers. Baseline IRC has been widely studied, and it indeed provides significant gains for cell-edge users in conventional cellular settings, especially when the base stations are deployed with a single transmission antenna [22]. Extending from IRC to full-fledged IC holds much promise.

The Gaussian Interference Channel (GIC) is a particularly simple and powerful model where elementary interactions between multiple interference-coupled systems can be analyzed [23–27]. The best known coding strategy in a GIC is based on Han-Kobayashi rate splitting [24, 25], where the transmitters split their messages into two parts, one (the public part) intended to be decodable at both receivers, the other (private part) intended to be decodable only at the intended receiver. In such a scheme, receivers have to simultaneously handle three code words. This is a logical possibility different from legacy noninterference-canceling receivers, where only the intended codeword may
be processed, considering all other transmissions as noise, and from receivers capable of receiving Han- Kobayashi rate-split messages, which would need to be able to deal with three codewords. In an evolution of wireless communication receivers, loosening of the hardware constraint from dealing with one codeword to dealing with two in a SIC manner may be a reasonable step. As a simple and practical alternative, Successive Interference Cancelation (SIC) receivers have the potential to become mainstream in conventional cellular networks [12].

Accordingly, the potential provided by having SIC receivers in wireless networks has been widely studied. The Pareto boundary of the rate region for the symmetric two-user Gaussian interference channel with SIC receiver is characterized in [28]. Significant improvement of resource efficiency can be achieved with SIC in ad hoc networks [29]. Opportunistic use of SIC provides considerable gains in Multiple-Input and Single-Output (MISO) [30] and Multiple-Input and Multiple-Output (MIMO) [13] communications. When applied in cognitive radio networks [14], opportunistic SIC may effectively improve secondary rate as secondary transmitters know the instantaneous channel gain toward the intended receiver. In [15] it was shown that opportunistic cancelation with SIC receivers support remarkable throughput gain when combined with multicarrier spectrum shaping.

Cooperative or planned use of SIC further improves the potential benefits of network IC [8,31–35]. In [31], a distributed algorithm to provide rate splitting transmissions in a cellular downlink network with SIC-capable receivers was addressed. The ensuing algorithm is complex, as the number of possible orders in which interference from multiple sources can be canceled, grows hyper-exponentially in the number of interference sources. To solve the problem of hyper exponential complexity, it was suggested in [32] to concentrate on single-stage IC, where each receiver can decode at most one interfering signal. A max-min power control problem was addressed, finding the maximum SINR that all receivers in the network of Tx-Rx pairs may enjoy. The problem was shown to be NP-hard. In [35], this approach is generalized to multi-stage SIC. In [34], performance improvement of SIC and PIC in link activation optimization problem is presented.

IC is particularly interesting in a setting of fifth generation (5G) networks, where the concept of Non-Orthogonal Multiple Access (NOMA), has been discussed [36, 37]. The idea of NOMA is to apply SIC in a cellular setting, to enhance resource usage in a cell. In NOMA, two superposed messages with designed power and coding are transmitted by the same transmitter, while some receivers may use SIC to receive the high-SNR message. Possibilities to apply SIC arise in a natural manner from the inherent power differences experienced by cellular users.
2.2 D2D Communication Underlaying Cellular Network

D2D communications and cellular communications may use different air interfaces or share the same air interface. By using alternative air interface, e.g. WLAN, D2D ad hoc networks may be embedded to cellular networks as a relay to extend system coverage and increase system capacity cost efficiently [38–40]. Nevertheless, WLAN protocols may not be efficient enough for cellular relay application due to the poor interference management. When the same air interface is used, spectrum sharing between D2D and cellular networks can be orthogonal (overlay) or non-orthogonal (underlay) [41]. In [42], orthogonal resource allocation is applied for each D2D and cellular device in order to avoid interference between devices, which utilizes spectrum inefficiently. On the other hand, non-orthogonal spectrum sharing between D2D and cellular networks where D2D and cellular communication share the same air interface, has been investigated in [17, 18, 43–59], where D2D and cellular communication shares the same air interface. In these cases, interference coordination between D2D and cellular communication can be realized as D2D users are under control of cellular networks. However, according to [18, 59], non-orthogonal resource sharing between D2D and cellular communication does not always yield better performance than orthogonal resource sharing. In [46–48, 58], D2D transmission power in cellular uplink is determined in such way that cellular uplink transmissions only suffer from tolerable interference.

As proposed in [58], D2D communication underlaying cellular network is a practical method to improve spectral efficiency by allowing D2D devices to reuse radio resources under control of the underlaying cellular network. By transplanting communication specifications of the cellular network, D2D communication can be naturally synchronized and coordinated with cellular communications. Furthermore, the same frame structure and coding standard make it possible to decode both D2D and cellular transmission with a cellular receiver, which paves a flat road leading to interference cancelation. It is shown that integrating underlay D2D communication to LTE-Advanced network is promising [17, 43–45]. Similarly, there is also great potential for D2D communication underlaying 5G networks.

2.3 D2D Communication with IC

Interference cancelation strategies have been applied to D2D communication networks, with or without power control. Applying IC at D2D receivers has been shown to provide considerable gains in network capacity [60–66]. This is also addressed in [PI]. SIC gains in large-scale D2D-enabled cellular networks is validated with tools from stochastic geometry [60]. In [61], a rate splitting approach was used for D2D pairs. The approach has hyper-exponential complexity in transmission mode selection, and accordingly does not scale to
Background

instances with more than three Tx-Rx pairs. In [63], machine type D2D users applied a fixed low rate, which makes it possible for cellular downlink users to apply IC. In [64] it was further shown that zero outage can be achieved at the downlink cellular receiver, if joint detection is used in this scenario, while with SIC, outages persist. In [65], transmission capacity region is characterized for D2D integrated cellular networks, where power control and SIC are utilized. A joint rate and power control scheme is proposed in [66], where the transmission power and rate of the cellular users are adjusted to maximize cellular users’ data rate and protect D2D users from serious interference. The approach of [62] and [PI] is not limited to low-rate D2D users. The objective is, in a centralized way, to optimize network performance with IC. In [62], a greedy grouping of D2D users with SIC receivers was considered, while in [PI], a centralized scheduler was assumed. The scheduler performed Network Utility Maximization (NUM) across the power and IC resources of a cellular link, and D2D users.

2.4 Game Theory in Wireless Communications

Game theoretic approaches have been widely used in analyzing the behavior of wireless systems [67–77]. They have shown to provide a powerful tool to address power control [67, 68, 71, 75], resource allocation [69, 70] and multi-antenna precoding [74]. In all of these problems, the interaction between players is determined by involuntarily caused interference.

Game theoretic analysis for SISO, MISO and MIMO systems in interference channels is illustrated in [27]. MISO interference channel is analyzed from a game-theoretic perspective [78–82]. In addition to non-cooperative games, coalitional games have also been applied to communication networks [83–85]. Cooperative games appear to be a promising model for distributed algorithms in collaborative spectrum sensing [86,87] and interference alignment situations [88].

The Gaussian Interference Channel is a simple and powerful model for studying game theoretical approaches as well. Game theoretic analysis of GIC have been performed in [72, 73, 76]. Non-cooperative game theory in a case where rate splitting is not applied was addressed in [72]. It was shown that in a Nash Equilibrium (NE), both transmitters apply full power. In [76], the transmitters were allowed to use a rate-splitting strategy. Also here, in a NE, both transmitters apply full transmit power. If there were a transmitter not using all the power, the transmitter could use that power to transmit to a virtual user, who would achieve whatever rate it can treating all other users as noise. The receiver can then decode this virtual user first, and after canceling this signal, continue achieving whatever rate it had before the virtual user was added, plus the additional rate of the virtual user. In addition to [76], interference cancelation games have been addressed in the context of multiple access channels [75].

In order to reduce the additional network management complexity introduced
by D2D communication, it is desirable to distribute Radio Resource Management (RRM) decisions to D2D nodes. In particular, decisions of receiver’s IC, transmission rates and power are natural candidates to distribute, and game theoretical methods have been shown to be efficient tools for this. Distributed power control methods based on game theory were developed in [67,71], while in [72] it was shown that a game theoretical power control method with punishment strategies may achieve fair and efficient spectrum allocation.

Related to distributed management of IC, the Nash Equilibrium (NE) rate region of the two-user Gaussian interference channel is characterized in [76]. In [75], it is demonstrated that the probability of equilibrium for certain SIC power control games for DS-CDMA systems grows with increasing intervals in a discrete power control strategy set. In [PII, PIII], the existence of NEs and the efficiency of two player power control & SIC games is characterized. In [PIII], it is shown that the existence of a pure strategy NE is guaranteed for certain two player two-stage game, when the strategy decisions related to power, IC and rate are divided to two game stages. Existence is guaranteed if the first stage is a power game and the second stage is an IC and rate game. In these games, the interesting observation was made that a rational player in a strategic game may voluntarily lower its transmission power in order to get higher rate. In the literature, the combination of power control, IC and rate control is only addressed in [76][PIII]. In all other literature, rate is considered a dependent variable. For application to D2D, where the same frequency resource is reused by multiple D2D pairs to increase system spectral efficiency, it is of interest to investigate a situation where instead of two players, there is a generic number $N$ of strategic players in the network.

In most games it is assumed that players are rational and decide strategy according complete information. However, such assumption might be impractical for communication application, due to limited computational capability and information accessibility. To develop practical models, limited rationality games with level-$k$ thinking are studied [89–93]. In [93] it is shown that a Cognitive Hierarchy (CH) equilibrium can be reached by massive amount of devices with various levels of rationality, which follow Poisson distribution. Whereas in [90] expectation of rationality level decreases recursively. As in IC games, the IC strategies mainly depend on strategies of IC target, the rationality setting in [90] might suggest a simple and elegant model for limited rationality two-stage IC games.

### 2.5 Summary

In section 2.1, previous studies about SIC are reviewed. It is shown that single-stage SIC has potential to improve the spectrum efficiency with relaxed hardware requirement and low complexity. The single-stage SIC receiver only need to handle two code words simultaneously, where rate-splitting capable
receivers need to handle three. In case of network IC, the rate-splitting algorithm [31, 61] is too complex to be applied as practical real time RRM algorithm, as single-stage SIC is simpler and more practical. As proposed 5G technology, network controlled NOMA explore the diversity gain between multiple SIC receivers and one transmitter. In this dissertation, the network controlled NOMA of 5G is generalized to situations where there are more than one transmitter. Therefore generalized NOMA can also utilize the potential diversity between neighbor cellular downlinks and between D2D communications. Section 2.2 reviews different spectrum sharing methods between D2D and cellular networks. It is shown that integrating underlay D2D communication to cellular network is promising. As the underlay D2D communication can be naturally synchronized and coordinated with cellular communications, there is great potential for underlay D2D communication to improve spectrum efficiency by applying IC with same frame structure and coding standard. Relevant literature about applying IC in D2D communication network is reviewed in section 2.3. The centralized NUM algorithms which utilize power control and SIC may provide tremendous performance improvement. However, the complexity of NUM with power control and IC is not trivial, even with relatively simple SIC receiver. The problem involving discrete IC variable is mixed integer optimization problem, which is Non-Polynomial (NP) hard [32]. It is worth to study a method to solve the mixed integer optimization problem and derive centralized NUM algorithm with SIC receiver. The centralized NUM algorithms also require of massive signaling exchange, which consume radio resources and reduce the performance gain of applying IC. To reduce the signaling needed for centralized solutions, game theoretical distributed solutions may be considered. In section 2.4, game theoretic approaches used in wireless system are recalled. It is observed that the distributed algorithms, which is based on power control IC games, may improve network performance in D2D network underlaying cellular system. Due to various limitations, game with full rationality may not be practical. It is of interest to investigate performance gain and additional overhead of the distributed RRM solutions where multiple D2D and cellular users play one and two-stage power-IC-rate game with full or limited rationality.
3. Models and Methods

In this chapter, we first demonstrate the fundamental network model we applied in both distributed and centralized RRM. Then we briefly introduce the connection between power and SIC. Lastly, practical implementations that verify the feasibility of the considered SIC algorithms are reported.

3.1 Network Model

We consider a general network of $N$ pairs of transmitters (Tx) and receivers (Rx), in a D2D/cellular network. One or more of the Txs or Rxs may thus be a cellular base station. Each Rx is interested only in the message transmitted by the Tx belonging to the same pair. The transmitters do not cooperate in transmission, and the receivers do not cooperate in reception. The Tx-Rx pairs manage their use of radio resources based on a distributed or centralized optimization approach. In the distributed approach, each Tx-Rx pair acts as a strategic player maximizing its own utility. In the centralized approach, a cellular BS manages radio resources of all Tx-Rx pairs to optimize the utility of the whole network.

In each pair, there is a designated transmitter (Tx) and receiver (Rx). The pairs are indexed with numbers in $\mathcal{I} = \{1, 2, \ldots, N\}$. The network is modeled as an interference channel, with the channel between transmitter $i$ and receiver $j$ characterized by the channel gain $g_{ij}$. For simplicity, we concentrate on frequency flat channels. In wideband channels, separate coding per coherence bandwidth may be considered. Note that as the Rx and Tx in pair $j$ are at different locations, $g_{ij}$ is generically not equal to $g_{ji}$. The state of the network is characterized by the matrix $G$ of channel gains between the pairs. We assume that the channel gains are constant within the time frame of performing RRM.

The transmit power of transmitter $j$ is $P_j \leq P_{\text{max}}$, and its transmission rate is $R_j$. The rate may be the transmitted instantaneous rate, or an average received rate, depending on the applied communication protocols. All transmit powers in the network are collected in the vector $P$, and the rates of all transmissions in the vector $R$.

The receivers are equipped with two-stage Successive Interference Cancellers (SIC),
so that they may cancel the interference from one source before attempting a decoding of the transmission of interest. The Interference Cancelation (IC) state of receiver \(i\) is characterized by the variable \(c_i\). The value \(c_i = j\) indicates that Rx \(i\) attempts to cancel the interference from Tx \(j\) before decoding the payload from Tx \(i\). If no IC is attempted, \(c_i = i\). The overall IC state of the network is collected in the vector \(c = \begin{bmatrix} c_1 & c_2 & \ldots & c_N \end{bmatrix}^T\). For each player there are \(N\) different IC states, and in the whole network, there are \(N^N\) possible IC states.

If each player only considers canceling the interference which is transmitted from the nearest interferer, the number of possible IC states can be reduced to \(2^N\). While the generic analysis will be performed without restrictions on the IC states, the distributed RRM algorithms and simulations will be performed with this simplified IC assumption.

The SINR experienced by a transmission is characterized by all uncanceled interference plus noise. When interferer \(l\) is canceled, the transmission from transmitter \(j\) at receiver \(i\) has SINR

\[
\gamma_{ji}^{(l)} = \frac{P_j g_{ji}}{\sum_{k \neq j, l} P_k g_{ki} + N_0} 
\]

where \(N_0\) is additive Gaussian noise. We use the convention that \(\gamma_{ji} = \gamma_{ji}^{(j)}\) denotes the SINR when no interferer is canceled.

The amount of information that can be reliably transmitted with a given SINR is given by the transmission efficiency function \(f(\gamma)\). We assume that \(f\) depends on \(\gamma\) only, not on the IC state, and that it is monotonously increasing in \(\gamma\).\(^1\)

For example, if we assume that both noise and interference are white and Gaussian, with AWGN capacity achieving Gaussian codebooks we would have

\[
f(\gamma) = \log_2(1 + \gamma). \quad (3.2)
\]

Note that in real networks, interference is neither white nor Gaussian, and AWGN capacity achieving codebooks are not used. Nevertheless, it is known that modeling interference as Gaussian, and using a logarithmic efficiency function of the type (3.2), a rather good model of performance of a modern communication system can be achieved, if an dB-scale implementation margin is taken into account when estimating expected throughput [94]. Accordingly, in this thesis all numeric results will be produced with the efficiency function (3.2), with the understanding that the results are indicative of what can be achieved with a modern communication system.

We shall use the shorthand notations

\[
f_j^{(l)} \equiv f(\gamma_j^{(l)}) ; \quad f_{ji} \equiv f(\gamma_{ji}) ,
\]

for the transmission efficiencies of the desired signal, and the interference signals, respectively. These are implicit functions of the Tx-powers \(\mathbf{P}\). Note,

\(^1\)This is reasonable if the IC is perfect and there is no residual interference after canceling.
for example, when Rx \( j \) receives the wanted signal from Tx \( j \), not attempting interference cancelation, the efficiency is \( f_j^{(O)} \). For simplicity, the notation \( f_{jj} \) is also used for the same thing.

A transmission from Tx \( j \) with SINR \( \gamma_{ji} \) at Rx \( i \) (with or without IC) can be successfully received at \( i \) if

\[
f(\gamma_{ji}) \geq R_j .
\]  

(3.4)

The successfully received rate of player \( j \) is thus given by

\[
u_j = R_j \theta \left( f_{c_j} - R_j \right) \theta \left( f_{c_j} - R_j \right)
\]  

(3.5)

where \( \theta(x) \) is the step function

\[
\theta(x) = \begin{cases} 
0 & \text{if } x < 0 \\
1 & \text{if } x \geq 0 
\end{cases} .
\]  

(3.6)

Note that if the player does not cancel interference, then we have \( c_j = j \), and the utility is still given by (3.5); the two step functions are the same.

In Network Utility Maximization, there has to be a principle relating the rates experienced by different users. For this, a utility function will be used, where the rate (3.5) experienced by a user is transformed to a utility. This will be further discussed in Section 4.1. In distributed RRM, where D2D pairs act as strategic players, each player has a payoff function that should be maximized. In this work, we are ultimately interested in creating distributed RRM functions based on greedy optimization performed by the D2D pairs, such that greedy optimization provides solutions close to centralized ones. Accordingly, we adopt a simple payoff function proportional to realized rate. For any payoff function which is a monotonously growing function of the successfully received rate, one would get the same results. If a strategic game converges, the instantaneous rate experienced by the players would then equal a long-term average rate. Accordingly, the achievable rate \( u_j \) of (3.5) will be directly considered the payoff of a strategic D2D pair. This payoff function is applied in Chapter 5.

3.2 Successive Interference Cancellation

In this thesis, we assume that interference can be completely canceled. Receiver \( j \) may perform perfect IC without joint decoding if the SINR of transmission from Tx \( i \) to the interference victim Rx \( j \) is large enough to decode the transmission from Tx \( i \)

\[
f(\gamma_{ij}) \equiv f \left( \frac{P_i g_{ij}}{\sum_{k \neq i} P_k g_{kj} + N_0} \right) \geq R_i
\]  

(3.7)

From (3.7) we could observe that whether user \( j \) can successively cancel interference from user \( i \) depends on transmission power vector \( \mathbf{P} \), propagation vector \( \mathbf{G}_j = \begin{bmatrix} g_{1j} & g_{2j} & \cdots & g_{Nj} \end{bmatrix}^T \), noise level \( N_0 \) and user \( i \)'s rate \( R_i \). Note that player \( j \) may enable IC by decreasing its own transmission power \( P_j \) to fulfill
Models and Methods

inequality (3.7). With the transmission efficiency function 3.2, the IC power constraint of $j$ to implement IC can be derived from inequality (3.7) as

$$P_j \leq \frac{P_i g_{ij}}{g_{jj}(2^{R_i} - 1)} - \frac{\sum_{k \neq j, i} P_k g_{kj} + N_0}{g_{jj}}$$

(3.8)

If user $j$ successfully cancels interference from user $j$, the utility of $j$ can be improved from $f_j^{(i)}$ to $f_j^{(i)}$. Therefore a selfish user $j$ may voluntarily reduce transmission power $P_j$ to achieve better utility $f_j^{(i)}$ with IC. This self-motivated behavior may benefit all other users who share the same radio resource. However, in distributed RRM systems, all other users will also decide their rate according to interference from each other. Once user $j$ reduce its power, and user $i$ correspondingly increases its rate $R_i$ to improve its utility, the power reduction of $j$ may cause complicated consequences for all users. The analysis of network IC in both distributed and centralized RRM system will be introduced in subsequent chapters.

Although canceling interference can improve the radio resource efficiency, it should be noticed that there are costs to apply SIC receiver. In order to decode messages from different transmitters, the SIC receiver needs to run physical layer process twice, which includes synchronization, channel estimation, equalization, demodulation, decoding, and other necessary processes. The additional physical layer process and interference cancelation process consume more power and execution time. Moreover, additional signaling should be arranged to inform SIC receivers of the transport format information, which is required to cancel interference and decode intended messages. In Chapter 5, the amount of signaling overhead is compared for several network-IC algorithms. When implementing SIC receiver in the testbed, it is also found that reusing pilot radio resource for second pilot signal will introduce residual error to channel estimation. Additional pilot resources or process might be needed to avoid degraded channel estimation.

3.3 D2D SIC Receiver Implementation

To verify the feasibility of the SIC receiver discussed in the theoretical studies of the thesis, practical implementations have been done. A TD-LTE compatible SDR testbed was implemented with USRP front-end hardware. Multiple test scenarios were tested and reported [95–98]. We implemented a scenario where a cellular user share the uplink radio resource with D2D pairs which are located nearby the BS as shown in Figure 3.1. By canceling interference from D2D Tx, the BS can successfully decode remote User Equipment (UE)’s uplink transmission. The implementation is carried out on with parameters as shown in Table 3.1 and measurement results are reported in [95]. The experiments show that reusing the radio resource with controlled network IC is feasible.

The flow chart of the implemented SIC receiving process is shown in Figure 3.2. In this implementation, D2D devices synchronize to the cellular network and
Figure 3.1. D2D and cellular user share uplink resource.

### Table 3.1. Implementation Parameter

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duplex method</td>
<td>LTE TDD</td>
</tr>
<tr>
<td>Uplink/Downlink</td>
<td>Uplink</td>
</tr>
<tr>
<td>UD configuration</td>
<td>2</td>
</tr>
<tr>
<td>Carrier frequency</td>
<td>2.4 GHz</td>
</tr>
<tr>
<td>Channel bandwidth</td>
<td>5 MHz</td>
</tr>
<tr>
<td>Channel Coding</td>
<td>LTE Turbo</td>
</tr>
<tr>
<td>MCS for both links</td>
<td>10</td>
</tr>
<tr>
<td>Modulation</td>
<td>LTE OFDM/QPSK</td>
</tr>
<tr>
<td>Channel estimation averaging window</td>
<td>Per resource block</td>
</tr>
<tr>
<td>SIR for cellular link</td>
<td>-6 dB</td>
</tr>
<tr>
<td>IC type</td>
<td>Single-state IC</td>
</tr>
</tbody>
</table>

Figure 3.2. Successive interference cancelation implementation.
apply the same frame structure, turbo coding and pilot sequence generator as a
UE. This will greatly reduce the complexity of SIC receivers. In this way the IC
functionality can be added to a normal LTE receiver as an additional attachment.
In Figure 3.2, the block surrounded by the black dashed line shows the IC branch.
In order to do equalization also for the interference signal, channel estimation
of the interference channel is essential. Since D2D transmissions apply the
same frame structure as the UE does, D2D pilot sequences are overlapping with
UE pilot sequences. However, the result of practical experiments show that
although the D2D transmitter applies an orthogonal pilot sequence, the UE’s
channel estimation is still contaminated by D2D pilots. This is due to the fact
that orthogonality between pilot sequences is distorted as the delay from each
transmitter is different. The non-orthogonal pilot sequences interfere each other
and introduce residual error to channel estimation. In this implementation,
the channel estimation of the UE is implemented after removal of estimated
D2D pilots. The residual error of UE’s channel estimation leads to imperfect
IC in practical applications. When the D2D signal is much stronger than the
UE signal, the residual error of channel estimation is trivial. Otherwise the
performance of SIC receiver is constrained by degraded channel estimation.
However, this can be easily avoided by assigning different pilot resource to D2D
and UE.

From this implementation, we learned that underlaying D2D communication
with SIC receiver is practical and reasonable. The receiver complexity can be
dramatically decreased by reusing cellular synchronization, frame structure,
pilot sequences and many other cellular configurations. It also shows that
perfect IC may require special pilot resource arrangement, due to the fact that
pilot sequences are not orthogonal with different delay.

The implementation of opportunistic SIC in a MTC random access scenario is
also carried out, and reported in [96]. In the course of the work, two additional
papers [97, 98] related to the testbed implementation were written as well.

Note that the testbed is only built to verify the feasibility of practical SIC
receiver discussed in this thesis, the algorithms introduced in following chapters
are not implemented in the testbed.
4. Centralized Interference Canceling Network RRM

This chapter studies a centralized interference canceling Network RRM optimization algorithm, based on Network Utility Maximization (NUM). Network Utility Maximization has been studied with a coupled utility model in [99, 100]. Nevertheless, similar methods cannot be applied to problems with IC receiver since it is mixed integer optimization problem with discrete IC options. In this chapter, the integer problem is first converted to convex problem in higher dimension by looking at all IC states simultaneously. Then the convex problem is addressed with well-known NUM methods. The derived NUM algorithm optimizes the utility of one isolated cell with D2D communication underlaying the cellular network. In the derived NUM algorithm, all D2D and cellular users’ transmission power, IC and rate will be optimized to achieve the best network utility. The performance of derived NUM algorithm is demonstrated by simulation.

4.1 Network Utility Function

We study an isolated cell where one cellular uplink user, Tx\(_1\) and N-1 D2D pairs (Tx\(_i\),Rx\(_i\)), \(i=2,3,4\ldots N\), share the available radio uplink resource as illustrated in Figure 4.1. The objective is to determine the IC-configuration, and the transmit

![Figure 4.1. The example of uplink scenario where three D2D pairs share the same cellular uplink resource with a cellular user.](image-url)
powers, so that the well-being of the receivers is maximized. To simplify the optimization, we assume that there is a utility function $f(R)$ characterizing the well-being of a user, which is directly dependent on the rate $R$ received. For concreteness, we consider $\alpha$-proportionally fair utility functions [101]. The parameter $\alpha$ characterizes the degree of fairness, so that

$$f(R) = \begin{cases} 
\frac{1}{1-\alpha} R^{1-\alpha} & \text{if } \alpha \neq 1 \\
\log R & \text{if } \alpha = 1
\end{cases} \quad (4.1)$$

Given the utility of a user, the network utility is

$$U = \sum_{i=1}^{N} f(R_i). \quad (4.2)$$

We shall specifically consider the cases $\alpha = 0$, where the sum rate is maximized, and $\alpha = 1$, corresponding to conventional proportional fairness.

### 4.2 Network Utility Optimization Algorithm

The objective is thus to maximize the network utility (4.2) subject to the individual power constraints $0 \leq P_i \leq P_{\max}$, and the rate functions $f_{c_i}^i$. The variables optimized are the transmit powers $P_i$, and the IC configuration $c_i$. For generic $\alpha$, at least for $\alpha = 0$, optimization over transmit powers is a non-convex problem [102]. The selection of IC configuration adds mixed integer programming to the problem, which is NP-hard at least for minimum rate maximization [32].

#### Dominant Interference Cancelation

To simplify the combinatorial optimization, we assume that a Rx only considers canceling the dominant interferer with the smallest path loss. Thus Rx$_j$ either cancels the signals from Tx$_k$ with

$$k = \arg\max_{k \neq j} g_{kj}, \quad (4.3)$$

or does not perform IC. Then for a network with $N$ Tx-Rx pairs in total, $2^N$ alternative IC configurations exist. We further relax the problem by simultaneously considering all of these IC configurations. Each of the $2^N$ alternatives is assigned with a weight $w$, so that of the total amount of resources, a fraction $w$ is assigned to this configuration. We assume that the resources are infinitely divisible, so that the $w$ are real numbers in $[0,1]$, constrained by

$$\sum_{i=1}^{2^N} w_i = 1. \quad (4.4)$$

Selecting the IC configuration thus becomes a scheduling problem in IC configurations.
In each IC configuration $i$, we have transmission powers $\{P^i_j\}_{j=1}^N$, and rates $R^i_j = f^c_j(P^i_k)$. The total rate of wanted transmissions to receiver $j$ is then

$$R_j = \sum_{i=1}^{q_N} w_i R^i_j$$

where $R^i_j$ is the rate of Tx-Rx pair $j$ in IC configuration $i$. Now, with a concave utility function, such as (4.1), and fixed transmission powers, the optimization problem in the variables $w$ is convex. We have exchanged the integer hardness in selecting the IC-configuration to a continuous-valued convex optimization problem, where the number of variables is exponential in $N$.

We solve the joint scheduling and power allocation problem in an iterative manner. For each IC configuration $i$ separately, we optimize the set of transmission powers $P^i_j, j \in \{1,2...N\}$, with fixed weights $w_i$. Then, with fixed powers $P^i_j$, we optimize the scheduling weights $w_i$. We do not attempt global optimization of the transmit powers. Instead, we perform a gradient ascent in power and scheduling weights. As a result, a local optimum is reached, but not necessarily a global one.

### 4.2.1 Power Update

In each iteration, transmission power is optimized for each IC configuration. The gradient in power domain is

$$\frac{\partial U}{\partial P^i_j} = \sum_{k=1}^{N} \frac{\partial f(R_k)}{\partial P^i_j}.$$ (4.6)

The update of the transmit powers is eased by the fact that each is individually constrained. We have a step size $\Delta p$ in the gradient search. However, with $\alpha > 0$, in the utility function (4.1), the gradient is unbounded, and becomes infinite at a point where the rate of a user is 0, i.e. when $P^i_j = 0$ for user $j$ for all $i$. To handle this, we have to add a maximum step length $s_{\text{max}}$. The change in a power variable is thus

$$\Delta P^i_j = \text{sign} \left( \frac{\partial U}{\partial P^i_j} \right) \min \left\{ \left| \frac{\partial U}{\partial P^i_j} \right| \Delta p, s_{\text{max}} \right\},$$ (4.7)

and the update rule for the transmission powers is

$$P^i_j = \min \{ P_{\text{max}}, \max \left( 0, P^i_j + \Delta P^i_j \right) \}.$$ (4.8)

As there are no constraints binding the powers to each other, one may take care of the lower and upper bounds separately.
Centralized Interference Canceling Network RRM

**IC Configuration Scheduling Update**

The scheduling constraint (4.4) acts on all weights, so we need to use projected gradient search. First we calculate the unconstrained gradient

\[
g_i = \frac{\partial U}{\partial w_i} = \sum_{k=1}^{N} \frac{\partial f(R_k)}{\partial w_i}.
\]

(4.9)

Then we project the gradient to the constraint surface (4.4) by subtracting mean value of unconstrained gradient,

\[
G_i = g_i - \frac{1}{2N} \sum_{i} g_i.
\]

(4.10)

At each stage, some of the scheduling alternatives are non-active, with \(w_i = 0\). If a non-active configuration has \(G_i < 0\), it is non-updatable. To keep the schedule in a feasible region, these are removed from the update by setting \(G_i = g_i = 0\). The gradient projection (4.10) is then redone for the updatable weights. We repeat this until each configuration with \(G_i < 0\) has weight \(w_i > 0\). Then the weight is updated as

\[
w_i = w_i + G_i \Delta w
\]

(4.11)

where \(\Delta w\) is the step size of the scheduling weight. For a non-infinitesimal \(\Delta w\) it is possible that a weight becomes negative after update. If this happens, it is set to zero and all other weights are scaled so that their sum is one.

**4.2.2 Iterative Power and IC Configuration Optimization Algorithm**

We iterate between power and IC optimization. In one iteration of the overall algorithm, all transmission powers for each IC configuration are updated once, followed by IC configuration scheduling update. The algorithm is presented in Publication I, Sec. 3.

With infinitesimal maximum power step length \(s_{\text{max}}\) and infinitesimal scheduling step size \(\Delta w\), the algorithm is an ascent algorithm, and converges to a local optimum of the network utility, subject to the limitation (4.3) on the IC configuration considered.

As we are dealing with a non-convex problem, the choice of initial point may have an effect on the result. In the simulation study, we have selected a simple initial point as a non-IC configuration. That is, all powers are set to \(P_j^i = P_{\text{max}}\), and the scheduling weight for the configuration without IC is set to \(w_1 = 1\), and all other configurations start at \(w_i = 0\).
4.3 Verification

4.3.1 Simulation Result

We evaluate the performance of interference canceling D2D communication in a single-cell scenario. With two different user utility functions, we study the algorithm’s characteristics with different parameter settings.

The path loss between transmitters and receivers is given by a single slope path loss model with path loss exponent 4,

\[ L_p = 40 \log_{10} d, \quad (4.12) \]

where \( d \) is distance measured in meters. We consider a microcell with a circular coverage area with a radius of 100 meters. One cellular user and 5 D2D pairs are randomly dropped inside the cell coverage area. To get insight into the intra-D2D distance on performance, we drop the D2D pairs such that the distance between a D2D Tx and its Rx is a fixed number \( L \). The ratio between the maximum transmit power and the noise power, \( P_{\text{max}}/N_0 \), is 80dB.

In order to get insight of the system characteristics, we measure the numerical result at \( L = 5, 10, 15 \) meter D2D separation, for both sum rate utility and proportional fairness utility.

Figure 4.2 shows an example of the algorithm’s convergence process. A sum rate maximization is considered, for nearby D2D users with \( L = 5 \). The algorithm converges to a local maximum and keeps stable after several iterations. The upper figure depicts the sum rate, whereas the lower picture depicts the rates of the individual D2D pairs, and the cellular user.

Figure 4.3a shows the Cumulative Distribution Function (CDF) of user spectral efficiency simulated by 1000 random drops with sum rate utility optimization. The three dashed curves from right to left separately depict CDF result with \( L = 5, 10, 15 \), when no IC is performed, and all transmit powers are equal to \( P_{\text{max}} \).
More than 10 percent of the users are in outage due to the heavy interference environment. The three continuous curves from right to left represent spectral efficiency with sum rate optimization for $L = 5, 10, 15$. Significant gains for almost all users with good spectral efficiency is observable. The price is that some low rate users suffer worse connections.

In Figure 4.3b, results with power and IC configuration optimization for Proportional Fair (PF) utility maximization ($\alpha = 1$) are shown with continuous curves, for $L = 5, 10, 15$. Comparing to Figure 4.3a, Figure 4.3b shows a very different pattern. The dashed curves of both figures are the same, representing non-optimized networks. PF optimization removes outage altogether, and considerably improves the performance of the lowest quartile of the users. Some 5% of users still, however, suffer from a very low rate due to the heavy interference situation. These users are mostly cellular users. As the cellular receiver is in the center of the cell, with interfering transmissions uniformly distributed in the cell, the BS is the point of highest interference power. With a very small distance between the D2D Tx-Rx pair, such as $L = 5$, interference has little effect on D2D communication, as the wanted signal is strong enough. In that case, most of the gain from allowing IC comes for the cellular transmissions.

### 4.4 Conclusion

In this chapter we discussed interference canceling RRM optimization for underlay D2D communication using a centralized method. A centralized optimization method (NUM) is developed, in which transmission power and IC configurations are adjusted across the D2D and cellular transmissions. The result show significant gains in spectral efficiency. The shown results provide an upper limit with complete centralized CSI. The feasibility of IC application discussed in this chapter is also verified by practical implementation on a TD-LTE testbed.
This chapter discusses distributed strategic game theoretical RRM for D2D communication underlaying and overlaying cellular networks. First, a one-shot game and several two-stage variants are introduced. Then the NE of each game is analyzed for two-player and multiplayer cases. After that the connection between these games are revealed. Lastly, simulations of corresponding distributed game theoretical RRM methods are presented and compared to centralized network utility maximization method discussed in the previous chapter.

5.1 Game Model

The network model is discussed in section 3.1. Here, we shall treat network RRM as a strategic game model, where the Tx-Rx pairs are selfish players. The objective of this modeling is to design a simple distributed RRM mechanism which performs close to a network Pareto optimum.

When deciding how to transmit, the Tx-Rx pair \( j \) considers three strategy variables: transmission power \( P_j \), receiver IC state \( c_j \), and transmission rate \( R_j \). The IC strategy is discrete, whereas the power and rate strategies are continuous.

In this setting we shall consider a one-shot game model, which we call \((P, C, R)\). In addition, we shall consider two-stage variants, where the strategy variables are grouped to a 1st stage subset \( \mathcal{S}^1 \) and a 2nd stage subset \( \mathcal{S}^2 \). We denote the two-stage games as \((\mathcal{S}^1, \mathcal{S}^2)\). As we are not after a model for self-interested market actors, but a simple model for machines to perform distributed management, we assume that all two-stage games are played with Subgame Perfect (SGP) strategies, if possible. This sometimes leads to second stage strategies being fixed.

The underlying assumption when analyzing the games is that each player has complete information about the game, i.e. it knows \( G \), as well as the pay-off functions and strategy sets of all other players. We shall also consider limited rationality players, which do not need complete information.
Also, we assume that each stage of the games is played simultaneously by the players. That is, there is no sequential play in the stages. Based on this, we strive to find Nash Equilibria of the games. When creating distributed RRM strategies related to such NEs, in Section 5.5, myopic best response iteration may be used, with incomplete information about the opponents’ channels.

A full strategy of a player \( j \) in a two-stage game consists of a strategy \( S^1_j \) for the first stage, and a family of strategies \( S^2_j \) for each possible set of multiplayer strategies for the first stage.

5.1.1 Equilibrium Concepts

As the final objective is to develop distributed RRM mechanisms, we shall only be interested in pure strategy NEs, not considering mixed strategies, where players randomly choose from sets of strategies.

To understand the relationship between NEs of the one-shot game and the different two-stage games, we need operations that map these to each other.

**Realized part of multi-stage game**  The realized part of a two-stage game strategy consists of the first-stage strategies of the players, and the 2nd stage strategies in the branch of the game defined by the 1st stage strategies.

The realized part of the games considered here are thus uniquely described by the values of the strategy variables at the NEs of games and subgames: \( P^*, C^* \) and \( R^* \). Now consider a one- or two-stage game \( G_a \) with first stage strategy variables \( S^{a,1}_a \) and 2nd stage variables \( S^{a,2}_a \). If \( S^{a,2}_b = \emptyset \), we have a one-stage game. For another game \( G_b \), some of the 1st stage strategy variables in \( G_a \) have been changed to 2nd stage strategy variables.

**Derived NE**  A derived Nash Equilibrium of a two-stage game \( G_b \) is a subgame perfect NE which has the same realized part as a NE of a game \( G_a \) with the same strategy variables and \( S^{b,1}_b \subset S^{a,1}_a \).

**Subgame Perfectness**  In multi-stage games, we shall mostly be interested in Subgame Perfect (SGP) solutions. When players choose 2nd stage strategies in an SGP manner, each 2nd stage subgame, for a given outcome of the first stage, is played greedily to maximize payoff given the first stage outcome. This means that in a corresponding SGP Nash Equilibrium, reaching the equilibrium is not based on non-credible “threat” strategies in unrealized 2nd stage parts of the game.

5.1.2 Dependence Loops in \( N > 2 \) Player Games

Note that with \( N > 2 \) players, in any of these games dependence cycles may exist that prevent the existence of pure strategy equilibria in the subgame where IC is played. The expected payoff depends on the expected IC success, while IC success depends on the rates expected to be chosen by the other players. This leads to the possibility of dependence cycles in the IC subgame. Analyzing
whether IC fails or not becomes complex. If an IC-cycle has an even number of players, two subgame equilibria may exist, while in a cycle with an odd number of players, no subgame equilibria exists with certain game configurations. See Figure 5.1 for an illustration of these. In this example, we have simplified the setting so that each player only has one potential IC target, which may or may not be cancelled. In reality, depending on the network configuration $G$, the situation may be more complex.

5.2 One and Two-stage Power-IC-Rate Games

5.2.1 Link Adaption Protocols

Consider a communication protocol between a transmitter and a receiver with unknown path loss, and unknown interference level. To determine the appropriate rate of transmission, there has first to be a pilot transmission from the Tx, which is measured at the Rx. The Rx then recommends a Tx power and a rate to be used by the Tx, based on the measured channel, the measured interference and noise level. One such link adaption protocol which describes link adaptation in a one stage Power-IC-Rate game is depicted in Figure 5.2. In Figure 5.2, three transmissions $n-1$, $n$ and $n+1$ from Tx $i$ and their corresponding feedback from Rx $i$ are demonstrated. The Tx transmission $n$ consists of pilot and the payload. The pilot and the payload is transmitted with selected power $P_i^{(n)}$. The Rx $i$ receives the signal which may contain overlapping transmissions from other interfering Txs. The path loss from each Tx to Rx $i$ can be measured from the pilot transmission, assuming that maximum signal power is known. Based on these measurements and received historical feedback from other Rx, Rx $i$ then sends the feedback to Tx $i$, which suggests a transmitting power $P_i^{(n+1)}$ and a rate $R_i^{(n+1)}$ for transmission $n+1$. 

![Figure 5.1. Example of IC-cycle with odd and even number of players.](image-url)
In one-stage game link adaptation protocol, the Tx power $P_{i}^{(n+1)}$ and rate $R_{i}^{(n+1)}$ suggested by Rx $i$ are calculated according to measured interference level in transmission $n$ instead of $n+1$. Once other Txs change power in transmission $n+1$, the suggested transmitting power and rate may not be appropriate. To properly select the rate of transmission, it is beneficial to know the interference situation that the transmission will experience. Therefore the link adaptation protocol can be improved if a two-stage game model is applied, where the transmitting power $P_{i}^{(n)}$ of each Tx are known before transmission rate $R_{i}^{(n)}$ is suggested. The two-stage game link adaption protocol is demonstrated in Figure 5.3. As shown in Figure 5.3, the transmitting power of payload in transmission $n+1$ is transmitted in the second pilot of transmission $n$. Therefore the Rx can always foreknow the interference level from each interfere in next transmission and estimate suitable power and rate strategy accordingly. This should lead to better convergence than one-stage game protocol. Note that some additional information is needed for strategy selection in two stage games. Therefore additional information feedback signal should be added to feedback transmission from Rx $i$, which cost a bit more overhead than one-stage game protocol. The detailed overhead analysis is included in section 5.4.2. There is also additional channel estimation error in the link adaptation protocol due to shifted pilot allocation.

Given different link adaptation protocol, the decision logic can be more or less complicated. We investigate the one-stage logic, related to the first type of protocol, and different two-stage logic related to the second type of protocols.
More involved infinite horizon dynamic logic can be considered, but the simplest alternatives should be investigated first. Also, to simplify game analysis, we assume IC to be a hard strategy. If $c$ is a 1st stage strategy, and player $j$ chooses to cancel interference from opponent $i$ in the first stage, the receiver has to use its SIC receiver against $i$, as shown in Equation 3.5. Accordingly, we concentrate on the two-stage games $(P, C | R)$ and $(P | C, R)$.

5.2.2 $(P, C, R)$ One Shot Game

In $(P, C, R)$, each player $j$ selects $P$, $C$, and $R$ at the same time. Given other players’ strategies, the best response function of player $j$ is:

$$B_j = \arg\max_{P_j, c_j, R_j} R_j \theta(f_{c,j} - R_{c_j}) \theta(f_{c_j} - R_j),$$  \hspace{1cm} (5.1)

and at a pure strategy NE, the strategy of each player $j$ is the best response to the strategies of the other players $\neg j$. For a rational player $j$, the rate strategy $R_j$ is a dependent strategy. If IC does not succeed, $R_j$ is irrelevant since the payoff is always zero. Otherwise, rate depends on power and IC strategy as $R_j$ must be less or equal to $f_{c_j}$ for $j$ to have non-zero payoff. At an equilibrium, the rate strategy of each user depends on the power strategy of all users. Having all strategies determined in one shot sometimes leads to an equilibrium not existing.

5.2.3 $(P, C | R)$ Two-stage Game

In $(P, C | R)$, the strategy variables of player $j$ are grouped to a 1st stage subset $\mathcal{S}_1^j = (P_j, c_j)$ and a 2nd stage subset $\mathcal{S}_2^j = R_j(P, C)$. Compared to $(P, C, R)$, a player can adjust the rate according to the 1st stage strategy of all players. The best response function of player $j$ for 1st stage game is

$$B_{P,C}^j = \arg\max_{P_j, c_j} \theta(f_{c,j} - R_{c_j}) f_{c_j}(P)$$  \hspace{1cm} (5.2)

where $R_i(P)$ represents the 2nd stage rate strategy of player $i$ as a function of $P$. In the first stage, where $P$ and $c$ are determined, dependence cycles of the type discussed in Figure 5.1 may exist.

In order to analyze the 1st stage, we shall first analyze the 2nd stage subgame.

Second Stage Rate Strategies

Given first stage strategies $P$ and $C$, the best response 2nd stage rate strategy for player $j$ is

$$B_j^R = \begin{cases} 
    f_{c_j}^{(j)} & \text{if } c_j = j \\
    f_{c_j}^{(c_j)} & \text{if } c_j \neq j, f_{c,j} \geq R_{c_j} \\
    \text{any valid value} & \text{if } c_j \neq j, f_{c,j} < R_{c_j}.
\end{cases}$$  \hspace{1cm} (5.3)

That is, when IC fails as a consequence of the first stage strategies chosen, there is a continuum of best response rate strategies for the players. All of these
continuum strategies are sub-game perfect, while they may lead to different NEs of the full game.

The rate strategy $f_{j}(c_{j})$ is possible also in the case when IC fails, and is a weakly dominant strategy of the 2nd stage game—the payoff of the player in 2nd stage would never improve by changing this strategy. Choosing the 2nd stage strategy $R^{(0)}_{j} = f_{j}(c_{j})$, irrespectively of possible IC-success, makes the rate a fully dependent variable, so that the 1st stage can be directly analyzed.

However, in cases when IC fails, departing from $R_{j}^{(0)}$ may change the full game outcome. For example, playing a high rate when IC fails is a "threat" strategy, e.g. choosing $R_{j} > \max_{k \neq j} f_{jk}$ guarantees that no user can cancel interference from $j$. In contrast, playing a low rate when IC fails can be considered as "cooperative", e.g. applying $R_{j} = 0$ allows all other player cancel interference from $j$.

**Level-m Thinking**

To compare $(P,C|R)$ to $(P|C,R)$, we shall need, in addition to the weakly dominant strategy $R_{j}^{(0)}$, a set of semi-cooperative 2nd stage strategies in the case of IC failure for a user. This will become clear in the following section. For $(P,C|R)$, strategies where the player applies zero rate if IC fails will be considered. Note that playing any other rate than $R_{j}^{(0)}$ in the 2nd stage will be a non-dominant strategy. Compared to playing $R_{j}^{(0)}$, the player may lose payoff if playing some other rate, depending on the strategy choices of the other players.

Complete analysis of such semi-cooperative subgame NEs would require complete information. Accordingly, in this paper we consider limited rationality strategies, where the player does not fully analyze the 2nd stage. We apply different levels of thinking [89,90], related to how deeply the game is analyzed, to estimate whether IC is successful. This level of analysis is used both when choosing the first stage strategy based on assumptions on how the 2nd stage is played, and when playing the 2nd stage game itself. Note that here, we treat level-$m$ thinking as a limit on the rationality of the players, and correspondingly on the applicable strategies, when analyzing equilibrium strategies. In [90], level-$m$ thinking was used in the framework of best-response dynamics of two-stage games.

A 2nd stage rate strategy, based on level-$m$ thinking is defined as

$$R_{j}^{(m)} = \begin{cases} f_{j}(c_{j}) & \text{if } m = 0 \\ f_{j}(c_{j}) \theta(f_{c_{j}} - R_{j}^{(m-1)}) & \text{if } m \geq 1 \end{cases}$$

Note that the level-$m$ thinking defined in this dissertation are different from cognitive hierarchy theory model in [92,93], where all players’ rationality level are concerned with Poisson distribution. In (5.4) and (5.7), only $m$ players are considered relevant and their rationality levels are assumed to be descending recursively. In addition, the definition of level-0 thinking is different from cognitive hierarchy theory, where level-0 thinking players decide their strategy randomly.

When the level-$m$ thinking is used we define a Sub-game Perfect Outcome
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Level-\(m\) (SPOL-\(m\)) as an outcome of the game where in the second stage level-\(m\) thinking is used to determine an outcome and in the first stage, players play a Nash equilibrium strategy for an induced game in which their pay-off is given by the corresponding level-\(m\) outcome in stage 2. Note that if we replace level-\(m\) outcomes in stage 2 with Nash equilibria of that sub-game, then this corresponds to the usual definition of a Subgame Perfect Nash Equilibrium (SPNE). We denote SPNE and SPOL-\(m\) collectively as Subgame Perfect Outcome (SPO) for simplicity.

It should be noted that the weakly dominant strategy discussed above is precisely the level-0 thinking rate strategy. In [PII, PIII], we studied 2-player PC-IC games. In the terminology developed here, the analysis in these papers was related to level-0 thinking. We shall use notation \((P, C | R^{(m)})\) for \((P, C | R)\) with a level-\(m\) 2nd stage rate strategy.

5.2.4 \((P|C,R)\) Two-stage Game

In \((P|C,R)\), the strategy variables of player \(j\) are grouped to a 1st stage subset \(\mathcal{S}_j^1 = P_j\) and a 2nd stage subset \(\mathcal{S}_j^2 = (c_j(P), R_j(P))\). In a complete strategy, each player prepares both IC and rate strategies for each possible power & strategy combination. The best response function of player \(j\) for the 1st and 2nd stage games are

\[
\mathcal{B}_j^P = \text{argmax}_{P_j} f_j^{(i)} \theta (f_{ij} - R_i(P)) , \text{ where } i = c_j(P) \tag{5.5}
\]

\[
\mathcal{B}_j^{CR} = \text{argmax}_{c_j, R_j} R_j \theta \left( f_{j}^{c_j} - R_j \right) \theta \left( f_{c_j} - R_{c_j}(P) \right) , \tag{5.6}
\]

where \(c_j(P)\) represents player \(j\)'s IC strategy and \(R_i(P)\) represents player \(i\)'s rate strategy, both as a function of the power vector \(P\). It is straightforward to see that with SGP the best response rate strategy is given by \(R_j = f_j^{c_j}\), which depends on the best response IC strategy. As shown in (5.6), each player's best 2nd stage strategy depends on other players' rate strategies (namely on the rate of the “IC-target”). It is difficult to analyze the best IC and rate strategy for each subgame without fully analyzing the 2nd stage game. As in the case with semi-cooperative rate in \((P, C|R)\) depicted in Figure 5.1, there may be multiple subgame NEs, or states with no pure strategy subgame NEs.

Targeting practical distributed RRM, here we again determine IC and rate strategies based on level-\(m\) thinking. The situation differs from the \((P, C|R)\) case analyzed before, however. In the \((P, C|R)\) case, a player \(j\) assumed that at level 0, all \(m\)th order opponents played their dominant rate strategy \(R_j^{(0)}\). Then player \(j\) analyzed \(m\) levels of decisions of the opponents, until finding its assumed 2nd stage response \(R_j^{(m)}\) at level \(m\). For \((P|C,R)\), we have to determine the naive expectation of the \(m\)th order opponents at level-0. For this, we use a reference IC-state vector \(\tilde{c} = [\tilde{c}_1, \tilde{c}_2, \ldots, \tilde{c}_n]\), which acts as a “center” of thinking of the players' IC-strategies. The opponents at level-0 are assumed to play the IC-strategy \(\tilde{c}\), and the corresponding dominant rate strategy. Then, at level \(m - 1\), the players find their best action based on this assumption, and so on.

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This approach makes it possible to compare level-$m$ $(P, C|R)$ NEs to $(P|C, R)$ ones, such that the level-$m$ strategies in $(P|C, R)$ apply the realized $\hat{c}$ of an NE in $(P, C|R)$ as a reference IC-state vector.

The level-$m$ IC strategy of player $j$, with reference IC-state $\hat{c}$ is thus defined as:

$$c_j^{(m|\hat{c})} = \begin{cases} \hat{c}_j & \text{if } m = 0 \\ \arg\max_k f_j^{(k)} \theta \left( f_{kj} - R_k^{(m-1|\hat{c})} \right) & \text{if } m > 0 \end{cases}$$

(5.7)

where the level-$n$ rate of player $i$ is defined as the dominant rate strategy $R_i^{(n|\hat{c})} = f_i^{(l)}$, when $i$ is canceling opponent $l = c_i^{(n|\hat{c})}$. We use shorthand notation $(P|\hat{c}^{(m)}, R)$ to denote $(P|C, R)$ with level-$m$ 2nd stage strategy based on reference vector $\hat{c}$.

### 5.3 Two-player Game NE Analysis

With two players, the channel is simplified to a Gaussian interference channel, as shown in Figure 5.4. In this simplified game, the Nash Equilibria in the one-stage game $(P, C,R)$, and the two-stage games $(P,C|R)$ and $(P|C,R)$ can be analyzed in closed form. Following [PII][PIII] and [PIV], we only consider pure strategy NEs. When the two-stage games are played with SGP strategies, we find that there is a relationship between the NEs of these games. If there is a NE in $(P, C,R)$, there is a SGP NE in the two-stage games. If there is a NE in $(P,C|R)$, there is a NE in $(P|C,R)$. These NEs can be understood as $(P,R)$ subgame NEs, which are 2nd stage NEs in the $(C|P,R)$ game, i.e. NEs in a game with fixed IC selections for the players.

Note that for a two-player game, we are applying the equivalent standard form for the Gaussian interference channel [24], where $g_{ii} = g_{jj} = N_0 = 1$. In the analytical part of this section we use standard-form channels. Also, the ideal transmission efficiency function (3.2) is used. As there is only one potential IC-target, we adopt the shorthand of calling the IC-strategies "IC" or "noIC".
Figure 5.5. NE region for $(P,C,R)$ game while $P_{1}^{\text{max}} = P_{2}^{\text{max}} = 1$
5.3.1 One-shot \((P,C,R)\)

First we analyze the strategies of the players in the one-shot game. In \((P,C,R)\), each player chooses all strategies at the same time, and the strategy of \(i\) is \(S_i = (P_i, c_i, R_i)\). When interference cancelation is not applied, player \(j\)'s best choice is transmitting with maximum power \(P_{\text{max}}^j\) at rate \(f_j\). When player \(j\) is canceling interference from Tx \(i\), player \(j\) should be able to decode the message of Tx \(i\) which requires that

\[
\log_2(1 + \gamma_{ij}) \geq R_i. \tag{5.8}
\]

This leads to the following power constraint of player \(j\):

\[
P_j \leq \frac{P_{\text{max}}^i g_{ij}}{2^{R_i} - 1} - 1. \tag{5.9}
\]

The best power response for player \(j\) when playing IC is

\[
P_{\text{IC}}^j = \min \left( P_{\text{max}}^j, \frac{P_{\text{max}}^i g_{ij}}{2^{R_i} - 1} - 1 \right), \tag{5.10}
\]

and the overall best response strategy of \(j\) is

\[
S_j = \begin{cases} 
\left( P_{\text{max}}^j, f_j^j, \left( P_{\text{max}}^j \right) \right) & \text{if } \frac{P_{\text{max}}^j}{g_{ij} + 1} \geq P_{\text{IC}}^j \\
\left( P_{\text{IC}}^j, i, f_i^j \right) & \text{otherwise}
\end{cases} \tag{5.11}
\]

By matching the best response strategies of the players, we derive conditions for different types of NE. We denote a NE as \(E^{(\text{IC}_1, \text{IC}_2)}\), where \(\text{IC}_1 = c_1 - 1\), \(\text{IC}_2 = 2 - c_2\), according to the IC strategies of the players.

**Equilibrium \(E^{(0,0)}\)**

At this NE both players choose the noIC strategy. Given the opponent’s strategy \(P_i = P_{\text{max}}^i, R_i = f_i^j(\text{P}_{\text{max}}^j)\), as well as (5.10) and (5.11), the noIC condition for player \(j\) becomes

\[
\frac{P_{\text{max}}^j}{P_{\text{max}}^i g_{ij} + 1} \geq g_{ij}(\text{P}_{\text{max}}^i G_{ji} + 1) - 1. \tag{5.12}
\]

\(E^{(0,0)}\) exists when this is fulfilled for both players simultaneously. The NE region for \(E^{(0,0)}\) is depicted in Figure 5.5a, for the case \(P_{\text{max}}^1 = P_{\text{max}}^2 = 1\).

**Equilibrium \(E^{(1,0)}\)**

At this equilibrium noIC of player 2 and IC of player 1 are best responses to each other. From (5.10) and (5.11) we find the stability condition for \(E^{(1,0)}\) for player 1 to achieve better rate with IC to be

\[
\frac{P_{\text{max}}^j}{P_{\text{max}}^i g_{ij} + 1} \leq \tilde{P}_{\text{IC}}^j, \tag{5.13}
\]

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where \( j = 1, i = 2 \),

\[
\hat{P}_{IC}^j = \begin{cases} 
\min \left( \frac{[P_j^{\text{lim}}]_+}{g_{ij}g_{ji}} + P_j^{\text{max}} \right) & \text{when } g_{ij}g_{ji} < 1 \\
P_j^{\text{max}} \theta \left( P_j^{\text{max}} - P_j^{\text{lim}} \right) & \text{when } g_{ij}g_{ji} > 1 \\
P_j^{\text{max}} \theta \left( 1 - g_{ij} \right) & \text{else}
\end{cases}
\] (5.14)

and

\[
P_j^{\text{lim}} = \frac{1 - g_{ij}}{g_{ij}g_{ji} - 1}.
\] (5.15)

On the contrary, player \( i \) achieves better rate without IC, leading to

\[
P_j^{\text{max}} \geq g_{ji} - 1.
\] (5.16)

The NE region where \( E^{(1,0)} \) is stable is depicted in Figure 5.5b, for \( P_1^{\text{max}} = P_2^{\text{max}} = 1 \). The NE condition and NE region of \( E^{(0,1)} \) is a mirror image of \( E^{(1,0)} \) in the change \( 1 \leftrightarrow 2 \).

**Equilibrium \( E^{(1,1)} \)**

While both players receive strong interference from the opponent, NE \( E^{(1,1)} \) exists. This means that it is beneficial for both players to choose IC while the opponent is also applying IC. This leads to the condition

\[
P_j^{\text{max}} \leq \hat{P}_{IC}^j \frac{P_i^{\text{max}}}{g_{ij} + 1} 
\] (5.17)

where

\[
\hat{P}_{IC}^j = \min \left( \frac{[g_{ij} - 1]_+}{g_{ij}g_{ji}} + P_j^{\text{max}} \right)
\] (5.18)

The NE region of \( E^{(1,1)} \) is depicted in Figure 5.5c, for the case \( P_1^{\text{max}} = P_2^{\text{max}} = 1 \).

**Region without NE**

Figure 5.5d shows all NE regions, for the case \( P_1^{\text{max}} = P_2^{\text{max}} = 1 \). There is an intersection region where both \( E^{(0,1)} \) and \( E^{(1,0)} \) exist. In addition, there are two regions \( \mathcal{A} \) and \( \mathcal{B} \) where no pure strategy NE exists. In these regions, the game is thus always unstable against changing the IC-subspace. More specified analysis about regions \( \mathcal{A} \) and \( \mathcal{B} \) is included in Publication III, Sec. 3.

Figure 5.6 shows refined NE regions of (P-IC-R), for the case \( P_1^{\text{max}} = P_2^{\text{max}} = 1 \). Each \( E^{c_1,c_2} \) region is further divided into smaller regions depending on whether maximum or limited power is used. The legend shows the NE strategies in these regions.

**5.3.2 Two-stage \( (P, C|R) \)**

The \( (P, C|R) \) game is played in two sequential stages. In the 1st stage players choose power and IC strategy, in the 2nd stage players choose rate according to the 1st stage strategies of both players. As rate is selected in the 2nd stage,
players can always select an achievable rate. As both players make a more informed rate decision, a possible source of instability is removed from the game.

Consider a NE of \((P, C, R)\) game \(\{S_1, S_2\}\), where the equilibrium strategies of the players are \(S_1 = (P_1, c_1, R_1)\), \(S_2 = (P_2, c_2, R_2)\). We define a derived strategy pair for the \((P, C|R)\) game as \(\{ (S_{11}, S_{21}), (S_{12}, S_{22}) \}\) where for player \(i\) the strategies in the two stages are

\[
\begin{align*}
S_1^1 &= (P_i, c_i) \\
S_2^1 &= \begin{cases} 
R_i & \text{if } S_1^1 = (P_i, c_i), \ S_2^1 = (P_j, c_j) \\
\phi_i (S_1^1, S_2^1) & \text{else}
\end{cases}
\]

Here \(\phi_i(S_{1i}, S_{1j})\) are rate strategies in unrealized parts of the game which are subgame perfect. If a derived strategy pair forms a NE, we call it derived NE.

For \((P, C, R)\), being a NE guarantees that a player cannot gain utility by changing any combination of its strategies. On the other hand, the \((P, C|R)\) NE guarantees that each player cannot gain utility by changing its own strategies, when its opponent can adjust the rate according to both players’ power and IC strategy. Postponing the rate decision to the second stage does not destabilize a NE. We proved in Publication III, Sec. 3 that when there is only two players

- If there exists a NE of \((P, C, R)\), there exists a corresponding derived NE of \((P, C|R)\).

Therefore we can derive NEs of \((P, C|R)\) from NEs of \((P, C, R)\). Moreover, for all NE regions of \((P, C, R)\) game, the derived NE is unique. Furthermore, in \((P, C|R)\), a NE also exists in region \(\mathcal{A}\) of Figure 5.5d, where no NE exists for \((P, C, R)\).

However, all strategy pairs in region \(\mathcal{B}\) of Figure 5.5d still remain unstable, as the IC strategy response of the opponent is not considered in the \((P, C|R)\) game. Thus the NE regions of \((P, C|R)\) are the same as in Figure 5.5 except that region \(\mathcal{A}\) is also an \(E^{(0,0)}\) type NE region.
5.3.3 Two-stage \((P|C,R)\)

In the \((P|C,R)\), IC is also decided in the 2nd stage. A player can decide the best IC and rate combination conditioned on power selections of the 1st stage. Given any first-stage choice of \((P_i, P_j)\), the best response strategy in the second stage subgame for player \(j\) is

\[
\mathcal{B}_{2,j} = \begin{cases} 
(j, f_{j}^{(j)}) & \text{if } \gamma_{ij} < \gamma_{ii}^{(i)} \\
(i, f_{j}^{(i)}) & \text{if } \gamma_{ij} \geq \gamma_{ii}^{(j)} \\
(c_i, f_{j}^{(c, i)}) & \text{otherwise}
\end{cases}
\]

By matching best response strategies of both players, it can be proved that for two-stage \((P|C,R)\) game, given any first-stage strategies, there exists one or two NEs for the second-stage subgame. Hence we can define a \((P|C,R)\) strategy derived from \((P,C|R)\) in a similar way as for \((P,C|R)\):

\[
\mathcal{A} \begin{cases} 
\mathcal{A}_j^1 = P_j & \text{if } \mathcal{A}_i^1 = P_i, \mathcal{A}_j^1 = P_j \\
(c_j, R_j) & \text{else}
\end{cases}
\]

where \(\psi_i(\mathcal{A}_i^1, \mathcal{A}_j^1)\) are rate and IC strategies in unrealized parts of the game which are subgame perfect, and \(R_i\) is the rate in the realized second-stage of the \((P,C|R)\) NE. In Publication III, Sect. 3, we showed the connection between two-player \((P,C|R)\) and \((P|C,R)\) games.

- If there exists a NE of \((P,C|R)\), there exists a corresponding derived NE of \((P|C,R)\).

Furthermore, in \((P,C|R)\) there is a NE in region \(\mathcal{B}\) as well. NEs of \(E^{(1,0)}\) and \(E^{(0,1)}\) type are stable in this region, with both players using \(P^{\max}\).

Accordingly, the NE regions of \((P,C|R)\) game are the same as in Figure 5.5d except that the region \(\mathcal{A}\) is an \(E^{(0,0)}\) type NE region and region \(\mathcal{B}\) is a double NE region with \(E^{(1,0)}\) and \(E^{(0,1)}\) NEs. By extending the one-shot game \((P,C,R)\) to two-stage \((P,C|R)\) and \((P|C,R)\) games, we can gradually reduce the region without NEs, and eventually achieve a NE for all configurations. It is remarkable that for \(N = 2\), the two stage \((P|C,R)\) game always has a pure strategy NE.

5.4 Multiplayer Game Outcomes Analysis

5.4.1 Equilibria, Game Outcomes and their Relationships

Concentrating on SPO simplifies game analysis. This holds, in particular, to games where R is a second stage strategy. In any game or subgame, where the
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powers of all players \( P \), and the IC-strategy \( c_j \) of player \( j \) are fixed, the best rate that \( j \) can choose is the level-0 rate expectation

\[
R_j(P, c_j) = R_j^{(0)} = f_j^{(c_j)}.
\]  

(5.19)

To understand the relationship between SPOs, we need to operations that map these to each other.

**Derived SPO** A derived Subgame Perfect Outcome of a two-stage game \( \mathcal{G}_b \) is a SPO which has the same realized part as a SPO of a game \( \mathcal{G}_a \) with the same strategy variables and \( \mathcal{S}_{b,1} \subset \mathcal{S}_{a,1} \). In Publication III, Sec. 4, the relationships of the SPOs of the different multiplayer games were analyzed. It was found that

- For \((P, C, R)\) and \((P, C|_{R^{(0)}})\), we find the following: The connection between two-player one-shot game \((P, C, R)\) and two-stage game \((P, C|_{R^{(0)}})\) also holds for multiplayer game. Thus a NE in \((P, C, R)\) yields a derived NE in \((P, C|_{R^{(0)}})\). The converse does not hold.

- For \((P, C|_{R^{(2)}})\) and \((P|_{\hat{C}^{(2)}, R})\), we find the following: For each Subgame Perfect Outcome \( E_R^{(2)} \) of the \((P, C|_{R^{(2)}})\) with realized IC strategy vector \( \hat{c} \), there exists a derived Subgame Perfect Outcome \( E_{\hat{c}, R}^{(2)} \) in the game \((P|_{\hat{C}^{(2)}, R})\) where 2nd stage is played with level-2 thinking having reference IC strategy \( \hat{c} \).

- For \((P, C|_{R^{(2)}})\) and \((P|_{C, R})\) we find the following: For each Subgame Perfect Outcome \( E_R^{(2)} \) of \((P, C|_{R})\), there exists a derived subgame perfect Subgame Perfect Outcome of \((P|_{C, R})\), or a non-NE where a player can improve its payoff when the opponent of its opponent changes its IC strategy.

This leads to the summary of the relation of the SPOs of the differently staged games:

**Theorem 1.** The NEs of \((P, C, R)\) are a subset of the realized part of NEs of \((P, C|_{R^{(0)}})\). The realized part of \( O_R^{(2)} \), a Subgame Perfect Outcome on Level-2 of \((P, C|_{R^{(2)}})\), with realized IC strategy \( \hat{c} \) are a subset of the realized part of \( O_{\hat{c}, R}^{(2)} \) of \((P|_{\hat{C}^{(2)}, R})\), where the 2nd stage is played with level-2 thinking having reference IC strategy \( \hat{c} \).

Figure 5.7 shows the relation between the realized part of the SPOs of the different games. With \( N = 2 \) rational players, there is special nesting between the realized part of NEs of \((P, C, R)\), \((P, C|_{R^{(0)}})\), \((P|_{C, R})\). With \( N > 2 \) rational players, \((P|_{C, R})\) does not keep in the nesting due to different game dynamics explained in the previous section. Examples that verify this figure can be found in the Appendix of Publication IV. Note that there exists network states where no NE exist for any referred game model. Proof is by examples in the Appendix of Publication IV. For limited rationality \( N \) player games, we have the SPOL-2 relations as described in Theorem 1.
5.4.2 Distributed Best Response RRM Algorithm

Above, the game models were considered for players with full or limited rationality. Here, we formulate distributed RRM algorithms, inspired by these games. The algorithms are based on iterated best responses. Best responses algorithms are conventionally used in one-shot games. Here, we investigate best response strategies for solving the multistage games discussed in the previous section. The performance of these algorithms is analyzed in the next section.

For two-stage games, they are formulated in terms of backward induction analysis of the second stage. Second stage analysis is simplified either by applying limited rationality, or by heuristics. The best informed party in a Tx-Rx pair is the receiver, so we assume that the RRM decisions for pair $j$ are taken at $Rx_j$.

We consider best response algorithms based on one-shot $(P,C,R)$, two-stage $(P,C|R)$ with 2nd stage strategy based on level-0 and level-2 thinking, as well as $(P|C,R)$ with a heuristic 2nd stage strategy, and with level-2 2nd stage strategy.

Depending on the game model inspiring the algorithm, the updating players need different information related to the channel states, and the strategies applied in the network. To simplify the algorithms, we formulate them in such a way that players only consider canceling interference from the nearest interfering transmitter. Then, the updating players in $(P,C,R)$, and the multistage games with level-0 thinking, only need information from one of the other players, while with level-2 thinking, information from two other players is needed.

If all Rxs hear all Tx-Rx pairs that they need information from, the information gathering can be arranged based on measurements and overhearing. Therefore communication overhead can be dramatically reduced by allowing Rxs to measure and overhear others’ Tx-Rx pairs’ link adaptation transmissions. Otherwise, more complicated protocols are needed and there will be serious overhead of information update. We assume that the protocols make it possible for $Rx_j$ to receive this information. For example, if the communication protocols involve a step where $Rx_l$ communicates the recommended rate $R_l$ to $Tx_l$, it may be possible that $Rx_j$ overhears this transmission, and accordingly gets hold of this information. The required information and the complexity in updating $Rx_j$ are gathered in Table 5.1. Measured (M), Communicated (C),
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and Overheard (OH) data is separately indicated. The complexity is computed in the number of static | dynamic real valued variables needed to communicate. Here \( k = \text{argmax}_{x \neq j} (g_{xj}) \) is the opponent of the updating player \( j \), and \( l = \text{argmax}_{x \neq k} (g_{xk}) \) is the opponent of \( k \). We assume that Gaussian noise \( N_0 \) and maximum power \( P_{\text{max}} \) are known. Note that the wanted signal SINRs measured at Rx \( j \) are with the Tx-power \( P_j \) of the previous update. In \((P|C,R)\), each updating player needs complete information about the network state, and the first stage strategy of all other players. The channel gains from each Tx to Rx \( j \) are collected in the vector \( G_j \), and all rest channel gains in the vector \( G_{\neg j} \).

**Table 5.1.** Required information and complexity in best response update for Rx \( j \) in the different algorithms.

<table>
<thead>
<tr>
<th>Game</th>
<th>Static information</th>
<th>Dynamic information</th>
<th>Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>((P,C,R))</td>
<td>( g_{jj}, g_{kj} )</td>
<td>( \gamma_{jj} ) ( P_k, R_k )</td>
<td>0</td>
</tr>
<tr>
<td>((P,C</td>
<td>R^{(0)}))</td>
<td>( g_{jj}, g_{kj} ) ( g_{kk}, g_{jk} ) ( \gamma_{jj} ) ( P_k, c_k ) ( \gamma_{kk}^{(l)} )</td>
<td></td>
</tr>
<tr>
<td>((P,C</td>
<td>R^{(2)}))</td>
<td>( g_{jj}, g_{kj} ) ( g_{kk}, g_{jk}, g_{jl}, g_{ll} ) ( \gamma_{jj} ) ( P_k, P_l, c_k, c_l ) ( \gamma_{kk}^{(l)}, \gamma_{ll}^{(c_l)} )</td>
<td></td>
</tr>
<tr>
<td>((P</td>
<td>C,R))</td>
<td>( G_j ) ( G_{\neg j} )</td>
<td>( P_{\neg j} ) ( N^2 - N )</td>
</tr>
<tr>
<td>((P</td>
<td>C</td>
<td>R^{(2)},R))</td>
<td>( g_{jj}, g_{kj} ) ( g_{kk}, g_{jk}, g_{jl}, g_{ll} ) ( \gamma_{jj} ) ( P_k, P_l, c_k, c_l ) ( \gamma_{kk}^{(l)}, \gamma_{ll}^{(c_l)} )</td>
</tr>
</tbody>
</table>

We assume that the distributed algorithms are based on asynchronous updates in a predefined order. The stage-1 update steps taken by Rx \( j \) are summarized in algorithms for \((P,C|R^{(2)})\), \((P|C,R)\) and \((P|C|R^{(2)},R)\), respectively. The update steps for the one-stage game \((P,C,R)\), and for the two-stage games with level-0 thinking, are straight forward. In the two-stage games, we need a synchronous round of 2nd stage updates for all players after each first stage update of a player. In the heuristic \((P|C,R)\) algorithm, the updating player \( j \) decides the second stage IC strategies for all other players. This is because of the fact that given the same 1st stage power vector \( P \), there can exist several 2nd stage subgame equilibria, as shown by the lower part of Figure 5.1. It is also possible that these subgame equilibria achieve the same payoff \( u_j \) for player \( j \). An algorithm performing full analysis would have to branch when such cases are encountered, which increases complexity exponentially during iterations. In the heuristic \((P|C,R)\) algorithm we let the updating player \( j \) randomly choose one subgame equilibrium instead of searching through all possible branches, if such cases are encountered. For the level-2 IC strategy game \((P|C^{(2)},R)\), the reference IC-state vector \( c \) is changing during the iteration, it is assumed to be the realized IC strategy vector in the previous update.

These RRM algorithms are direct implementations of the games of the previous sections. Accordingly, for \( N > 2 \) players, convergence cannot be proven, as there
always is a possibility of non-convergent network instances. Also, according to the results of previous sections, we know that some games have higher convergence probability than some others. This will be seen in simulations.

5.5 Simulation Results

5.5.1 Simulation Model

We consider a network which consists of $N$ Tx-Rx pairs in two scenarios. The first scenario includes only $N$ D2D pairs, and the second scenario includes $N - 1$ D2D pairs and one communication pair consisting of a cellular user and a base station. All Tx-Rx pairs are located in a circular cell with a radius of $r = 100$ m. The cellular Tx is randomly dropped in the circular area with uniform distribution, while the cellular base station receiver is located at the center of the cell. The D2D Tx-Rx pairs are dropped uniformly and at random in this area, with a predefined D2D distance $D$. The distance $D$ is used as a parameter to control the probability of D2D link crossing, and correspondingly, how much they interfere with each other. For small $D$, the D2D pairs are virtually isolated, and interfere weakly with high probability. If $D = 200$ m, all D2D links cross each other, and strong interference is likely. Here, we simulate distances between $D = 10$ and $D = 90$ m.

We assume distance dependent path loss defined as

$$L_p = hd^{-4}, \quad (5.20)$$

where $d$ is distance measured in meters and $h = \exp(1)$ if small scale Rayleigh fading is applied, otherwise $h = 1$.

When a cellular user is included, we use Cellular Power Control (CPC) to determine the maximum transmit power of both the cellular user and the D2D users. The algorithms of the previous section then determine the actual transmit power subject to the maximum dictated by CPC. CPC is performed according to the average path loss, which is modeled as (5.20). We use the CPC target

$$P_{0,i} = \begin{cases} \frac{P_{\text{max}}}{L_{\text{max}}} & \text{for cellular user } i = 0 \\ \frac{P_{\text{max}}}{A_{\lim}L_{\text{max}}} & \text{for D2D user } i > 0 \end{cases}, \quad (5.21)$$

where $L_{\text{max}}$ is the distance dependent path loss at cell edge. It is the average of (5.20) over Rayleigh fading, and cell edge is here given by $r = 100$ m. The maximum power of the D2D users is limited in a way that at the cellular Rx, the received interference from each D2D Tx is on average at least a factor of $A_{\lim}$ weaker than the received cellular signal. Here we use $A_{\lim} = 10$. Therefore the cellular user is protected from heavy interference.

Applying CPC, the maximum D2D Tx power depends on the location of the D2D transmitter. For D2D Tx $i$ at distance $d_{i_0}$ from the cellular base station, it
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is

\[ P_{i}^{\max} = P_{0,i} a_{i0}^4 \]  

(5.22)

The maximum transmit power of the cellular user would thus be \( P_{0}^{\max} \). In these simulations we use \( P_{\text{max}} = 10 \), such that the largest Tx power of a D2D, is the same as in the simulation with only D2D users. In addition to CPC, we use a protection margin \( A_{\lim} \) to protect the cellular user from excessive D2D interference. We shall use \( A_{\lim} = 10 \), indicating that the maximum D2D Tx-power is decreased 10dB from the number given by CPC.

When simulating the algorithms of the previous section, we assume a common initial strategy which includes maximum transmit power, no interference cancelation and level-0 expectation of rate.

Statistics are collected from \( 10^5 \) random instances for a given \( D \) and game model. In each instance, the simulation will iterate through a finite number of rounds, in which each player will iteratively optimize its own payoff by changing its own strategies. In each round, once a player changes its 1st stage strategy, all other players will adjust their 2nd stage strategy (if any) to perform the 2nd stage game. During finite number of rounds, if no player would change its strategy and convergence is achieved, payoff of each player is recorded as ten identical copies. Otherwise, the payoff of the last ten rounds will be recorded in order to show the outage effect of non-convergence. Since we are not applying exhaustive search, there might be very rare corner cases which are not revealed.

5.5.2 Simulation Results with Two D2D Players

For \( N = 2 \) D2D players, we simulate the Gaussian interference channel without fading, i.e., \( h = 1 \). The ratio of the transmit power and noise power spectral densities is 100 dB, which corresponds to a maximum SNR of 100 dB, when the transmitter and receiver are co-located.

We assume that the Tx-Rx pairs are aware of all four channel gains \( g_{ij} \). For \( g_{ij}, i \neq j \), and the wanted signal channel \( g_{ii} \), this can be arranged by measurements at the nodes, whereas for the opponent gain, we assume overhearing of broadcast transmissions of the opponent pair. From this information, the Tx-Rx pairs can deduce a NE if it exists, and use the corresponding strategies. For (P-IC;R) game without NE, the first stage subgame is myopically played, with perfect information of the SGP 2nd stage selections.

Figure 5.8 illustrates the non-convergence probability of the P-IC-R and (P-IC;R) games, i.e. the probability that there is no NE in an instance. The horizontal axis represents the D2D distance \( D \). As shown in Figure 5.8, the non-convergence probability of one shot P-IC-R game first increases with growing D2D distance and reaches a maximum of 39% at \( D = 60m \), then falling down to 28% at \( D = 90m \). The non-convergence probability of (P-IC;R) is much smaller. It has an ascending trend and reaches a maximum 7% when \( D = 90m \). This reflects the probability of region \( \mathcal{B} \), which is in the strong interference region. The larger the D2D distance, the more probable it is that interference is strong.
The non-convergence probability of \((P;IC-R)\) vanishes, as a NE always exists.

![Figure 5.8. Non-convergence probability as function of D2D distance when \(P_{\text{max}} = 100\text{dB}\).](image)

The Cumulative Distribution Function (CDF) of the realized rate for the different games is depicted in Figure 5.9, with the rate without IC as a reference. This is given by the payoff function (3.5) with the strategy variables of the realized part of a NE. For no-NE regions, since there are repeated sequential play loops, the results are collected from one corresponding loop for each network instance.

First one observes that opportunistic use of IC considerably improves spectral efficiency, and the improvement grows with increasing D2D distance. The \((P,C,R)\) and \((P,C|R)\) games have high outage probabilities. When the channel gains are such that there is no NE, in myopic play the players sometimes transmit with a rate that is not realizable, leading to outage.

The outage probability for different D2D distances are shown in Table 5.2. Although the non-convergence probability of \((P,C,R)\) is as high as about 40% when \(D = 60\text{m}\), the corresponding outage probability is just about 10%. The outage probability is smaller than the non-convergence probability, as in sequences of myopic play, outage happens every third or fourth game, depending on the

![Figure 5.9. Spectral efficiency CDF of corresponding games in a circular area with 100 meter radius](image)

(a) \(D = 40\text{m}, \text{SNR}=100\text{dB}\)  
(b) \(D = 80\text{m}, \text{SNR}=100\text{dB}\)
Table 5.2. Outage probability of the IC-games in the D2D network.

<table>
<thead>
<tr>
<th>D(m)</th>
<th>40</th>
<th>60</th>
<th>80</th>
<th>100</th>
<th>120</th>
<th>140</th>
<th>160</th>
<th>180</th>
</tr>
</thead>
<tbody>
<tr>
<td>((P, C, R)) (%)</td>
<td>8.2</td>
<td>10.3</td>
<td>9.3</td>
<td>6.5</td>
<td>4.6</td>
<td>3.6</td>
<td>3.2</td>
<td>3.1</td>
</tr>
<tr>
<td>((P, C</td>
<td>R)) (%)</td>
<td>0.8</td>
<td>1.5</td>
<td>2.2</td>
<td>2.6</td>
<td>2.2</td>
<td>1.9</td>
<td>2</td>
</tr>
<tr>
<td>((P</td>
<td>C, R)) (%)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

no-NE region.

5.5.3 Simulation Results with Multiplayer

Overlay Network with \(N\) D2D users

In simulations with \(N > 2\) D2D players, the maximum transmit power of D2D transmitters \(P^\text{max} = 1\) are used, and the noise power is \(N_0 = 10^{-8}\). Again, no fast fading is considered, such that \(h = 1\). We assume a common initial strategy which includes the maximum transmit power, no interference cancelation and level-0 expectation of rate.

Statistics are collected from \(10^5\) random instances for given \(D\) and game model. In each instance simulation will loop finite number of rounds, in which each player will iteratively optimize its own payoff by changing its own strategies. In each round, once a player changes its 1st stage strategy, all other players will adjust their 2nd stage strategy (if any) to perform the 2nd stage game. There is a maximum number of rounds played. If before the maximum number is reached, no player would change its strategy during a full round of the game, convergence is achieved, and payoff of each player is recorded. Otherwise, if the maximum number of rounds is reached without convergence, the average payoff of the players from the last ten rounds will be recorded. Since we are not applying exhaustive search, there might be rare corner cases which are not revealed.

Figure 5.10 illustrates the non-convergence probability of each game with \(N = 6\), i.e., the probability that at an instance does not have a SPO. The horizontal axis represents the D2D distance \(D\). As shown in Figure 5.10, the non-convergence probability of the \((P, C, R)\) game first increases with growing D2D distance, reaching a maximum of 27% at \(D = 20\) m, then falls down to 1.9% at \(D = 90\) m. The other games share a similar shape of the non-convergence curve with maxima at \(D = 20\) m or \(D = 30\) m.

Note that \((P|c^{(2)}, R)\) has lower non-convergence probability than \((P, C|R^{(2)})\). This follows directly from Proposition 1. In addition, it is interesting that \((P, C|R^{(2)})\) has higher non-convergence probability than \((P, C|R^{(0)})\). In Publication IV, Sec. 4, no conclusive relationship was observed between the equilibria domains of these two games. However, in the simulation scenario analyzed,
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As shown in previous section, two-player \((P|C,R)\) was shown to always have an NE. This does not hold for multiplayer \((P|C,R)\). As discussed in the context of Figure 5.1, in any game with \(N > 2\) players, there may be IC-cycles that prevent convergence. However, the non-convergence probability is significantly smaller for the two-stage games than for the one-shot game.

Overall, the non-convergence probability of \((P|c^{(2)},R)\) is the lowest, even lower than for the complete rationality game \((P|C,R)\). The reason for this is that in \((P|c^{(2)},R)\), a player is less affected by actions deep in the network. As we shall see below, this leads to a reduced use of IC in the second stage, which again leads to less power changes, and better convergence of the first stage power game.

The Cumulative Distribution Function (CDF) of players’ payoff in different games for \(D = 30\) m is depicted in Figure 5.11. The rates achieved by the game-inspired distributed RRM methods are compared to the rate achieved with full power and no IC. In addition, results of centralized Network Utility Maximization (NUM) optimization of Tx-power and network IC-state are reported. The principles of centralized NUM of Publication I are followed for this. NUM is realized with different levels of \(\alpha\)-fairness [103]. The value \(\alpha = 0\) leads to network sum-rate maximization, while \(\alpha = 1\) corresponds to a proportionally fair allocation of network power and interference cancelation resources.

From the results we see that Max-sum-rate NUM with Power Control (PC) and IC is qualitatively similar to the baseline result with PC. The gains are predominantly for high rate devices.

Interestingly, the distributed RRM algorithms controlling power and IC, inspired by strategic games, are capable of improving the fairness of the users. This is remarkable, as these algorithms are based on greediness of the players, each D2D pair trying to select the power and IC state that is most beneficial for the pair. The increased fairness is in part due to the overall reduced interference.

Figure 5.10. Probability of non-convergence as function of \(D\) in different games.
when a D2D pair voluntarily lowers its transmit power to enable IC, and in part due to the inherently equalizing feature of IC which is capable of removing strong interferers.

### Table 5.3

|       | no IC | $(P,C,R)$ | $(P,C|R_{0})$ | $(P,C|R_{2})$ | $(P|C,R)$ | $(P|c_{2},R)$ | IC NUM $\alpha = 0$ |
|-------|-------|-----------|---------------|---------------|-----------|---------------|---------------------|
|       | $R_{5\%}$ | 0.02 | 0 | 0.46 | 0.22 | 0.38 | 0.12 | 0.02 |
| $D=30m$ | $R_{mean}$ | 0.70 | 0.84 | 0.96 | 0.97 | 0.96 | 0.86 | 1.08 |
|       | Outage(%) | 0 | 13.84 | 0.20 | 1.74 | 0 | 2.66 | 0 |
|       | $R_{5\%}$ | 0.01 | 0 | 0.36 | 0.26 | 0.37 | 0.24 | 0.01 |
| $D=50m$ | $R_{mean}$ | 0.49 | 0.86 | 0.94 | 0.94 | 0.94 | 0.87 | 1.12 |
|       | Outage(%) | 0 | 8.68 | 0.10 | 1.16 | 0 | 1.86 | 0 |
|       | $R_{5\%}$ | 0.01 | 0.12 | 0.38 | 0.34 | 0.35 | 0.32 | 0.01 |
| $D=70m$ | $R_{mean}$ | 0.37 | 0.86 | 0.89 | 0.88 | 0.89 | 0.87 | 1.07 |
|       | Outage(%) | 0 | 3.5 | 0.01 | 0.24 | 0 | 0.55 | 0 |

In Table 5.3, we compare the fifth percentile rate and the mean rate achieved by the different RRM algorithms to the proportionally fair NUM. The mean rate represents the typical rate experienced by devices, and is an indication of network capacity. The 5th percentile indicates the rate experienced by users with bad channel conditions. It is remarkable, that the distributed two-stage games reach practically the same mean rate as the centralized proportionally fair algorithm, while still providing a significant fraction, up to $\sim 50\%$, of the 5th percentile rate. The outage probability of the different RRM algorithms is
also compared in Table 5.3. For the shorter D2D distance, the 1-stage game is in outage.

**Underlay Network with \( N - 1 \) D2D Users and One Cellular User**

In this simulation setting, the maximum transmit power of D2D transmitters is \( P_{\text{max}} = 1 \), and the noise power is \( N_0 = 10^{-8} \). Rayleigh fading is considered, in addition to distance-dependent path loss, such that the fading-induced gain is exponentially distributed with \( h = \exp(1) \). For D2D communication underlaying a cellular network, it is essential to protect cellular users from strong interference generated by nearby D2D transmitters. As discussed above, in this simulation we set a threshold \( A_{\text{lim}} = 10 \) to prevent cellular users from suffering strong interference.

The CDF of user rates are depicted in Figure 5.12. The results are compared with a reference algorithm taken from [104]. In [104], circular guard areas with radius \( r_{\text{guard}} \) are considered, and D2D Txs located within the guard area will be muted in order to eliminate heavy interference. In [104], IC is used only at the cellular receiver. To have a comparable situation, we use a Cellular Power Control to limit the transmit powers in the reference algorithm as well, and we use the same \( A_{\text{lim}} \) to protect the cellular system from excessive D2D interference.

![Figure 5.12](image-url)

**Figure 5.12.** The CDF of a user’s rate with different algorithms, when \( D = 30 \) m, cell radius \( r = 100 \) m, \( N = 6 \) pairs, \( A_{\text{lim}} = 10 \) dB, \( r_{\text{guard}} = 10, 30, 50 \) m, compared to [104] with different \( r_{\text{guard}} \).

From Figure 5.12 we observe that the game based algorithms offer dramatic gains in terms of D2D network throughput, while the cellular user can achieve approximately same rate as when guard area radius \( r_{\text{guard}} = 30 \) m. The simulation shows that when \( D = 30, 50, 70 \) m, \( (P, C|R^{(0)}) \) game based algorithm can achieve 39%, 69%, 79% more D2D average rate than the reference algorithm applying \( r_{\text{guard}} = 30 \) m with even a slightly better cellular user average rate. The performance of the most vulnerable cellular users is, however, slightly compromised. Applying \( r_{\text{guard}} = 30 \) m improves the 5th percentile of the CDF with
43%, as compared to \((P, C|R(0))\). From the simulation results it can be deduced that the details of game do not have a great effect. The D2D UE outage is much dependent on the cellular UE location. To increase reliability, the staged games in a overlay D2D seems relevant. By applying the simple 2-stage game with rate a dependent variable, we can considerably increase reliability with small communication complexity.

5.6 Conclusion

In this chapter, we have analyzed a set of multiplayer Interference Canceling games, where \(N\) transmitter-receiver pairs use the same channel. We consider a multicarrier model, where all the channel gains are average signal qualities. The receivers are equipped with two-stage Successive Interference Canceling receivers. In addition to the IC state \(C\), the players determine the transmit power \(P\), and the rate \(R\) attempted in transmission.

We consider the one-stage game \((P, C, R)\), where all players simultaneously decide on the three strategy variables. In addition, we consider two-stage variants, where the rate decision, and possibly the IC-decision, is postponed to a second stage. When analyzing the two-stage games, we resort to a limited-rationality concept; when playing the first stage, the players only analyze the possible second stage outcomes up to level-\(m\) thinking. This means that the consequences of the opponents’ actions is only analyzed to a depth \(m\). In particular, we consider the multiplayer game \((P, C|R(0))\), where the second stage rate strategies are performed without considering possible opponent second stage strategies at all. This second stage strategy is found to be weakly dominant. It is proven that this two-stage game has better stability than the one-shot game \((P, C, R)\).

Considering games where, in addition to rate, IC-decision is done in the second stage, we proved that \((P|\tilde{C}(2), R)\) is more stable than \((P, C|R(2))\). In contrast to a two-player situation, where \((P|C, R)\) always has a pure strategy Nash Equilibrium, for \(N > 2\), the \((P|C, R)\) game does not always have a NE.

Based on the considered games, we have constructed a set of distributed RRM algorithms for D2D networks controlled by cellular systems. For the case where the games do not have an equilibrium, RRM decisions can be achieved by limiting number of game iterations. It is shown that the distributed RRM algorithm based on the \((P, C|R(0))\) game gives considerable improvement of throughput in D2D networks, with low complexity, and reliable convergence. Applying a distributed RRM algorithm based on this game may be a simple and efficient solution for D2D networks.

The game-inspired distributed RRM method with coordinated cellular users and D2D users is also simulated. In order to protect the cellular users from D2D interference, D2D transmission power is constrained to a lower CPC level. The simulation result is presented and compared with a reference method [104]. By applying coordinated game-inspired distributed RRM methods, the spectrum
efficiency of D2D transmissions can be dramatically improved with a slight influence on cellular user.
6. Cellular Network IC

This chapter studies a network IC method, cell-edge inversion, that improves the downlink data rate of IC-capable cell-edge users in a cellular downlink scenario, as shown in Figure 6.1. A distributed network utility optimization problem is formulated to exploit this possibility. The simulation of this method is also presented.

6.1 Cell-edge Inversion

We assume a set of cells $\mathcal{C}$, each served by a base station. All base stations transmit with full power. For each cell $c \in \mathcal{C}$, the set of neighboring cells is $\mathcal{N}_c$, and the set users who would select $c$ as their best cell is $\mathcal{U}_c$. With interference cancellation, each user $v \in \mathcal{U}_c$ can also receive a transmission from a neighbor cell $c' \in \mathcal{N}_c$ after canceling the signal from $c$. Thus the network may decide that $v \in \mathcal{U}_c$, located at cell-edge in $c$, cancels the signal from its strongest cell $c$, and data to $v$ is transmitted from the second strongest cell $c'$ received by $v$, instead of conventionally receiving from strongest cell. Here this concept is called cell-edge inversion.

Figure 6.1. The example of downlink scenario where three cells serve several cellular users.
inversion. We call $c$ the primary cell of such a user $v$, and the other cell an inversion cell.

**Definition 1**: A cell-edge inversion is a condition where user $v$ belonging to the coverage area of cell $c$ receives a transmission from neighboring cell $c'$. The transmission in cell $c$ is link adapted so that $v$ may decode this transmission, and cancel it before receiving the transmission from $c'$.

As shown in Figure 6.2a, user $v$ is called the inverting user and user the $u$ supporting user. One supporting user could support multiple inverting users at same time, as shown in Figure 6.2b. In general user $u$ could belong to the coverage area of any cell. In a more general setting, the transmission to $v$ may be from the own cell as well, in which case we have downlink NOMA. The general setting is very complicated. Here we consider the case when supporting users belong to the coverage area of $c$. Note that cell-edge inversion can happen in each cell and each frequency domain resource block independently. There may be one supporting user in each resource block in each cell.

The transmission canceled by $v$ needs not be intended to $v$, but to any user $u \in \mathcal{U}_c$. In this case it is said that the transmission to $u$ supports the cell-edge inversion of $v$, which is inverting to cell $c'$. Note that here we exclude the possibility that the transmission canceled by $v$ is to a user that has inverted from another cell $c''$ to $c$.

As shown in Figure 6.3, each transmission can support multiple inverting users, and each inverter could be supported by many supporters.

**Definition 2**: If the supporting transmission in cell $c$ is to the inverting user $v$ itself, the user $v$ is said to be in soft handover (SHO).

Note that the soft handover considered here differs from conventional soft handover in 3G systems, as the receiver does not combine the transmissions from two cells, but decodes them both, using interference cancelation. It is worth noting that with ideal coding and modulation, the data rate supported by such IC-SHO equals the rate achievable with perfect maximum ratio combining of the transmissions from the two cells. Also, it is interesting that the order of decoding does not matter. If $S$ and $S'$ are the received signal powers from cells $c$
Figure 6.3. In soft handover, user $v$ decodes downlink transmission from $c'$ after receiving and canceling transmission from $c$ to $v$, the decoding order does not influence the total rate of $v$.

and $c'$ at $v$, respectively, and $I_0$ denotes noise and other interference, which is considered Gaussian. We have

$$\log \left( 1 + \frac{S}{S' + I_0} \right) + \log \left( 1 + \frac{S'}{I_0} \right) = \log \left( 1 + \frac{S + S'}{I_0} \right)$$

Thus the communication rate achieved with IC-SHO coincides with the rate achieved e.g. with perfect macro diversity space-time coding. The difference is that in IC-SHO, the transmitting base stations have only to coordinate the data rates used, and the decoupling of the transmissions is left to the receiver.

### 6.2 Resource Optimization Problem

#### 6.2.1 Resource in a Cell

Each cell $c$ has $N = |\mathcal{N}_c|$ neighbors. Resources used for transmitting to its own cell users are characterized by the intended receiver $u \in \mathcal{U}_c$, and the $N$-dimensional vector $\mathbf{v}$ of supported transmissions of inversions to the $N$ neighbors. The vector $\mathbf{v}$ takes values in $(\{0\} \cup \mathcal{U}_c)^N$, where the entry $v_j = 0$ indicates that no user in $c$ uses a transmission in this resource to support an inversion transmission from the $j$th neighbor of $c$. Since each inverting $v$ can receive a transmission from one neighboring cell, each $v$ may be present in $\mathbf{v}$ at most once.

Possible inversion configurations are thus characterized by the set of vectors $\mathcal{O}_c$ where the elements are ordered $N$-element subsets of a set consisting of $\mathcal{U}_c$ and $N$ copies of 0. With $U = |\mathcal{U}_c|$ being the number of users in $c$, we have
\[ \sum_{n=0}^{\min(N,U)} \binom{N}{n} \binom{U}{n} \] possible configurations in \( \Theta_c \).

For simplicity, we assume that all resources in the cell are identical. The information rate per unit resource that is used when transmitting to \( u \) a transmission which is supporting inversions \( v \) is thus

\[ \mu_{uv} = \min_{u' \in \{u\} \cup \{0\}} \mu_{u'c}, \] (6.1)

where \( \mu_{uc} \) is the information rate per unit resource that user \( u \) can receive from cell \( c \), when no IC is applied. The proportion of resources in cell \( c \) that are intended to own cell users, supporting inversions \( v \), is given by the scheduling weight \( w_{uv} \).

When a user is receiving an inversion transmission from a cell \( c' \), the information rate per unit resource is denoted by \( \mu_{iuc'} \). The proportion of resources given in cell \( c' \) to an inverting user \( u \) from another cell is denoted by \( w_{iuc'} \).

The total rate of user \( u \) with primary serving cell \( c \) is thus

\[ r_u = \sum_{v \in \Omega_c} w_{uv} \mu_{uv} + \sum_{c' \neq c} w_{iuc'} \mu_{iuc'}. \] (6.2)

For simplicity, we shall consider inversion configurations, where a user may only invert to its second best cell. This restriction makes sense, as we consider two-stage IC receivers. Only with multistage SIC, would it make sense to receive a transmission from a base station which is not one of the two best.

### 6.2.2 Constraints

The optimization is over the scheduling decisions in the cells, characterized by the scheduling weights \( w_{uv} \) and \( \mu_{uc} \). The scheduling decisions are restricted by

- **Resource constraints:** For each cell \( c \), all resources are allocated at most once:

\[ \sum_{u \in U_c} \sum_{v \in \Omega_c} w_{uv} + \sum_{u \in U_{c'}, c \neq c'} w_{iuc'} \leq 1. \] (6.3)

- **Support constraints:** For each inverting user \( v \), the resource allocated by inverting cell \( c_k \) should be overlapped with supporting resource allocated by serving cell \( c \).

\[ \sum_{u \in U_c} \sum_{v \in \Omega_{c_k}} w_{uv} \geq w_{iuc_k}. \] (6.4)

In a Lagrangian formulation, there is a Lagrange multiplier \( \lambda_c \) for resource constraint in each cell \( c \). And there is a Lagrange multiplier \( \phi_{vc_k} \) for inversion of each user \( v \) to each neighbor \( c_k \in \mathcal{N}_c \).

### 6.2.3 Distributed Algorithm

The optimization is convex, but with a high number of variables. The support constraints intertwine the decisions in multiple cells. To cope with the complexity, we distribute the algorithm so that each cell \( c \) decides on the resource
allocation of the users $u \in U_c$ primarily served by itself. Each cell allocates a fraction of its resources to its neighboring cells, for neighbor-cell users that invert into the cell.

We consider a primal decomposition where all constraints hold with equality. It is straightforward to see that with the system model considered, the resource constraints (6.3) are fulfilled with equality at a network utility maximum. Furthermore, from (6.1) it follows that any configuration where the support constraints (6.4) are not fulfilled with equality, can be mapped to a configuration with the same inversion transmissions $w_{uv_{ck}}$, but with equality support constraints, and the same or better network utility.

Assuming that support constraints (6.4) are fulfilled with equality, we may remove the variables $w_{uv_{ck}}$ from the problem. Then in the resource allocation problem of cell $c$, the derivative of the cell utility $f_c = \sum_{u \in U_c} f(r_u)$ with respect to the resource $w_{uv_{vc}}$ becomes

$$\frac{\partial f_c}{\partial w_{uv_{vc}}} = f'(r_u)\mu_{uv_{vc}} + \sum_{v_k} f'(r_{vk})\mu_{vk_{ck}}$$

(6.5)

where the sum is over the elements in the vector $v$, i.e. users $v_k$ in cell $c$ that invert to neighboring cell $c_k$, supported by the transmission $w_{uv_{vc}}$ to $u$, and getting rate $\mu_{vk_{ck}}$ from the cell-edge inverted transmission.

The resource optimization within cell $c$ can be performed based on cell-utility gradients of the type (6.5). To properly solve the primal resource allocation within each cell, where resources are given to other cells, the price of the resources has to be taken into account. An infinitesimal increase in $w_{uv_{ck}}$ according to (6.5) incurs an infinitesimal utility loss in cell $c_k$ due to the reduction of resources available to serve the users in cell $c_k$. We write formally

$$\Pi_{c'} = -\frac{\partial f_c}{\partial w_{c'}},$$

(6.6)

where $w_{c'} = \sum_{u \in U_{c'}} \sum_{v \in O_{c'}} w_{uv_{vc}}$ is the sum of all resources in $c'$ used for transmitting to its own users. This is a price for cell $c'$ to give resources to inverting users from other cells.

From these, we can construct the gradient of the network utility with respect to the resources in cell $c$, assuming that all other constraints except the resource constraint (6.3) in $c$ hold with equality:

$$\frac{\partial f_N}{\partial w_{uv_{vc}}} = \frac{\partial f_c}{\partial w_{uv_{vc}}} + \sum_{c_k | v_k \neq 0} \Pi_{c_k}$$

(6.7)

Here $f_N = \sum_c f_c$. This can be used as a distributed gradient or ascent algorithm to maximize the network utility.

It should be kept in mind that the proportionally fair utility function considered here, as well as many other utility functions, is not bounded from below. Accordingly, Lipschitz continuity does not hold, and convergence of ascent algorithms can be guaranteed only if the change in the variables is bounded to be finite.
To simplify the algorithm, we have used a normalized steepest descent for the $l_1$ norm [105]. In the resulting algorithm, the resource with largest $\frac{\partial f_N}{\partial w_u}$ is incremented, and in each cell involved, the resource with smallest $\frac{\partial f_N}{\partial w_u}$ is reduced. The algorithm is distributed to the network in a periodic and asynchronous manner, so that each cell updates its resource allocation at a given time. An update in a cell $c$ involves 1) allocating resources to other cells based on requests, 2) calculating new derivatives $\frac{\partial f_N}{\partial w_u}$ for all own cell resources, 3) reducing the weight $w$ of the resource with non-zero $w$ and smallest derivative, and correspondingly increasing the weight of the resource with largest derivative, 4) signaling the changes in resource requests to other cells 5) calculating a new price $\Pi_c$ for the resources given to other cells, and signaling these to neighboring cells.

For a cell $c$ running the distributed cell inversion algorithm, the only information required from its neighboring cell $c'$ is the inverting price coefficient $\Pi_{c'}$. The channel information of inverting users from neighboring cell are also useful, which can be directly measured. Therefore the overhead should be limited, considering that data speed of backhaul connection is very high and information update is only needed from neighboring cells for this distributed algorithm.

With an infinitesimal resource increment, the function is an ascent function in terms of the network utility, and thus converges to the unique solution of the convex optimization problem. With a finite resource increment, one has to add a stopping criterion which can be optimized for performance or convergence speed. For simplicity, we apply non-optimized fixed step size in the simulation and results are demonstrated in next section.

### 6.3 Simulation Results

To assess the performance of cell-edge inversion, we have performed simulations in a small-cell network. A deployment model recommended in [106] is used. In Scenario 2a of [106], a hot spot system consisting of four BS and 20 UE is considered. The BSs are dropped within a radius $r_1 = 50m$, and the UEs within

<table>
<thead>
<tr>
<th><strong>Table 6.1. Simulation parameters.</strong></th>
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<tr>
<td><strong>Transmit power</strong> $P_{BS}$</td>
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<tr>
<td><strong>Carrier frequency</strong> $f_c$</td>
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<tr>
<td><strong>Antenna gains</strong> $G_{BS}$</td>
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<tr>
<td>$G_{UE}$</td>
</tr>
<tr>
<td><strong>Bandwidth</strong> $W$</td>
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<tr>
<td><strong>Noise Figure</strong> $N_F$</td>
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<tr>
<td><strong>Thermal noise level</strong> $N$</td>
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</tbody>
</table>
Figure 6.4. Example instance of BS and UE deployment. There are macro-cellular BSs represented by triangles, micro-cellular BSs represented by large dots, and randomly dropped users represented by small dots.

A radius $r_2 = 70m$. The nodes are dropped uniformly and at random, except that there is a minimum distance of $d_{\text{min-bs-bs}} = 20m$ between BSs, and a minimum distance of $d_{\text{min-ue-bs}} = 5m$ between a UE and a BS. An instance of such a deployment is depicted in Figure 6.4. The non-line-of-sight path loss model

$$L = 36.7 \log_{10} d + 22.7 + 26 \log_{10} f_c$$

(a) Normal scale.

Figure 6.5. CDFs of user spectral efficiency (user rate/system bandwidth), proportionally fair scheduling with full cell-edge inversion, with SHO, and with conventional hard handover.

(b) Zoom to 5% of CDF.
where $\gamma$ is the SINR of the transmission, and $\lambda = 2\text{dB}$ is an implementation loss. In practical case, the reasonable resource increment is limited by the channel coherence time, the number of frequency resource blocks and other conditions. For example, given frequency $f_c = 3.5$ GHz, UE moving speed $v = 2$ m/s and speed of light $c = 3 \times 10^8$ m/s, the Doppler frequency is $f_m = \frac{v}{c} f_c = 23.33$ Hz. The channel coherence time can be estimated as \[ T_c = \sqrt{\frac{9}{16\pi}} \frac{1}{f_m} \approx 0.01813\text{s} = 18.13\text{ms}. \] (6.9)

With 5G NR numerology $\mu = 1$, the slot time is $T_{\text{slot}} = 0.5$ ms and there are $N_{RB,DL} = 55$ resource blocks for 20 MHz bandwidth. Considering one resource block in one slot as the smallest resource unit in scheduling, the total number of scheduling units within channel coherence time is

\[ N_u = \frac{T_c}{T_{\text{slot}}} \times N_{RB,DL} = 18.13 \times 0.5 \times 55 \approx 1994. \] (6.10)

Then the smallest resource increment is $1/N_u \approx 0.0005$. The step length of 0.0005 has been used in simulations to optimize the cell-edge inversion with a non-optimized distributed algorithm.

Simulation results resulting from resource allocation optimization in 1000 instances of the deployment model can be found in Figures 6.5a and 6.5b. The experimental Cumulative Distribution Function (CDF) of the user rate after proportionally fair network utility maximization is reported. Results for full cell-edge inversion have the legend “Inversion”, for IC-SHO only have the legend “SHO”, and the vanilla system, where no multi-cell coordination is performed, has the legend “HHO”. We observe that IC-SHO provides nice gains by improving the rate of some 70% of the users, and full inversion provides further gains for these users. In Figure 6.5a, we observe that these gains come with nearly negligible losses for users in good channel states. Figure 6.5b provides a zoom-in to the experience of cell-edge users. For the users at the 5th percentile of the CDF, often considered as typical cell-edge users, the gains from IC-SHO and cell-edge inversion are significant.

The numerical gains observed in this scenario can be found in Table 6.2. It is interesting to observe that with both IC-SHO and full cell-edge inversion, significant gains in cell-edge performance can be achieved without decreasing the mean throughput. In fact both IC-SHO and full inversion provide a moderate gain in cell throughput.

<table>
<thead>
<tr>
<th></th>
<th>IC-SHO</th>
<th>Inversion</th>
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<tbody>
<tr>
<td>mean user rate</td>
<td>6%</td>
<td>7%</td>
</tr>
<tr>
<td>cell-edge (5%) rate</td>
<td>37%</td>
<td>64%</td>
</tr>
</tbody>
</table>

Table 6.2. Gains from cell-edge inversion.
7. Conclusion and Future Work

Successive interference cancelation is a promising method to increase spectral efficiency in wireless networks where serious interference is encountered. Such technology can improve QoS and achieve better fairness for users suffering from heavy interference. The performance gain can be further improved by applying centralized RRM control. The uplink and downlink scenarios in cellular networks are chosen to demonstrate potential applications of SIC.

In the uplink scenario, underlay D2D communications share cellular uplink resource with centralized or distributed RRM setting. By transplanting cellular uplink specifications, D2D communication can be easily realized with a slightly modified cellular transceiver. Use of the same radio specification also enables a dramatically simplified design of the SIC receiver, which provides a cost-efficient solution for D2D and SIC devices. The centralized RRM optimization method based on NUM offers a dramatic performance gain in an isolated cell, but the algorithm complexity and control channel consumption will grow as the number of users increases in practical applications where optimization is operated in multi-cell systems. Therefore the distributed RRM algorithm appears to be a desirable alternative, which can distribute optimization calculations and decisions to each individual device with a requirement of timely state information update. For such a case, game theoretic methods, based on distributed decision making, seem to be an appropriate model. Considering that cooperation between devices is not generally available, strategic game models may be considered to have more practical potential. The simulation results show that the distributed game theoretic RRM algorithm with SIC significantly improve spectrum efficiency and even slightly improve fairness despite being based on decisions of selfish users. Although the existence of NE is not guaranteed for the considered multiplayer games, the truncated algorithm based on \((P, C|\bar{R}(0))\) game still provides considerable gain with low complexity and low requirement for message exchange.

In the downlink scenario, the distributed optimization algorithm of each cell's resource allocation is designed with the cell-edge inversion method for cellular networks. Each user may be served by the second closest cell applying interference cancelation on the transmission from the closest cell. By distributed
optimization of resource allocation of the IC configuration for each cell, the experience of cell-edge users can be improved.

One possible direction for future research includes estimating and improving performance of RRM algorithm with imperfect SIC. In this dissertation it is assumed that interference cancelation can be implemented perfectly. From experimental verification we learn that implementing perfect IC is not trivial. Residual errors will be generated in channel estimation as pilots of the wanted signal and interference overlap with different delays. Therefore it is necessary to study the effect of imperfect IC and how to minimize it. One solution is to synchronize transmissions. Assume that CSI information of related channels is available at the intended transmitter of SIC receiver, the delay of intended transmission can be adjusted to same as delay of the transmission which will be canceled. Then the pilot signals are orthogonal and there is no more residual error in channel estimation. This method can only be applied to two-stage SIC receiver and requires more signaling between SIC receiver and its intended transmitter. Another possible solution is to allocate different subcarriers to different pilot sequences, which slightly reduces spectrum efficiency. Both methods require additional resources for pilots or signaling. It is interesting to study the performance of RRM algorithms which take such SIC related overhead and resource consumption into consideration.

Another possible direction is extending two-stage SIC to more stages, which allows the receiver to cancel more than one interferer. Although multi-stage SIC may achieve better rates by canceling more interference, the requirements of SINR and rate are rarely fulfilled. It is also worth investigating whether multi-stage SIC are practical with imperfect channel estimation. It is also possible to investigate more general models for cell-edge inversion method. If an inverting user and supporting user can be any user in any cell, and transmission power for each user is also considered as an optimization parameter, the potential of IC in a cellular system can be further explored.

It is also of interest to study the dynamic games instead of static games, where games can be repeated finitely or infinitely for finite or infinite horizon games. Instead of game theoretical algorithm, the reinforcement learning methods may also be investigated for the concerned optimization problems. The algorithms for dynamically changing channel situation should also be explored for practical applications.
References


References


Errata

Publication III

In Proposition 2, \((P, C, R)\) should be replaced by \((P|C, R)\).