POZNAN UNIVERSITY OF TECHNOLOGY

FACULTY OF COMPUTING AND TELECOMMUNICATION
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Doctor of Philosophy Dissertation

ENERGY-EFFICIENT RESOURCE ALLOCATION IN OFDM SYSTEMS WITH COMPUTATIONAL AWARENESS

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To my family
and friends

Abstract

Energy Efficiency (EE) is the crucial consideration in designing the current and future wireless communication systems. Devices connected to the Internet have produced 3.5% of global CO_2 emissions in the last 10 years, and it is anticipated that this nuber will increase to 14% by 2040. Moreover, in 2025, it is expected that the Information And Communications Technology (ICT) will be responsible for 20% of all the world's electricity becoming the largest global energy users. Therefore, EE has become one of the Key Performance Indicators (KPI) in designing the Fifth Generation (5G) networks, and the power consumption in 5G networks is aimed to be 10% of the power consumed by ICT infrastructure in 2015. Furthermore, the paradigms for future 5G systems are: 1000 times the capacity, 10 times connection density, 10 times experienced throughput, 3 times spectrum efficiency, 100 times energy efficiency of the contemporary Fourth Generation (4G) networks, and latency lower than 1 ms.

In this dissertation, algorithmic solutions have been proposed to provide high energy efficiency of the Orthogonal Frequency Division Multiplexing (OFDM) based wireless communication systems with the *computational awareness*. Here, the computational awareness of an intelligent radio communication system means that in the algorithms for EE optimization, the power consumption of required signal processing and computations are taken into account, both at the transmitter and the receiver.

First, the state of the art with the original classification of the key aspects of energy-efficient resource allocation in the context of OFDM is presented. The definition of the EE metric with the ways its maximization are presented. Moreover, the analysis of each aspect and the relation between them have been discussed. Then, the investigated energy-efficient resource allocation methods and solutions are presented for a single OFDM link, multiuser Orthogonal Frequency Division Multiple Access (OFDMA) networks and multiuser OFDMA relay networks.

Regarding a single OFDM link, a computationally-aware adaptive resource allocation algorithm has been proposed for energy efficiency. Research results show that the proposed algorithm increases EE and the average throughput, reduces the required transmit power and the total power consumption by the Adaptive Modulation and Coding (AMC) and transmit power selection.

In the context of multiuser OFDMA networks, an iterative algorithm is proposed to maximize the overall energy efficiency of the downlink transmission taking the limitations of the practical wireless communication systems into account, such as the fact that the allowable code rates take discrete values, and that subcarriers are grouped in resource blocks. It is also assumed that all Resource Blocks (RBs) assigned to the same user must use the same Modulation and Coding Scheme (MCS), as in the Long-Term Evolution (LTE) or 5G specification. In order to maximize EE, the author of this thesis proposes the iterative algorithm with fast convergence based on the Dinkelbach method. Simulation results show that despite the computational simplicity of the proposed solution, it achieves better results than the solutions known from the literature.

The joint subcarrier (SC) allocation, pairing and power loading for optimized energy efficiency

in multiuser, multicarrier downlink Decode and Forward (DF) relay interference networks with computational awareness has also been investigated in this thesis. In order to maximize EE of the network, the transmission mode is adapted to instantaneous channel conditions. For the benefit of spectral-efficiency, both direct- and relayed transmission is allowed to use the same SCs simultaneously. Linearly rate-dependent power consumption of signal processing is considered. The author develops an iterative algorithm based on the Successive Concave/Convex Approximation (SCA) and the Dinkelbach method to tackle the nonlinear fractional programming problem which maximizes EE of the system. Simulation results demonstrate the effectiveness of this solution for future relay networks.

Finally, in this thesis, the practicality of the energy-efficient resource allocation is discussed. The author also touches upon the problem of nonlinear Power Amplifier (PA) characteristics (causing distortions typical for OFDM signals) to be taken into account for energy-efficient resource allocation. The author discuss trade-offs and provides recommendations for future energy-efficient OFDM networks design.

Streszczenie

Efektywność energetyczna (ang. energy efficiency - EE) jest kluczowym czynnikiem projektowania obecnych i przyszłych systemów komunikacji bezprzewodowej. Obecnie urządzenia podłączone do sieci Internet są odpowiedzialne za $3,5\%$ globalnej emisji dwutlenku węgla a według przewidywań wartość ta wzrośnie do 14% w przeciągu 10 lat. Na dodatek, przewiduje się, że w 2025 roku technologie informacyjne i komunikacyjne będą zużywały 20% całkowitej światowej energii elektrycznej stając się największymi światowymi konsumentem energii. Dlatego też EE jest jednym z kluczowych wskaźników efektywności (ang. Key Performance Indicators - KPI) w projektowaniu sieci 5. generacji (ang. Fifth Generation - 5G), dla których zużycie energii powinno wynosić 10% mocy pobieranej przez infrastrukturę teleinformatyczną w 2015 roku. Ponadto, paradygmatami przyszłych systemów 5G są: 1000 razy większa przepustowość, 10 razy większa gęstość połączeń, 10 razy większa doświadczona przepustowość, 3 razy większa wydajność widmowa, 100 razy wyższa efektywność energetyczna w porównaniu do obecnych systemów 4G oraz opóźnienie niższe niż 1 ms.

W niniejszej rozprawie przedstawiono algorytmy przydziału zasobów zapewniające wysoką efektywność energetyczną systemów komunikacji bezprzewodowej opartych na technice OFDM (ang. Orthogonal Frequency Division Multiplexing) ze *świadomością obliczeniową*. Wspomniana świadomość obliczeniowa oznacza, że w algorytmach optymalizujących EE brana jest też pod uwagę moc niezbędna do realizacji przetwarzania sygnałów i potrzebnych obliczeń.

W pierwszej kolejności przedstawiony został stan wiedzy wraz z oryginalną klasyfikacją kluczowych aspektów energooszczędnej alokacji zasobów w kontekście techniki OFDM. Przedstawiono definicję metryki EE oraz sposoby jej maksymalizacji. Ponadto, przedstawiono analizę każdego z aspektów i zależności między nimi. Następnie przedstawiono oryginalne algorytmy optymalizacji efektywności energetycznej kolejno: dla pojedynczego łącza OFDM, sieci z wielodostępem OFDMA (ang. Orthogonal Frequency Division Multiple Access) oraz wielodostępowych sieci przekaźnikowych OFDMA.

Jeśli chodzi o pojedyncze łącze OFDM, zaproponowano efektywny energetycznie adaptacyjny algorytm przydziału zasobów ze świadomością obliczeniową. Wyniki badań pokazują, że zaproponowany algorytm zwiększa EE oraz średnią przepustowość, zmniejsza wymaganą moc nadawczą oraz całkowity pobór mocy poprzez zastosowanie adaptacyjnego wyboru modulacji i kodowania (ang. Adaptive Modulation and Coding - AMC) oraz mocy nadawanej.

W kontekście wielodostępnych sieci OFDMA zaproponowano iteracyjny algorytm maksymalizacji całkowitej efektywności energetycznej transmisji w dół, uwzględniający ograniczenia praktycznych systemów komunikacji bezprzewodowej, takie jak fakt, że dopuszczalne szybkości kodowania przyjmują wartości dyskretne, a podnośne są pogrupowane w bloki zasobów (ang. Resource Blocks - RBs). Zakłada się również, że wszystkie bloki zasobów przypisane do tego samego użytkownika muszą wykorzystywać ten sam schemat modulacji i kodowania (ang. Modulation and Coding Scheme - MCS), tak jak w specyfikacji LTE (ang. Long-Term Evolution) lub 5G. W celu

maksymalizacji EE, autor rozprawy proponuje algorytm iteracyjny o szybkiej zbieżności oparty na metodzie Dinkelbacha. Wyniki symulacji pokazują, że pomimo prostoty obliczeniowej proponowanego rozwiązania, osiąga ono lepsze wyniki niż rozwiązania znane z literatury. W niniejszej pracy badano również łączny przydział podnośnych (ang. subcarrier - SC) oraz alokowanie mocy w celu optymalizacji efektywności energetycznej w wielodostępnych sieciach przekaźnikowych w łączu w dół działających w trybie zdekoduj i przekaż (ang. Decode and Forward DF) ze świadomością obliczeniową, tzn. z uwzględnieniem energii związanej z obliczeniami. W celu maksymalizacji EE sieci, tryb transmisji jest dostosowywany do warunków kanału. Ze względu na efektywność spektralną, dozwolone jest jednoczesne korzystanie z tych samych SC zarówno w transmisji bezpośredniej jak i z wykorzystaniem przeźnika. W celu rozwiązania problemu optymalizacyjnego autor opracował iteracyjny algorytm oparty na metodzie sukcesywnej aproksymacji funkcji wypukłej/wklęsłej (ang. Successive Concave/Convex Approximation SCA) i metodzie Dinkelbacha, który maksymalizuje EE systemu. Wyniki symulacji pokazują skuteczność tego rozwiązania dla przyszłych sieci przekaźnikowych.

Na zakończenie rozprawy autor porusza również problem nieliniowości wzmacniacza mocy (ang. Power Amplifier - PA) powodujących zniekształcenia typowe dla sygnałów OFDM, które należy uwzględnić przy projektowaniu algorytmów maksymalizujących efektywność energetyczną. Autor omawia również praktyczne aspekty projektowania przyszłych energooszczędnych sieci OFDM oraz przedstawia stosowne rekomendacje dla ich wdrażania.

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Acronyms

3GPP	3rd Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
6G	Sixth Generation
ADC	Analog-to-Digital Converter
AF	Amplify and Forward
AMC	Adaptive Modulation and Coding
AWGN	Additive White Gaussian Noise
BB	Baseband
BEP	Bit Error Probability
BER	Bit Error Rate
BLER	Block Error Rate
BRB	Basic Resource Block
BS	Base Station
BSAA	Binary Search Assisted Ascent
CC	Convolutional Code
CMOS	Complementary Metal-Oxide-Semiconductor
CSI	Channel State Information
DAB	Digital Audio Broadcasting
DAC	Digital-to-Analog Converter
DC	Difference of Concave/Convex
DF	Decode and Forward
DPD	Digital Pre-Distortion
DVB-T	Digital Video Broadcasting-Terrestrial
EE	Energy Efficiency
EESM	Exponential Effective SINR Mapping
FFT	Fast Fourier Transform
FPGA	Field Programmable Gate Array
GABS	Gradient Assisted Binary Search

GBD	Generalized Benders Decomposition
HARQ	hybrid automatic repeat request
ICT	Information And Communications Technology
IEEE	Institute of Electrical and Electronics Engineers
IFFT	Inverse Fast Fourier Transform
IoT	Internet of Things
ISI	intersymbol interference
KKT	Karush-Kuhn-Tucker
KPI	Key Performance Indicators
LDPC	Low Density Parity Check
LNA	Low Noise Amplifier
LO	Local Oscillators
LTE	Long-Term Evolution
LUT	Look-Up-Table
MAC	Medium Access Control
MCS	Modulation and Coding Scheme
MIMO	Multiple-Input and Multiple-Output
MINLFP	Mixed Integer Nonlinear Fractional Programming
MRC	Maximum Ratio Combining
NP	Non-deterministic Polynomial-time
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
PA	Power Amplifier
PAPR	Peak-to-Average Power Ratio
PCC	Punctured Convolutional Code
PER	Packet Error Rate
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
RB	Resource Block
RF	Radio Frequency
RN	Relay Node
SC	subcarrier
SCA	Successive Concave/Convex Approximation
SE	Spectral Efficiency

SFN	Single Frequency Network
SINR	Signal to Interference and Noise power Ratio
SNDR	Signal to Noise and Distortion power Ratio
SNR	Signal to Noise power Ratio
SQNR	Signal to Quantization Noise Ratio
TC	Turbo Code
TS	Time Slot
TTI	Transmission Time Interval
UE	end-user
USB	Universal Serial Bus
WiMAX	Worldwide Interoperability For Microwave Access
WLAN	Wireless Local Area Network
WMAN	Wireless Metropolitan Area Network
WPAN	Wireless Personal Area Network

Introduction

In the era of ubiquitous Internet access, exponential growth of telecommunication traffic can be observed every year. According to Cisco predictions there will be 4.8 billion of global Internet users in 2022 and 28.5 billion networked devices and connections [1]. Moreover, the mobile data traffic will increase to 930 eksabytes annually in 2022. According to the Ericsson Mobility Report [2], communication of 26.9 billions of machines and devices that are expected by 2026 to comprise the Internet of Things (IoT) poses challenges, never encountered before. One of these challenges is an increase of energy consumption associated with the data-traffic growth worldwide. That is why reduced-energy wireless communication has been in the focus of research and industry interest for the recent years, aiming at achieving 10 times the EE in the 5G radio systems compared with the 4G of these systems [3]. Moreover, so-called *zero-energy* radios are envisioned for future Sixth Generation Sixth Generation (6G) systems as their technology enablers [4]. According to this vision, drivers from society, including the United Nations sustainability goals, will shape 6G communication systems. Moreover, high energy efficiency to reduce the overall network energy consumption will be a critical requirement for these future systems.

On the completion of 3GPP Release 15 [5] and Release 16 [6] (as of today, Release 17 being under way), the set of 5G standards has been defined. As in 4G LTE standard, the OFDM has been proposed for 5G systems. Moreover, OFDM has been also successfully applied in other radio communication systems, such as Wireless Local Area Networks (WLANs), including IEEE 802.11a/g/n, Wireless Metropolitan Area Networks (WMANs), including Worldwide Interoperability For Microwave Access (WiMAX) standard, Wireless Personal Area Networks (WPANs), including MultiBand - OFDM in the $3.1 - 10.6$ GHz band, as well as in the Digital Audio Broadcasting (DAB) or Digital Video Broadcasting-Terrestrial (DVB-T) systems. Popularity of the OFDM technique results from its known advantages: high Spectral Efficiency (SE) compared to other double sideband modulation schemes, flexibility and adaptation potential to channel conditions, robustness against intersymbol interference (ISI), efficient implementation using Fast Fourier Transform (FFT), low sensitivity to time synchronization errors and facilitation of the Single Frequency Networks (SFNs) [7]. Finally, OFDMA is the popular OFDM-based method for Medium Access Control (MAC) layer to facilitate multiple users network access.

Motivated by the increased mobile communication traffic, required high data-rates and associated energy-consumption on one hand, and the applicability of the OFDM/OFDMA techniques in contemporary and prospective radio communication systems on the other, in this dissertation, the author presents his research that led to new approaches and promising methods to optimize wireless OFDM/OFDMA links and networks. Contrarily to the traditional approach to minimize the transmission power for the assumed target bit-rate, the author focuses on advanced power-consumption models and optimization of the energy efficiency metric defined as the number of successfully transmitted and received bits per Joule. This is because depending on the link quality, power consumption of different causes, e.g., Radio Frequency (RF) signal radiation at a transmitter, analog circuits and components, or Baseband (BB) digital signal processing both at a transmitter and at a receiver, may dominate over each other, and may be worth minimization for overall energy efficiency. Moreover, the optimization algorithm itself also consumes energy, that needs to be accounted for. Thus, the power consumption modelling of wireless communication systems must take necessary computations into account, both at the transmitter and the receiver, and not just the transmitted power (as in the conventional approach). Intelligent utilization of such a model in the link- and network- energy-efficiency optimization algorithms, is here below called *computational awareness.*

Dissertation thesis and main goals

The thesis of this dissertation is the following:

New algorithms can be devised, more effective than the existing ones, for OFDM/OFDMA-based systems that allow for maximization of the energy efficiency taking into account the baseband processing power consumption.

The main goal of the thesis is to propose such enhanced techniques and in particular:

- To develop the effective, low-cost algorithm for the maximization of the energy efficiency metric in computationally-aware OFDM link with adaptive transmission power and adaptive modulation and coding selection (This goal is addressed in Chapter 2).
- To develop the algorithm for energy-efficient resource allocation in the multiuser OFDMA network which takes the limitations of the piratical wireless communication systems into account (This goal is addressed in Chapter 3).
- To solve the optimization problem for energy efficiency maximization in multiuser decode and forward relay interference network with computational awareness (This goal is addressed in Chapter 4).
- To identify recommendations for future energy-efficient OFDM networks design (This goal is addressed in Chapter 5).

Overview of the dissertation contributions

In Chapter 1, the state of the art and the key aspects of the energy-efficient resource allocation in the context of OFDM systems are presented. The definition of the energy efficiency metric and the ways to maximize it are discussed. Moreover, the problem of the transmission data rate and power consumption estimation in wireless systems are discussed. The approaches to data rate and power consumption estimation with their advantages and disadvantages have been distinguished in this chapter, as well. Then, the general view of the system limitations and requirements in the context of energy-efficient resource allocation is presented. Finally, the overview of the optimization methods are presented that can be applied to solve the problem of the energy efficiency metric maximization.

Chapter 2 is devoted to the energy-efficient resource allocation in the context of a single OFDM link. The aspects of the energy-efficient resource allocation provided in Chapter 1 are first reviewed in the context of a single link scenario. Moreover, the author of this thesis proposes the algorithm for the energy-efficient resource allocation in a computationally-aware adaptive OFDM system. Here, by *resources*, the power, the subcarriers or resource blocks are meant. The proposed algorithm maximizes the energy efficiency metric which takes not just the transmit power, but also the transceiver computation-power consumption into account by adaptive transmit power and AMC selection. The AMC selection causes that the defined optimization problem belongs to a broader class of Mixed Integer Nonlinear Fractional Programming (MINLFP) programming problem what means that the optimization variables take continuous and discrete values. Therefore, the optimization problem has been transformed by introducing the decision matrix, the Dinkelbach method and than solved using dual decomposition method. The analytical solutions are derived by the numerical method according to the Lagrange multipliers and Karush-Kuhn-Tucker (KKT) conditions. Simulation results show that the adaptive modulation and coding techniques allow for: increased energy efficiency, increased average throughput, reduced required transmit power and reduced total power consumption. Moreover, there exists the optimal point for the transmit power maximizing the energy efficiency. Finally, the results show that the EE values obtained by the proposed algorithm are achieved with superlinear convergence.

In Chapter 3, the author of this thesis focuses on the energy efficiency maximization in the multiuser OFDMA network. First, analogously as in the previous chapters, the data rate, power consumption, system limitations and requirements as well as optimization aspects are reviewed in the context of multiuser network. An iterative algorithm is proposed to maximize the overall energy efficiency of the downlink transmission by allocating the RBs and the transmit power, which is constant for all RBs assigned to a given user. Moreover, the author assumes that all RBs assigned to the same user must use the same MCS, as in the LTE and 5G specifications. Due to the continuous values of the Signal to Noise power Ratio (SNR) and discrete values of the SE and code rate the defined optimization problem is MINLFP programming problem. Moreover, because the modulation and coding scheme for each user has to be chosen from the finite set the optimization is combinatorial. Therefore, the optimization problem is very difficult in the original form and cannot be solved analytically. Thus, in order to maximize EE, the author of this thesis proposes the iterative algorithm with fast convergence based on the Dinkelbach method. In each iteration, the solution for the power and resource blocks allocation is derived by the numerical method using the KKT multipliers and KKT conditions, while MCS, for each user, is obtained by the iterative algorithm. Simulation results show that despite the computational simplicity of the proposed solution, it achieves better results than the solutions known from the literature.

The energy-efficient resource allocation in the multiuser OFDMA relay network is addressed in Chapter 4. The different system models in the context of the relay network with the data rate, power consumption estimation and system limitations and requirements are discussed. First, the optimization methods mainly applied in the context of the relay network are reviewed. Then, the author of this thesis investigates joint SC allocation, pairing and power loading for optimized energy efficiency in multiuser, multicarrier downlink DF relay interference networks with computational awareness, i.e., taking computations-related energy into account. In order to maximize EE of the network, the transmission mode is adapted to instantaneous channel conditions. For the benefit of spectral-efficiency, both direct- and relayed transmission is allowed to use the same SCs simultaneously. Linearly rate-dependent power consumption of signal processing is considered. The formulated optimization problem is the nonconvex MINLFP problem, which has NP-hard complexity. Hence, the author approximates the problem by the series of equivalent convex problems applying convex relaxation techniques such as a SCA. Based on these transformations, the author develops an iterative algorithm exploiting the Dinkelbach method to tackle the nonlinear fractional programming problem which maximizes EE of the system. Simulation results demonstrate the effectiveness of this solution for future relay networks.

In Chapter 5 the author of this thesis discuss the practicality of the energy-efficient resource allocation. The author also touches upon the problem of nonlinear PA characteristics (causing distortions typical for OFDM signals) to be taken into account for energy-efficient resource allocation. The author discuss trade-offs and provides recommendations for future energy-efficient OFDM networks design.

Finally, this dissertation is concluded in Chapter 6, in which the main findings of the author regarding energy-efficient resource allocation in OFDM systems with computational awareness are summarized.

Author's published contributions

The above-described major contributions of this dissertation have been published in a number of papers listed below.

Papers in international journals and magazines:

1. B. Bossy, P. Kryszkiewicz, and H. Bogucka, "Energy Efficient Wireless Relay Networks With Computational Awareness," *IEEE Transactions on Communications*, vol. 68, no. 2, pp. 825–840, Feb. 2020.

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1. B. Bossy, P. Kryszkiewicz, and H. Bogucka, "Energy Efficient Resource Allocation in Multiuser DF Relay Interference Networks," in *IEEE Global Telecommunications Conference Workshops 2018 (IEEE GLOBECOM Wkshps 2018)*, pp. 1–6, Dec 2018.

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Chapter 1

Energy-Efficient Resource Allocation

Energy-saving or energy-efficient operation of communication and computing networks is typically evaluated using metrics related to either a total energy-consumption figure or the expected performance per energy unit. The later is called energy efficiency, and can be expressed in the number of successfully transmitted bits per Joule or the number of computational operations (clock cycles) per Joule or the number of transported and processed computational tasks per Joule. This thesis concentrates on wireless networks exploiting OFDM/OFDMA flexibility for energy-efficient communication. For such networks, the energy efficiency metric η is commonly defined as a benefit-cost ratio, where the achieved data rate is divided over the associated power consumption:

$$\eta \left[\frac{\text{bit}}{\text{Joule}}\right] = \frac{\text{data rate [bit/s]}}{\text{power consumption [W]}}. \tag{1.1}$$

Thus, this EE metric determines the number of successfully transmitted, received and processed bits per energy unit, and should be maximized. Here, processing of bits refers to digital signal processing both at the transmitter and at the receiver, which is required for successful transmission and reception of information. In Figure 1.1, the relation between the energy efficiency and transmit power for different values of the SNR is presented[1] for a single link. Let us observe that there exist the optimal point for the transmit power that maximizes EE. It means that there exists a trade-off between the data rate (which is dependent on the transmission power) and the total power consumption which allows for energy-efficient transmission. Moreover, for the higher SNR values, the optimal point is reached for lower transmission power.

Thus, in order to maximize the energy efficiency of wireless communications systems, one of three ways can be chosen:

(i) The maximization of the data rate, whilst minimizing the total power consumption. This approach is practically infeasible because the achievable data rate strictly depends on the transmit power (and the overall power consumption) and vice versa.

(ii) The maximization of the data rate with a minimum possible increase in power consumption (e.g., minimum increase of the transmit power can cause a significant gain in the date rate, particularly for low SNR values).

(iii) The minimization of the power consumption with a minimum reduction of the data rate (e.g. by applying less advanced coding decoding energy can be reduced, particularly at short communication distances).

[1] Note that because in this chapter, the author of this thesis aims at discussing the general problems of rate and power estimation, in Figure 1.1 and in several following figures, particular values on the axes are omitted. This is intentional to show the general trends and relations between graph coordinates, abstracting from particular simulation scenarios.

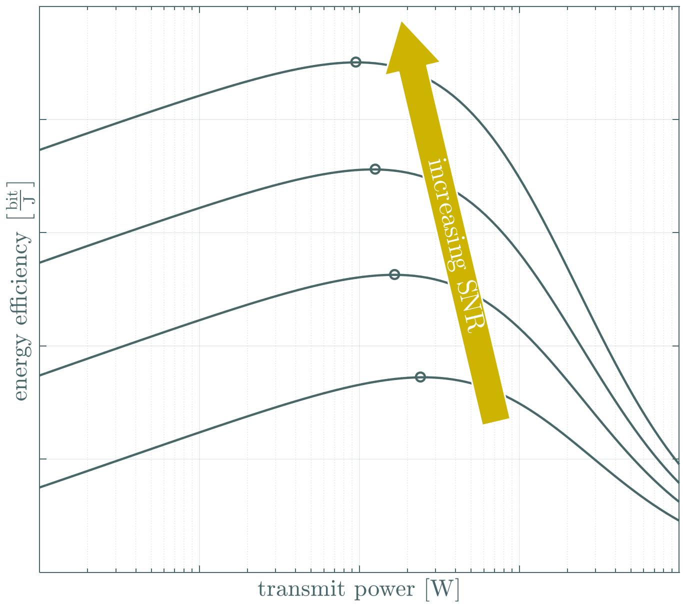

Figure 1.1: Relation between the EE and transmit power for different values of the SNR.

In the context of the energy-efficient resource allocation exploiting OFDM/OFDMA techniques, the second and third approaches are usually chosen because in OFDM/OFDMA based networks, the total available bandwidth and power are partitioned into a number of SCs or RBs. For each of them, the transmission parameters can be determined and adopted, depending on the channel conditions. Moreover, the short time-scale approach can be applied to maximize the energy efficiency metric. It means that the resource allocation is realized in the frequency domain for a given time slot.

Here, by *resources* the author means energy-related communication means (such as transmit power, basic resource blocks, MCSs and other transmission parameters) and network means (such as relying nodes) that can be adjusted, depending on channels and network conditions. Optimization of resource allocation for energy efficiency involves estimation of the transmission rate and power consumption as well as taking all transmission limitations and network requirements into

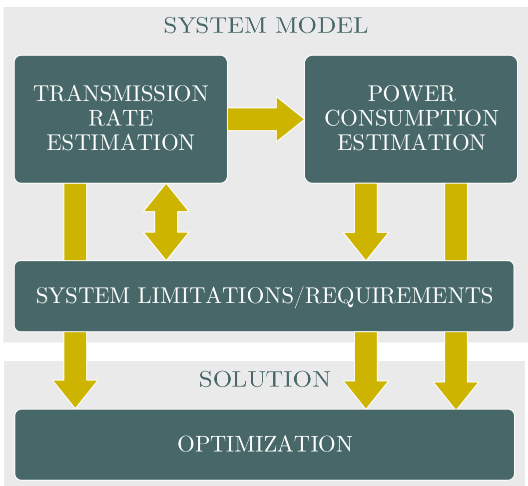

Figure 1.2: Interaction between the tasks of energy-efficient resource allocation in wireless communication systems.

account what has been elaborated in the following subsections, in detail. Regarding the first two tasks, namely *transmission rate-* and *power consumption estimation*, they are required for the energy efficiency metric definition. Based on the literature review, the author distinguishes different approaches to estimate the data rate and power consumption, and analyze them. Regarding the system *limitations/requirements* identification task, the author concentrates on the system and network constraints and requirements which have to be fulfilled, and demonstrates their impact on the energy efficiency. Finally, in the *optimization* task, the challenges and problems related to finding the solution of the EE optimization problem are discussed, allowing for the design of the energy-efficient resource allocation algorithm.

Figure 1.2 shows how the considered tasks interact with each other. Specifically, the power consumption estimation is determined by the transmission rate estimation (e.g. if coded transmission is considered, the power consumed by the encoder and decoder should be taken into account). The system limitations and requirements have an impact on transmission rate estimation (for example, when the fairness constraint or/and subcarriers grouping into resource blocks are considered). The transmission and power consumption estimations determine how the system limitations/requirements are met, while all aspects have an impact on the solution of the optimization problem which allows for energy-efficient resource allocation.

1.1 Estimation of the transmission data rate

The crucial aspect of the energy-efficient resource allocation is the estimation of the data rate and power consumption - the numerator and denominator of (1.1) respectively. In this subsection, the main approaches to the transmission rate estimation are described. Having in mind the diversity of wireless communication systems, the transmission rate estimation is not a trivial task. In the literature (not just that related to energy-efficient resource allocation), three main approaches of transmission rate estimation can be distinguished:

(i) based on the Shannon formula,

(ii) estimated by the Shannon formula with scaling factors,

(iii) based on the error-rate function and the SE of the applied MCS.

The Shannon formula for transmission rate estimation is the most commonly used approach. In general, the data rate described by Shannon formula is given by:

$$R\left[\frac{\mathrm{bit}}{\mathrm{s}}\right] = \Delta f \cdot \log_2\left(1 + \frac{P_{\mathrm{R}}}{\sigma_{\mathrm{N}}^2 + \sigma_{\mathrm{I}}^2}\right), \tag{1.2}$$

where Δf is the channel (and the signal) bandwidth, P_{R} is the average received signal power over that bandwidth, while σ_{N}^2 and σ_{I}^2 are the average powers of the noise and interference respectively over bandwidth Δf. The Shannon formula can be easily adopted to OFDM/OFDMA subcarrier-channels as well as to different network scenarios e.g. multi-cell, heterogeneous or cooperative network. Moreover, according to (1.2), R for $\sigma_{\mathrm{I}}^2 = 0$ is the concave function of the signal power P_{R}, while when $\sigma_{\mathrm{I}}^2 \neq 0$, there exist techniques which allow to transform it into the concave one. (Note that concavity of this function results in relatively low computational complexity of its optimization, as well as optimization of the energy efficiency, which is in the focus of this thesis.) The Shannon formula formulates the upper bound of the data rate which is not achieved by any practical wireless system. Therefore, using (1.2) for data rate estimation can be treated as idealistic approach which does not take the limitations of practical communication systems (e.g., such as a limited set of the modulation and coding schemes) into account.

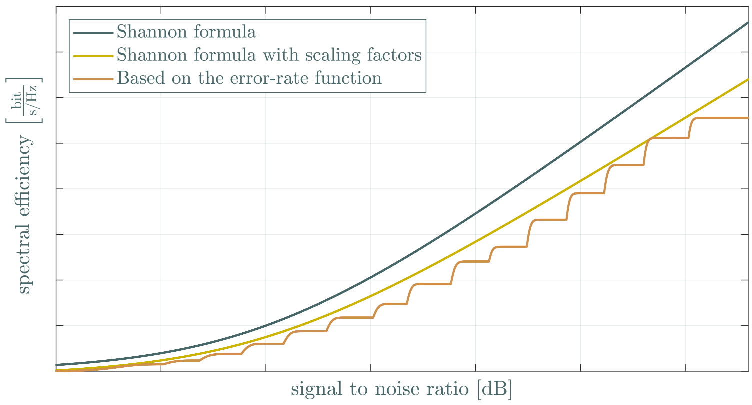

Figure 1.3: The spectral efficiency as a function of SNR for three approaches of the data rate estimation.

In order to account for practical limitations of a wireless communication system, the data rate can be estimated by:

$$R\left[\frac{\mathrm{bit}}{\mathrm{s}}\right] = \xi \cdot \Delta f \cdot \log_2\left(1 + \frac{\nu \cdot P_{\mathrm{R}}}{\sigma_{\mathrm{N}}^2 + \sigma_{\mathrm{I}}^2}\right), \tag{1.3}$$

where ξ and ν are the scaling factors fitting the Shannon formula to a practical system. The scaling factors can fit Shannon formula to single MCS and spectral efficiency or to the whole set of them. Such an approach for rate estimation has been first considered in [8] where scaling factor ν depending on the bit error probability has been introduced. Based on [8] and the assumed code rate, the coding gain and bit error probability for various MCSs, the data rate has been estimated in [9]. Similar approximations for a whole range of the MCSs can be found in [10–12]. In the last case (in [12]), the Shannon formula is scaled just by factor ξ (assuming $\nu = 1$). The Shannon formula with scaling factors (formula (1.3)) reflects achievable rate in a practical communication system, and can still be the concave function of the signal power if the factors are appropriately chosen. Thus, using it for rate estimation is more accurate than using (1.2), and results in acceptable computational complexity of the considered optimization tasks.

The third approach to data rate estimation which is considered as accurately characterizing practical wireless communication systems is based on SE and the error rate function of the applied MCS, e.g., the Block Error Rate (BLER), the Packet Error Rate (PER) or Bit Error Rate (BER). This approach depends on the parameters of the modulation and coding scheme, e.g., on the applied (de)modulation and (de)coding algorithms, the packet size, the number of decoder iterations, etc. In general, the data rate in this approach can be expressed by [13–16]:

$$R\left[\frac{\mathrm{bit}}{\mathrm{s}}\right] = \Delta f \cdot \zeta_{\mathrm{SE}} \cdot \left[1 - \mathrm{err}\left(\mathbf{x}\right)\right], \tag{1.4}$$

where ζ_{SE} is the spectral efficiency in bit/s/Hz, $\mathrm{err}\left(\cdot\right)$ is the function of error rate, while $\mathbf{x}$ is the vector of the parameters on which this function depends e.g. SNR, modulation and coding scheme. The data rate estimation by BLER function can be found in [14] where BLER curves have been approximated by the complementary error function $\mathrm{erfc}\left(\cdot\right)$ with two scaling factors in a function of effective Signal to Interference and Noise power Ratio (SINR). Moreover, in [16], the scaling factors for the MCS set of LTE network are provided. The approximation of PER based on the non-central chi-square distribution has been introduced in [17], and then applied in [18] in the context of the energy efficiency maximization for hybrid automatic repeat request (HARQ) in a Rician fading channel. Other approximations of PER in systems applying HARQ be found in [19, 20].

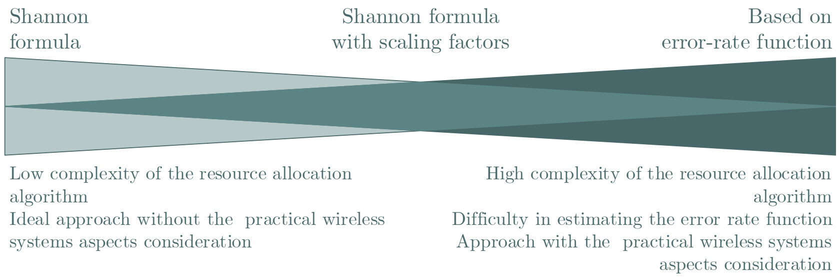

Figure 1.4: Trade-off observed in the data rate estimation.

In Figure 1.3, SE as a function of SNR for transmission rate estimation based on the Shannon formula, estimated by the Shannon formula with scaling factors and based on the block-error rate are plotted. It can be observed that the Shannon formula deviates from the real communication system. On the other hand, the data rate resulting from the block error-rate is a non-convex function of the signal power (and SNR) making the prospective energy efficiency optimization problem very hard (complex) to solve. In Figure 1.4, the trade-off between the accuracy of data rate estimation and the complexity of the optimal, energy-efficient resource allocation algorithm is illustrated. Note that for the low accuracy of data rate estimation (according to the Shannon formula), usually, the energy-efficient resource allocation algorithm with low complexity can be designed. On the other hand, the estimation with high accuracy causes high complexity of the energy efficiency optimization problem. Therefore, the Shannon formula with scaling factors seems to be a good trade-off between accurate mapping of practical system data rates and the complexity of solving the considered optimization problem.

Finally, the pros and cons of data rate estimation for the three described approaches are summarized in Table 1.1.

Table 1.1: Pros and cons of the data rate estimation

	Pros	Cons
Shannon formula	• the universal approach allows for describing the different systems • allows for determining the upper bound of the energy efficiency in the system • allows for applying optimization techniques with low complexity	• the ideal case which does not take the aspects of the practical wireless communication systems into account
Shannon formula with scaling factors	• brings the Shannon formula closer to the practical wireless communication systems • allows for applying optimization techniques with low complexity • better representation of the practical communication systems than Shannon formula without scaling factors • scaling factors can consider different aspects of the practical wireless communication systems	• does not take all aspects of the practical wireless communication systems into account • worse representation of the practical communication systems than approaches based on error rate function • the need to obtain the scaling factors • the scaling factors depend on the considered system
based on error rate function	• the best representation of the practical communication systems • take the aspects of the practical wireless communication systems into account	• makes the optimization problem non-convex which is very difficult to solve • the need to find the mathematical function which describes the error-rate function • the error-rate function highly depends on the parameters of the modulation and coding scheme

1.2 Total power consumption estimation

Estimation of the power consumption (the denominator in (1.1)) in a network is the crucial aspect in designing the energy-efficient wireless communication systems. In general, the power consumption models consist of the power required to transmit the signal P_{T} and the power consumed by the circuits P_{C} which can be divided into power consumed by the BB digital signal processing P_{BB} and by the analog radio-frequency (including intermediate-frequency) signal processing P_{RF} (see Figure 1.5):

$$P\,[\mathrm{W}] = P_{\mathrm{T}} + \underbrace{\underbrace{P_{\mathrm{BB-TX}} + P_{\mathrm{BB-RX}}}_{P_{\mathrm{BB}}} + \underbrace{P_{\mathrm{RF-TX}} + P_{\mathrm{RF-RX}}}_{P_{\mathrm{RF}}}}_{P_{\mathrm{C}}}, \tag{1.5}$$

where $P_{\mathrm{BB-TX}}$ and $P_{\mathrm{RF-TX}}$ are the powers consumed by baseband and radio frequency signal processing in the transmitter while $P_{\mathrm{BB-RX}}$ and $P_{\mathrm{RF-RX}}$ in the receiver, respectively. In case of the OFDM/OFDMA technique, the transmission power P_{T} is equal to the sum of powers allocated to subcarriers which are determined by the designed resource allocation algorithm that responds to instantaneous channel conditions. The issue is more difficult in the case of the estimation of power consumed by the transmitter and receiver digital and analog circuits. The main difficulty results from different types of transmission and reception techniques, applied technologies, standards, algorithms implementations, etc. In the literature, three approaches of power consumption modeling can be distinguished:

(i) high-level power consumption model,

(ii) estimating power consumption based on the measurements,

(iii) the estimation of the power consumed by each transmitter and receiver components.

The high-level models can determine the power consumption of different techniques in a universal way but at the expense of the low accuracy of estimation. The simplest total power consumption model can be found in the early papers focusing on the energy-efficient resource allocation [21, 22]. In these papers, the total power consumption model consists of the constant circuit power and the transmit power allocated at each OFDM subchannel. The constant circuit power includes the power consumed by the baseband- and radio frequency signal processing at the transmitter and at the receiver, while the transmit power dynamically changes according to instantaneous channel conditions.

In [9, 23, 24], the power dissipation in a chip is modelled as the sum of a static term and a dynamic term. The latter depends on, among other parameters, the supply voltage, the clock frequency and the circuit capacitance. It is assumed that the dynamic term depending on the clock frequency is scaled with the data rate. Thus, the circuit power is modelled as the linear

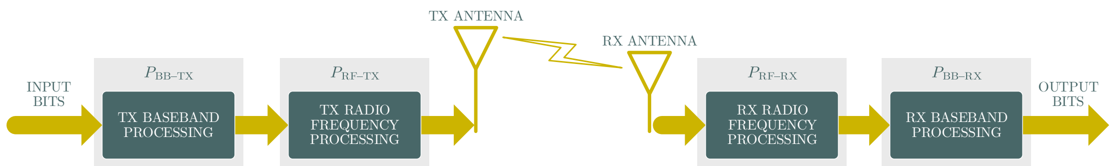

Figure 1.5: The general block diagram of the transmitter and receiver with the power consumption description related to each element.

function of the achieved data rate:

$$P_{\mathrm{C}}\,[\mathrm{W}] = \alpha + \beta \cdot R, \tag{1.6}$$

where α is the static term, and β is the implementation-dependent factor determined in W/ (bit/s). These high-level power consumption models are commonly used in the energy-efficient resource allocation optimization.

The second approach to estimate the power consumption of wireless devices is based on measurements. Such an approach guarantees high accuracy of power estimation but it highly depends on the equipment/link/network configuration, implementation, vendors, etc. In this approach, the total consumed power (including transmission power) is measured. It means that the transmission power allocation algorithm can not be applied with such models because the transmit power and the circuit power are not separable, thus the relation between them can not be determined a posteriori (after measurement). In [25–29], the authors describe measurements of the power consumption of a set of commercially available devices, in the number of configurations. In [26], the stochastic power consumption models have been proposed based on measurements of a range of transceivers offered by various vendors. The authors of [26–29] have focused on the WiFi standards while in [25] the set of measured devices includes cellular network USB modem e.g. LTE as well as WiFi USB modem. Moreover, these papers provide the analytical models of the power consumed by devices. Although the power consumption modelling based on measurements highly depends on the devices hardware and software implementation, application techniques, vendors, etc., they can be useful to design the high-level models by the means of interpolation of measurement points or statistical approach.

The most accurate but also the most complex approach is to estimate the power consumption of each transmitter- and receiver-component separately. Having in mind the fact that the transceiver is integrated into one chip, the measurement of each its component is very difficult and practically impossible. Therefore, in the literature, the estimation of each transceiver component power consumption is usually based on its architecture. (The block diagram of the coded OFDM transmitter and receiver is presented in Figure 1.6.) In this approach, the power consumption model by circuits is given by:

$$\begin{aligned} P_{\mathrm{C}}\,[\mathrm{W}] = {} & \underbrace{P_{\mathrm{ENC}} + P_{\mathrm{MOD}} + P_{\mathrm{IFFT}} + P_{\mathrm{DAC}}}_{P_{\mathrm{BB-TX}}} + \underbrace{P_{\mathrm{LPF}} + P_{\mathrm{ADC}} + P_{\mathrm{FFT}} + P_{\mathrm{DEMOD}} + P_{\mathrm{DEC}}}_{P_{\mathrm{BB-RX}}} \\ & + \underbrace{P_{\mathrm{PA}} + P_{\mathrm{MIX}} + P_{\mathrm{LO}}}_{P_{\mathrm{RF-TX}}} + \underbrace{P_{\mathrm{RFF}} + P_{\mathrm{LNA}} + P_{\mathrm{MIX}} + P_{\mathrm{LO}}}_{P_{\mathrm{RF-RX}}}, \end{aligned} \tag{1.7}$$

where P_{PA}, P_{LNA}, P_{LO}, P_{RFF} and P_{MIX} describe the power consumption of the PA, Low Noise Amplifier (LNA), Local Oscillators (LO), RF filter and mixer, respectively. The power consumed by baseband processing includes power consumption of the Analog-to-Digital Converter (ADC) P_{ADC}, the Digital-to-Analog Converter (DAC) P_{DAC}, modulation P_{MOD} and demodulation P_{DEMOD}, encoding P_{ENC} and decoding P_{DEC}, low-pass filter P_{LPF}, Inverse Fast Fourier Transform (IFFT) P_{IFFT} and fast Fourier transform P_{FFT}. It can be observed that depending on the structure of a transceiver, the power consumption model can be different. Nevertheless, some elements are common for the most digital transmission systems. The power consumption models of these components consuming most considerable amount of power can be found in [30–33]. There, the total power spent in the communication link is the sum of power consumed by the power amplifier, the low noise amplifier, the ADC and the error-correcting decoder. More system-level energy models for the radio frequency front-end components of a wireless transceiver with the exemplary power

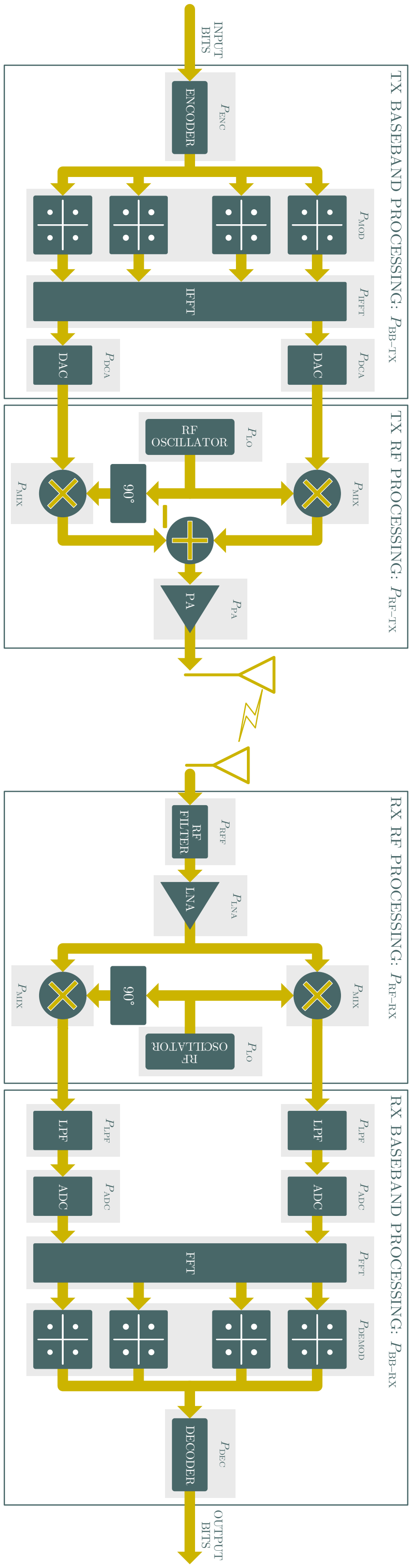

Figure 1.6: The block diagram of OFDM transmitter and receiver with the power consumption description related to each element.

Table 1.2: The review of the power consumption models of the transmitter/receiver components.

Power	Model parameters	Reference
P_{PA}	class A power amplifier; parameters: the Peak-to-Average Power Ratio (PAPR) and the drain efficiency of the power amplifier	[30–33]
	class A power amplifier; parameters: PAPR, the proportionality constant and the output power proportional to the detected signal power at the receiver	[34]
	class A, AB and B power amplifier; parameters: PAPR, the drain efficiency of the power amplifier and the transmit power factor	[35]
P_{LNA}	the power gain, the noise figure, the operating bandwidth, the thermal noise and the figure-of-merit	[30–33]
	the gain, the noise figure and some proportionality constant parameter	[34]
P_{MIX}	the gain, the noise figure and some proportionality constant	[34]
P_{LPF}	the proportionality constant depending on the filter topology and the active elements used, the quality factor, the corner frequency and SNR	[34]
P_{LO}	the parasitic capacitance loading of the RF circuits, the reference frequency, is the supply voltage, the LO frequency, the proportionality constants	[34]
P_{ADC}	the resolution, the bandwidth, the thermal noise and some proportionality constant depending on the ADC architecture	[30–33]
	the minimum channel length for the given Complementary Metal-Oxide-Semiconductor (CMOS) technology, the power supply, the signal and sampling frequency and the resolution which depends on PAPR and the Signal to Quantization Noise Ratio (SQNR)	[34]
P_{DAC}	the parasitic capacitance of each switch, the oversampling rate, the signal bandwidth, the power supply, the unit current source per least significant bit and the resolution which depends on PAPR and SQNR	[34]
P_{ENC}	the number of operations needed to encode or decode the information bit	[38]
	the clock frequency, CBS (not explained in the paper)	[39]
P_{DEC}	Low Density Parity Check (LDPC) codes; parameters: the number of ones in each column, the number of iterations, the data rate, the bandwidth and the constant parameter	[31, 32]
	the number of operations needed to encode or decode the information bit	[38, 40]
P_{MOD}	Quadrature Amplitude Modulation (QAM) modulator; parameters: the clock frequency and the number of the quantization bits	[39]
P_{IFFT}	the clock frequency, the number of the quantization bits and IFFT size	[39]

consumption values from most commonly refereed publications can be found in [34]. The components include ADC, DAC, the reconstruction and anti-aliasing filters, the mixers, the frequency synthesizer, PA, LNA, and the baseband amplifier. In [35], more exemplary power consumption values are listed in the context of LTE technology. The power consumption models from the papers cited above have been adapted to multiuser massive Multiple-Input and Multiple-Output (MIMO) scenario in [36, 37]. In addition to adapting existing models of energy consumption, the model has been extended by elements specific to the presented scenario, such as energy consumption by the channel estimation process, by the load-dependent backhaul or linear processing at the Base Station (BS).

In most of the papers cited above, the authors focus on the power consumption of the RF front-end and channel coding, neglecting the power consumed by other baseband signal processing algorithms which have a significant share in power consumption, in case of short links. In [38–42], more attention is put to this aspect. In [38, 40], the number of operations needed to encode or decode the information bit for the channel coding algorithms was determined. Then, knowing the energy consumption per operation, the total power consumed by channel coding can be determined. In [41], a dynamic power estimation methodology for Field Programmable Gate Array (FPGA) based system has been presented. The methodology has been evaluated on the LTE downlink physical layer and provides fast and accurate power estimation. Similarly as in the general power consumption model presented in [23], the power consumed by FPGA is also divided into static and dynamic power. In the proposed methodology, the total dynamic power is determined by the power estimations of each sub-element in the system e.g. in the wireless communication scenario, the power is estimated for channel coding, modulation, fast Fourier transform etc. That work has been continued in [39, 42] where the more advanced scenarios are considered, and the power consumption values of each system element are presented. Moreover, the extension to other FPGAs by introducing a scaling factor has been introduced. As overviewed above, diverse power consumption models can be considered for distinct transmitter and receiver components. In Table 1.2, key parameters of the power consumption models for distinct transmitter and receiver components known from the literature are summarized.

Finally, Figure 1.7 illustrates the trade-off between the accuracy of the power consumption models and the difficulty in defining them while in Table 1.3 presented thier pros and cons. It can be observed that if the power consumption model is easy to define, the representation accuracy of the real system is low. On the other hand, if the accuracy of the power consumption model is high, the model is really difficult to determine, for example, due to the fact that all transmitter/receiver components are integrated in a single chip. Therefore, the power consumption based on the measurements and augmented with the interpolation or stochastic modelling seems to be a good trade-off.

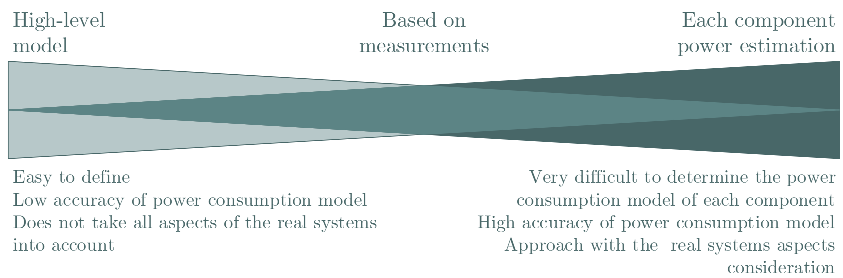

Figure 1.7: Trade-off observed in the power consumption estimation.

Table 1.3: Pros and cons of the power consumption estimation

	Pros	Cons
high-level model	• easy to define • the universal approach allows for describing the different systems • allows for applying optimization techniques with low complexity • low-dependent on the implementation, systems, parameters etc. and mathematically simple	• does not take all aspects of the real systems into account
based on measurements	• better representation of the real systems than high-level model • takes some aspects of the real systems e.g. data rate, path loss into account	• the measurements of the power consumed by the transmitter and receiver are required • the power consumption model depends on the implementation, system, parameter etc. • the energy consumption of the individual components of the transmitter and receiver is unknown
each component power estimation	• the best representation of the real systems • takes the aspects of the real systems e.g. parameters of transmission into account	• very difficult to determine the power consumption model of each component • the power consumption model depends on the implementation, system, parameter etc.

1.3 System limitations and requirements

The maximization of energy efficiency metric as defined by (1.1) without constraints is not practical for multiple reasons.[2] In the optimization, physical limitations of the network such as the maximum transmit power, minimum guaranteed throughput or particular standard requirements (e.g. the spectrum emission mask) have to be taken into account. Therefore, the energy efficiency optimization problem is usually defined as the objective function with constraints. Moreover, some limitations of wireless communication systems can be included in the objective function, e.g., grouping the subcarriers into resource blocks. The most common constraints known from the literature are listed below:

- *the maximum transmission power constraint* ensures that the sum of the transmission power allocated to the subcarriers is lower than or equal to the maximum assumed value. In the case of downlink transmission, this constraint typically limits the transmission power of the base station while, for the uplink, the transmit power of each end-user (UE) is limited. This constraint results from practical aspect of designing wireless communication systems where the total transmission power is limited by standards.

- *the requirement on the minimum data rate* aims at providing the end-user quality of service. In this case, the achieved data rate has to be higher than or equal to assumed threshold. In the literature, this constraint is typically considered in the short-term context. It means that in a given time slot, the resource allocation algorithm has to provide the required data rate. From the energy efficiency point of view, the data rate for a user with poor channel conditions can be extremely low, even zero, if this constraint was not applied. Thus, such constraint is necessary in the practical radio communication networks.

- *the subcarrier/resource block allocation constraint* which guarantees that the same subcarriers can be assigned to a certain, limited number of users. This constraint is relevant in the case of a multiuser scenario in order to avoid interference between users. In the case of homogeneous network, it means that a particular subcarrier or RB can be assigned to at most one end-user. However, there exist scenarios, e.g. heterogeneous or relay networks, where the same subcarriers can be utilized by more than one user, resulting in interference between users. Note that a properly designed resource allocation algorithm, in an interference network, can increase the energy efficiency compared to the network without users interference. From the optimization point of view, this constraint requires the introduction of binary decision variables (representing each subcarrier assignment or no-assignment to a particular user) making the optimization problem a MINLFP problem which is very difficult to solve in its original form.

- *the fairness constraint* is introduced to maintain the transmission rate among users with a predetermined proportion. Thus, it is considered in the multiuser system model.

1.4 Optimization of energy efficiency metric

The design of the energy-efficient resource allocation algorithm usually comes down to solving the optimization problem defined as the maximization of the energy efficiency metric. Because of the fractional form of the energy efficiency metric, the optimization problem belongs to a broad class

[2] Without mentioned constraints, the maximal energy efficiency could be achieved if no transmission takes place.

of fractional problems, i.e. to find:

$$\mathbf{x}^\star = \arg\max_{\mathbf{x}} \frac{R(\mathbf{x})}{P(\mathbf{x})}, \tag{1.8}$$

subject to:

$$f_i(\mathbf{x}) \leq b_i, \quad i = 1, \ldots, m. \tag{1.9}$$

Here, the vector $\mathbf{x}^\star = (x_1^\star, \ldots, x_n^\star)$ contains the *optimal* values of the *optimization variables* $\mathbf{x} = (x_1, \ldots, x_n)$, the ratio of functions $R : \mathbb{R}^n \to \mathbb{R}$ and $P : \mathbb{R}^n \to \mathbb{R}^+$ is the *objective function*, the functions $f_i : \mathbb{R}^n \to \mathbb{R}$, $i = 1, \ldots, m$ are the (inequality) *constraint functions*, and the constants $b_1, \ldots, b_m$ are the limits, or bounds, for the constraints.

Since the objective function in (1.8) is in general non-concave, standard convex optimization algorithms are not guaranteed to converge to global optimum and specific algorithms are required. In the literature, four approach to solve the fractional programming problem can be found:

(i) the Dinkelbach's method [43],

(ii) the Charnes-Cooper transform method [44],

(iii) solution of the quasi-concave optimization problem,

(iv) suboptimal solution of the optimization problem.

The Dinkelbach method and the Charnes-Cooper method can be used if the numerator of the objective function is concave while the denominator is convex or if the numerator is affine, the denominator does not have to be restricted in sign. Otherwise, if the optimization problem can not be transformed into concave one, the designing of the special algorithm or heuristic to solve the optimization problem is required. In this case the Dinkelbach's method the objective function is transformed into a new parametrized concave function with parameter λ can be applied:

$$\mathbf{x}^\star = \arg\max_{\mathbf{x}} g_0(\mathbf{x}, \lambda) = \arg\max_{\mathbf{x}} \left(f_0(\mathbf{x}) - \lambda^\star h_0(\mathbf{x})\right), \tag{1.10}$$

subject to (1.9). Let $\mathbf{x}^\star$ be the optimal solution set in (1.10), and $\lambda^\star = \frac{f_0(\mathbf{x}^\star)}{h_0(\mathbf{x}^\star)}$. The following statements are equivalent:

$$\begin{aligned} g_0(\mathbf{x}^\star, \lambda) > 0 &\Leftrightarrow \lambda < \lambda^\star \\ g_0(\mathbf{x}^\star, \lambda) = 0 &\Leftrightarrow \lambda = \lambda^\star \\ g_0(\mathbf{x}^\star, \lambda) < 0 &\Leftrightarrow \lambda > \lambda^\star \end{aligned}$$

Solving the problem (1.8) is equivalent to finding the unique zero of $g_0(\mathbf{x}^\star, \lambda)$. In order to find the root of (1.10), the Dinkelbach's algorithm can be applied, i.e., an iterative algorithm to find the λ value by solving the parameterized problem in each iteration. The Dinkelbach's algorithm converges to the optimal solution with a superlinear convergence rate. The generalized form of Dinkelbach's algorithm is presented in Algorithm 1.

Another approach to tackle a fractional optimization problem is the Charnes-Cooper transform method [44], which is able to convert a fractional problem into an equivalent convex problem, provided that f_0 is concave, g_0 is convex, and the feasible set is also convex:

$$\mathbf{y}^\star = \arg\max_{\frac{\mathbf{y}}{t}} t f_0\left(\frac{\mathbf{y}}{t}\right), \tag{1.11}$$

Algorithm 1 Generalized Dinkelbach's algorithm

initialize $\mathbf{x}$ and λ such that $g_0(\mathbf{x}, \lambda) > 0$, maximum error ε, maximum number of iteration I_{dink} and $i_{\text{dink}} = 0$
repeat
  solve $\mathbf{x}^\star = \arg\max_{\mathbf{x}} g_0(\mathbf{x}, \lambda)$
  $\lambda = \frac{f_0(\mathbf{x}^\star)}{h_0(\mathbf{x}^\star)}$
  $i_{\text{dink}} \leftarrow i_{\text{dink}} + 1$
until $|g_0(\mathbf{x}, \lambda)| \leq \varepsilon$ **or** $i_{\text{dink}} = I_{\text{dink}}$
assign $\mathbf{x} \leftarrow \mathbf{x}^\star$ and $\lambda \leftarrow \lambda^\star$
return $\mathbf{x}^\star$ and $\lambda^\star$

Table 1.4: The comparison of the methods to solve the fractional optimization problem

Dinkelbach method	**Charnes-Cooper method**	**Quasiconcave optimization**	**Suboptimal solution**
• transform the objective function into a new parametrized concave function • an iterative algorithm which solve the parameterized problem in each iteration is required • superlinear convergence of the Dinkelbach algorithm • standard optimization techniques can be used to solve the subproblem in each iteration	• the fractional problem transforms into an equivalent convex problem with one additional variable and two constrains • if the numerator is affine, the fractional problem transforms into an equivalent convex problem with one additional variable and one constrains • a single convex problem must be solved • standard optimization techniques can be used to solve the optimization problem	• the proof of quasiconcavity is required • the proof that the local maximum is also the global optimum is required in order to provide the global optimum • the special algorithm or heuristic has to be designed to solve the optimization problem	• the global optimum is not guarantee • the special algorithm or heuristic has to be designed to solve the optimization problem • low complexity solution can be provided

subject to (1.9) and

$$t \cdot h_0\left(\frac{\mathbf{y}}{t}\right) \leq 1,$$
$$t \geq 1,$$

where $\mathbf{y} = \frac{\mathbf{x}}{h_0(\mathbf{x})}$ and $t = \frac{1}{h_0(\mathbf{x})}$. If h_0 is affine, the first constraint is changed to $t \cdot h_0\left(\frac{\mathbf{y}}{t}\right) = 1$ and the assumption that t is nonnegative can be dropped. Unlike Dinkelbach's algorithm, in this approach a single convex problem must be solved, thus the iterative procedure is not required. On the other hand, the equivalent problem has one additional variable and constraint compared to problem (1.10).

Finally, in Table 1.4, the comparison of the methods to solve the fractional optimization problem is presented.

1.5 Chapter summary

In this chapter, the state of the art in energy-efficient resource allocation in the OFDM/OFDMA-based wireless communication systems has been reviewed. First, the author provided the definition of the EE metric, and discussed necessary steps towards its maximization. These steps (subtasks) have been classified by the author, and interaction between them have been considered in order to design the energy-efficient resource allocation algorithm. For each task, the author provided an literature review with the original classification of approaches which can be distinguished. Moreover, the author discussed pros and cons of investigated approaches as well as the observed trade-offs. The provided classification can allow to determine the best way of designing the energy-efficient resource allocation algorithm with a given accuracy and computational complexity.

Chapter 2

Single OFDM link flexibility for EE

In this chapter, the author of this thesis presents his original research and achievements regarding the energy-efficient resource allocation optimization in the context of a single OFDM link. Visualization of the example single link transmission with the related power consumption is presented in Figure 2.1. It can be observed that the user achieves some transmission rate as a result of per-subcarrier power allocation in response to the instantaneous channel conditions (visualized in Figure 2.1 as the magnitude of the instantaneous channel characteristic). In the presented example, the resource allocation algorithms come down to determining the values of transmission powers allocated to subcarriers. However, more degrees of freedom can be identified in the single link scenario. Depending on the considered system scenario, the transmit power can be allocated per subcarrier, per resource block consisting of many SCs or per user. Moreover, in practical wireless communication systems, modulation and coding schemes and other transmission parameters can be adaptively selected in order to maximize the energy efficiency.

In this chapter, the author first (in Section 2.1) reviews the aspects of energy efficiency optimization (rate and power estimation, appropriate constraints and the optimization problem) in the context of a single link scenario. Then, in Section 2.2 the author's original contribution to the problem of OFDM resource allocation is presented aiming at energy efficiency maximization, while taking the computational energy cost into account. (For this reason, the considered adaptive OFDM system is called *computationally-aware*.) Specifically, in Subsection 2.2.2, the system model is described, and the optimization problem of EE is formulated. The two-steps transformation of the optimization problem and its solution are proposed in Subsection 2.2.3. The simulation results are provided, and compared against the standard (not computationally-aware) *water-filling* performance in Subsection 2.2.5 together with detailed analysis. The chapter summary and conclusions are provided in Section 2.3.

2.1 State of the art

2.1.1 Estimation of the OFDM single link transmission rate

In the context of the single, uth user's OFDM link, transmission rate $R^{(u)}$ is determined by the sum of the rates $r^{(u,n)}$ achieved using the allocated resource units:

$$R^{(u)} = \sum_{n \in \mathcal{N}} r^{(u,n)}, \tag{2.1}$$

where $\mathcal{N}$ is the set of allocated resources. In the literature, the first two approaches to the data rate estimation mentioned in Section 1.1 are usually considered for a single link scenario. While in [23, 24, 44, 45], the data rate achieved per subcarrier is determined by the Shannon formula, the transmission rate in [9, 21, 22] is estimated using Shannon formula with a scaling factor related to an adopted modulation and coding scheme and a target bit-error probability.

Most importantly, the data rate estimation methods can have various complexity as a result of the number of degrees of freedom available in a given system. In [9], the scaling factors for the Shannon formula-based rate estimation, depending on the code rate, the coding gain, and the target bit-error probability are determined per subcarrier. This means that the modulation and coding schemes can vary among subcarriers. The assumption that different MCS can be used at each subcarrier requires potentially many parallel coding and decoding blocks to be run in a single UE, a solution infeasible in many hardware implementations. Two other limiting factors are: a non-flat wireless channel characteristic and a limited available amount of control information. A wireless channel is typically assumed to be invariant within time-frequency resource block when it is defined in the boundaries of the coherence time and the coherence bandwidth. This block, often called Basic Resource Block (BRB), usually contains several subcarriers and OFDM symbols that should be assigned the same MCS. The MCS allocation has to be preceded by the channel impulse response estimation, typically using pilots, and feedback reporting quantized channel quality. These two processes need some time-frequency resources to accommodate pilots or control messages, reducing available resources for user data. The problem of finding the balance between the accurate channel estimation and the reduction in data rate has been discussed in [46]. Thus, in many real-world OFDM-based systems, the available degrees of freedom in resource allocation are limited and the data rate can be estimated per block of several subcarriers. The authors of [21, 22] have considered grouping subcarriers into subchannels described by the effective power-gain of a channel. There, the data rate has been estimated by the Shannon formula with the scaling factors which have been obtained for the M-QAM transmission with Gray mapping, the Additive White Gaussian Noise (AWGN) channel and coherent detection. It has been shown that it depends on a data interval, a signalling interval, the number of transmitted symbols, the number of subcarriers in the subchannel and the SNR gap dependent on the applied modulation and coding scheme.

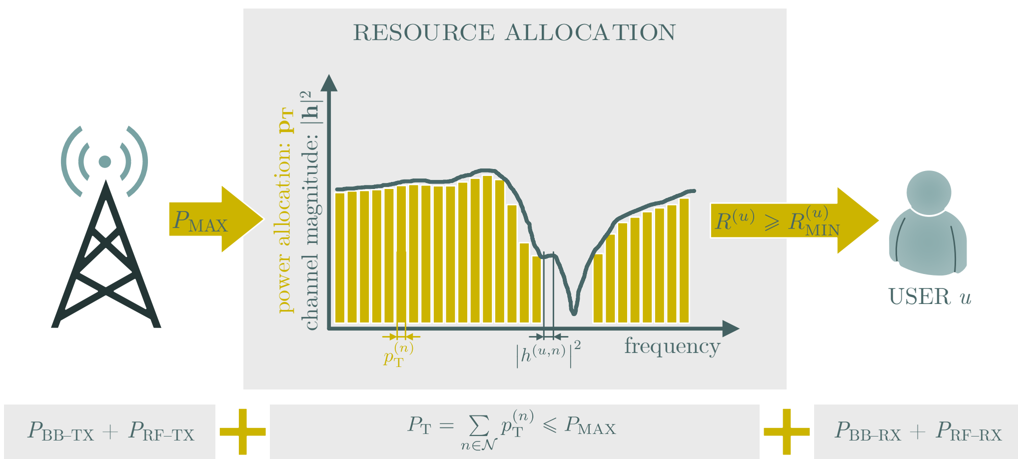

Figure 2.1: The single link scenario, where $p_{\mathrm{T}}^{(n)}$ determines the power allocated on SC $n \in \mathcal{N}$, the channel coefficient in the link is defined by $h^{(u,n)}$ while $R^{(u)}$ is the data rate achieved by user u. The variables related to the system constraints are denoted as P_{MAX} and $R^{(u)}_{\mathrm{MIN}}$ which define the maximum transmit power and the minimum data rate achieved by user, respectively.

2.1.2 Power consumption estimation for a single link

As shown in Figure 2.1, in the case of a single OFDM link, the total power consumption consists of the power consumed by BB and RF signal processing on the transmitter and receiver side as well as of the transmit power being the sum of powers allocated to subcarriers. Observe that, while the wireless channel frequency response has an influence on the optimal allocated powers, its sum is typically fixed. It influences indirectly the consumed power. Moreover, as shown in Section 1.2, the power consumed by the circuits depends on many system parameters, e.g., the modulation and coding schemes, implementation, circuits technology etc. what additionally complicates the estimation of the power consumption in wireless communication systems. Usually, the high-level power consumption model is used in the context of the single link scenario. One of these power consumption models considered in the literature assumes that the power consumption of BB and RF signal processing is expressed by one constant value. For example in [21, 22], the authors assumed that this value is constant, equal to 0.1 W, though the adaptive QAM scheme has been used wherein the power consumption can vary for different modulation orders. Nevertheless, the adaptive QAM scheme has an impact on the transmit power because of different scaling factors in the data rate estimation among the modulation orders.

In [44], the circuit power (understood as the sum of the power consumed by BB and RF signal processing) is assumed to be constant, but the transmission power is scaled by the parameter that expresses power amplifier inefficiency which is defined as a constant value. Nevertheless, the values of the circuit power and the power amplifier inefficiency as well as the numerical results have been not provided in this paper (only analytical analysis has been considered). Another high-level power consumption model considers variations in the circuit power [23, 24]. In this approach the circuit power is modelled as the sum of a static term and a dynamic term where the second of them depends on the sum rate. Moreover, the transmission power is scaled by the parameter related to the efficiency of the power amplifier which is given by the PAPR divided by the drain efficiency of the power amplifier. There the maximum, rarely observed PAPR, equal to the number of subcarriers for an OFDM system, is assumed. Although, the authors have not provided the value of the power consumption model parameters, they have shown the impact of these parameters on the energy efficiency metric. In [9] the modulation and coding scheme-dependent circuit power in the fast adaptive OFDM system has been considered. It means that the power consumption model does not depend only on the data rate and β parameter (as shows equation (1.6)) but also on the coding rate of applied modulation and coding scheme. Moreover, the data rate achieved per subcarrier has been estimated using Shannon formula with scaling factor which depend on the modulation and coding scheme as well. Therefore, the optimal transmit power can vary among the modulation and coding schemes for the same channel impulse response. The parameter describing the constant circuit power is equal 0.1 W while parameter $\beta = 5 \cdot 10^{-5}$ W/ (Mbit/s). Another high-level power consumption model consisting of the fixed circuit power and the variable power increasing with the number of utilized subcarriers has been presented in [45]. It can be observed that the above models present increasing complexity in order to reflect rising number of relations influencing an OFDM link power consumption. Though, the models are rather high-level and general, independent of specific transceivers architectures. This can be treated as an advantage of these models, making the derived resource allocation algorithm independent from the hardware platform. A set of transceiver-dependent parameters, e.g., β, can be adjusted individually without a need for reformulation of the optimization problem or its' solving algorithm.

The above-cited papers use the high-level power consumption models to optimize the energy efficiency. Sample results for maximization of EE have been generated in the single link scenario

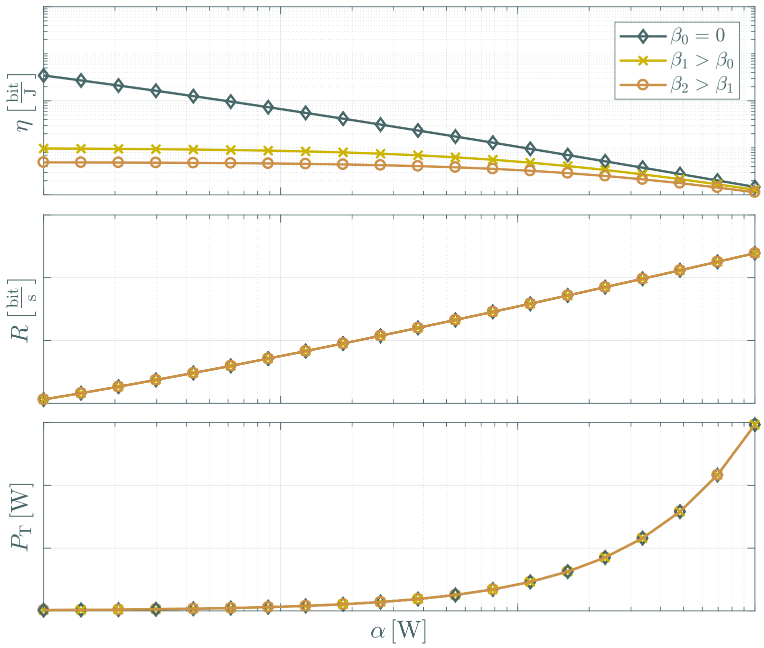

Figure 2.2: The energy efficiency, the data rate and the transmit power as a function of the static part of the circuit power α for different values of parameter β related to the dynamic part of the circuit power consumption.

with the linearly rate-dependent circuit power consumption model (described by equation (1.6)) are presented in Figure 2.2[1]. The energy efficiency, data rate and transmit power in a function of the static part of circuit power consumption model α are plotted. Let us observe that the data rate and transmit power are the same for different values of the parameter related to the dynamic part of the circuit power consumption (β). It means that the dynamic part does not affect transmit powers allocated on subcarriers but only energy efficiency value. Moreover, the transmit power increases with the static part of the circuit power (α) in order to eliminate the domination of static power over the transmission power.

However, there are some more detailed power consumption models considered in the literature as well. A single link transmission where the BB power consumption is modelled as the power consumed by each component is presented in [39]. The authors do not consider EE optimization. In [39,41] the authors propose the dynamic power estimation methodology for FPGA-based OFDM transceiver. Moreover, in [39], the authors proposed measurement-based power consumption models for the considered FPGA implementation.

2.1.3 Constraints for a single link

In Figure 2.1 it can be observed that the system can be limited by the maximum transmission power and the minimum required data rate. The important thing here is that if both constraints are considered the maximal transmission power has to be enough to provide the required data rate. Otherwise, the resource allocation is non-feasible.

The maximum transmission power constraint which ensures that the sum of the transmission power allocated on the subcarriers is less than or equal to the maximum assumed value has been

[1] Note that because in Section 2.1, the author of this thesis discusses the state of the art and general problems of EE optimization in a single OFDM link, in Figure 2.2 and in several following figures in this Section, particular values on the axes are omitted. This is intentional to show the general relations between graph coordinates, abstracting from particular simulation scenarios.

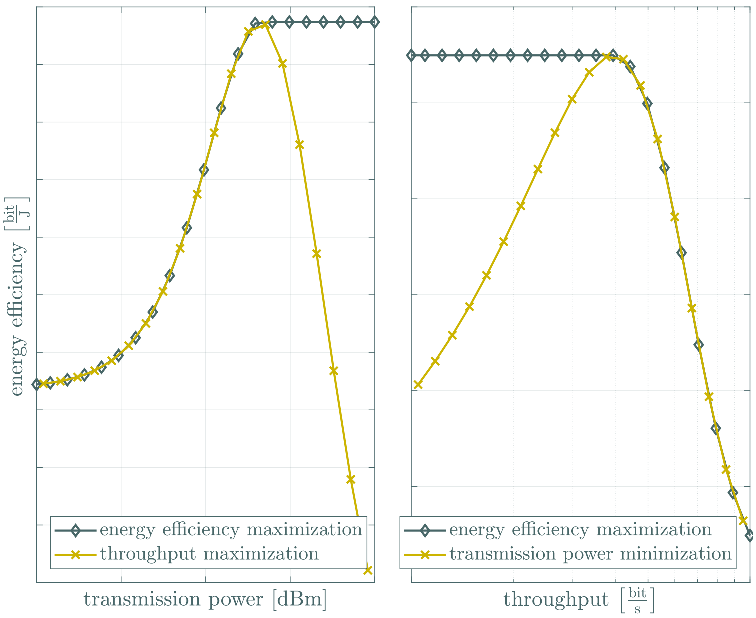

Figure 2.3: The energy efficiency as a function of available transmission power for the EE and throughput maximization (left subfigure), or as a function of the minimal throughput for the EE maximization and transmission power minimization (right subfigure).

considered, e.g., in [9, 21, 22]. Figure 2.3 illustrates the optimized energy efficiency for the constrained OFDM link. On the left side the energy efficiency as a function of available transmission power for the EE and throughput maximization are presented. In the case of EE maximization, the energy efficiency increases with the available transmission power and remains constant after reaching the maximum. For higher available transmission power value, it is not fully exploited. In contrast, the throughput maximization causes the energy efficiency to drop as a result of increasing data rate and fully utilized maximal transmit power.

The minimum data rate constraint provides the end-user's data rate higher or equal to the assumed threshold and has been considered, e.g., in [21, 22]. On the right side of Figure 2.3 the energy efficiency versus the minimum required throughput for EE maximization and transmission power minimization are plotted. It can be observed that with increasing the data rate requirement the energy efficiency decreases in both schemes above some point. However, for relatively low throughput requirements and the EE maximization, the energy efficiency takes constant value because the throughput resulting from optimization is higher than the data rate requirement.

2.1.4 Optimization of EE in an OFDM single link

The complexity of the energy-efficient resource allocation algorithm depends on the degrees of freedom of the considered system and on the utilized model of the data rate and power consumption as well as the system limitations/requirements. In the literature, two sets of the optimization variables are considered in the context of a single-link scenario: (i) the transmit powers allocated on the resource unit or related to them data rates achieved on the resource unit, (ii) the transmit powers/data rates on the resource unit and applied modulation and coding scheme. It means that in the first approach the data rate is estimated by the Shannon formula, thus only transmission power can be determined and the modulation and coding schemes are not selected. In contrast, in the second approach the data rate is esteemed by different methods where the transmit power and the modulation and coding scheme have be to determined. The first set of the optimization

Table 2.1: Summary of the energy-efficient resource allocation methods in a single-link scenario

Scenario	Optimization variables	Methods	Convergence	References
the data rate estimated by the Shannon formula, the linearly rate-dependent circuit power consumption model	transmit power allocated on subcarriers	Charnes-Cooper method	constant	[23]
the data rate estimated by the Shannon formula, the linearly rate-dependent circuit power consumption model	transmit power allocated on subcarriers	Dinkelbach method	superlinear	[24]
the data rate estimated by the Shannon formula, the constant value of the circuit power consumption	transmit power allocated on subcarriers	Dinkelbach method and Charnes-Cooper method	constant (Charnes-Cooper method), superlinear (Dinkelbach method)	[44]
the data rate estimated by the Shannon formula with the scaling factors, the linearly rate-dependent circuit power consumption model, adaptive OFDM system	transmit power allocated on subcarriers, modulation and coding scheme per SC selection	Dinkelbach method	superlinear	[9]
the data rate estimated by the Shannon formula with the scaling factors, the constant value of the circuit power consumption, uncoded M-QAM	transmit power allocated on subchannel	solve the quasiconcave problem by GABS and BSAA algorithms	linear	[21, 22]

variables has been considered in [23,24,44]. In [44] the authors have optimized the energy efficiency by selecting optimal transmission power using Dinkelbach method with superlinear convergence. Due to the rate-dependent circuit power consumption model, in [23, 24] the energy efficiency has been maximized by obtaining the optimal value of the data rate achieved on each subcarrier. Moreover, in [44] the Charnes-Cooper and Dinkelbach methods have been used to solve the energy-efficient resource allocation optimization problem. The authors have shown that both methods give the same optimal result. In [21,22] the energy efficiency is optimized for an uncoded M-QAM modulated OFDM link. The modulation order is expressed as the function of the data rate, thus, in fact, the data rate achieved per subcarrier is optimized. The authors has proven that the defined optimization problem is quasiconcave, thus if a local maximum exists, it is also globally optimal. In order to find the optimal data rate for the single subchannel transmission Gradient Assisted Binary Search (GABS) method has been proposed which then is used in the Binary Search Assisted Ascent (BSAA) algorithm to find the optimal solution in the multi-subchannel scenario.

The second set of optimization variables is considered in [9]. The transmit power and modulation and coding scheme are determined per each subcarrier in order to maximize the energy efficiency. In the first step of proposed algorithm the Dinkelbach method has been used to transform the objective function. Next, the transmit power for each MCS has been obtained. Finally, based on the cost-benefit function the modulation and coding scheme is selected per subcarrier.

In Table 2.1 the summary of the energy-efficient resource allocation methods in a single-link scenario is presented.

2.2 Optimization of energy efficiency in computationally-aware adaptive OFDM systems

In this Section, the original contribution of the author of this dissertation to the problem of computationally-aware EE optimization is presented. First, energy efficiency of an adaptive OFDM system is analyzed taking not just the transmit power into account, but also the transceiver circuit power consumption related to signal processing. Such an energy efficiency optimization problem belongs to a broader class of problems called convex-concave fractional programs, which in the case of the adaptive modulation and coding techniques is also a Mixed Integer Nonlinear Fractional Programming (MINLFP). In order to solve it, the author of this thesis proposes the joint adaptive power and AMC algorithm with fast convergence based on Dinkelbach method, where the analytical solutions are derived by the numerical method according to the Lagrange multipliers and KKT conditions. Simulation results show that the adaptive modulation and coding techniques allow for: increased energy efficiency, increased average throughput, reduced required transmit power and reduced total power consumption. Moreover, there exists the optimal point for the transmit power maximizing the energy efficiency.

2.2.1 Main contribution over the existing methods

It is well known that the energy efficiency will be a crucial factor in designing future wireless communication systems. The steadily increasing capacity and coverage of the wireless communication systems results in increasing power consumption by mobile terminals, base stations, and network infrastructure, while the batteries capacity increases very slowly.

Interestingly, enhanced capacity and service quality in wireless systems come at the expense of increased computational complexity of radio devices, and is related to more and more advanced signal processing (coding, decoding, modulation, equalization and other techniques). Thus, in the optimization of the energy efficiency, the power consumption of baseband processing should also be taken into account independently where the optimization is performed because the main algorithms of BB processing (coding, decoding, FFT, IFFT) are the same for both mobile terminals and base stations. However traditionally, wireless systems are optimized for EE by taking into account the signal transmission energy only, while the power consumption of analog and digital processing is usually neglected or is assumed to be constant.

In the recent years, the EE problem has been widely investigated for OFDM systems, and in the literature one can find a lot of works about energy-efficient resource allocation schemes. For example in [21] and [22] the authors focused on EE of adaptive (uncoded or fixed-code) OFDM modulation systems, where the total power consumption model does not include the power consumption of BB processing. In [23], OFDM link adaptation is based on finding the total throughput that minimizes the cost function being the energy consumption per bit. In order to find this throughput the water-filling principle is used. There, the analog circuit power is modeled as a linear function of the sum-rate, however, the model does not accommodate AMC-related power consumption of digital circuits. Similar considerations can be found in [24, 44] where the energy consumption per bit is determined by setting up a cutoff level. Moreover, in these works a constraint for the total transmit power (typically assumed in radio communication systems) is not considered. Raghavendra et al. [47] propose an energy-efficient water-filling algorithm for an OFDM system where the energy minimization problem is quite general and subsumes both rate maximization and power minimization problems as specific cases. In all of these papers, joint transmit power allocation, adaptive modulation and coding and adaptive decoding have not been considered. Moreover, dynamically changing complexity of digital signal processing in particular decoding, as a result of the applied adaptive coding and decoding, is not taken into account.

The novelty of contribution by the author of this thesis is in new AMC technique to maximize EE, while the power consumption model includes the BB processing power (related to computational complexity of such processing). This power depends on adaptively selected modulation and coding schemes, and in particular, the related decoding algorithms. Moreover in this chapter, the author of the thesis proposes the computationally-aware joint algorithm of power allocation and modulation and coding scheme selection for EE optimization with superlinear convergence.

2.2.2 System model and problem formulation

Let us consider an adaptive OFDM system with the set $\mathcal{N}$ of subcarriers and the set $\mathcal{M}$ of available modulation and coding schemes, and assume a frequency-selective channel and the perfect Channel State Information (CSI) availability at both the transmitter and the receiver. The transmitter applies adaptive selection of the transmit power and modulation and coding scheme at each SC, in response to the related subchannel's CSI and target Bit Error Probability (BEP).[2] Let us denote the channel characteristic at the nth SC as $h^{(n)}$, the code rate, the coding gain and the allocated power at this SC as $\rho^{(n)}$, $g^{(n)}$ and $p_{\mathrm{T}}^{(n)}$ respectively, and the power spectral density of the white noise as N_0. The data rate on this SC equals [48]:

$$r^{(n)} = \Delta f \rho^{(n)} \log_2 \left(1 + \frac{p_{\mathrm{T}}^{(n)} \left|h^{(n)}\right|^2 g^{(n)}}{\Gamma \Delta f N_0}\right), \tag{2.2}$$

where Δf is the SCs distance, $\Gamma = \frac{-\log(5 \cdot P_{\mathrm{E}})}{1.5}$ is an SNR gap for M-QAM [8], and P_{E} is the target BEP.

The total power consumption P consists of three parts: the transmit power P_{T}, the power consumption by analog circuits P_{AC} and the power consumption of digital circuits (BB processing including adaptive (de)modulation and (de)coding with related computational complexity) P_{DC}. Thus, for an adaptive OFDM link:

$$P = P_{\mathrm{AC}} + \sum_{n \in \mathcal{N}} p_{\mathrm{T}}^{(n)} + \sum_{n \in \mathcal{N}} p_{\mathrm{DC}}^{(n)}, \tag{2.3}$$

where $p_{\mathrm{DC}}^{(n)}$ is the BB processing power at SC n. This power is very difficult to determine because it is dependent on the encoder/decoder structures, hardware implementation, data-rates, wire-width etc. Here, a model as in [49], for the lower-bound of the power consumption by the encoder/decoder being the major source of computational complexity has been applied:

$$p_{\mathrm{DC}}^{(n)} = \beta(1 - \rho^{(n)}) r^{(n)}, \tag{2.4}$$

where β is a parameter dependent on the structure and hardware implementation of the encoder/decoder, BEP etc. Moreover, r_n depends on the applied modulation and coding scheme, and thus, on $g^{(n)}$, $\rho^{(n)}$ and $p_{\mathrm{T}}^{(n)}$.

Here, the EE metric is defined as the ratio of the throughput to the total power consumed in the link, i.e. as the number of successfully transmitted information bits (satisfying the assumed BEP) per unit energy consumption (Joule):

$$\eta = \frac{R}{P} \left[\frac{\text{bit}}{\text{Joule}}\right], \tag{2.5}$$

[2]This flexibility at each SC is meant for theoretical considerations on achievable rates and EE. In practice, a block of SCs may use the same modulation and coding scheme, as in LTE or 5G.

where R is the throughput equal to $R = \sum_{n\in\mathcal{N}} r^{(n)}$. The optimization problem is then defined so as to find a vector of the SCs powers $\mathbf{p}_{\mathrm{T}}^{\star} = \left\{p_{\mathrm{T}}^{(n)^{\star}}\right\}$, a vector of SCs modulation and coding schemes $\mathbf{\Omega}^{\star} = \left\{\rho^{(n)^{\star}}, g^{(n)^{\star}}\right\}$, (concatenation of a vector of code-rates and a vector of coding gains) that maximize η:

$$\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Omega}^{\star}\right) = \arg\max_{\mathbf{p}_{\mathrm{T}}, \mathbf{\Omega}} \ \eta\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Omega}\right), \tag{2.6}$$

subject to:

$$\sum_{n\in\mathcal{N}} p_{\mathrm{T}}^{(n)} = P_{\mathrm{TOT}}, \tag{2.7}$$

Constraint (2.7) guarantees that the total transmit power limit is met and used as power available for signal emission.

2.2.3 Proposed solution

A coding scheme is characterized by a number of parameters such as the length of code word, code rate, coding gain, the number of decoding iterations, etc., which are discrete values. Additionally, in case of M-QAM with the target BEP P_{E}, it can be assumed that the coding gains are also discrete values. Hence, the optimization problem defined in (2.6) is MINLFP which is very difficult to analytically solve in the original form. Moreover, the EE optimization problem belongs to a broader class of convex-concave fractional programs. Thus, the optimization problem will be transformed into a traceable form.

Transformation of the optimization problem

Let us introduce a matrix of binary values $\mathbf{\Psi}$, with $|\mathcal{N}|$ rows and $|\mathcal{M}|$ columns. If $\Psi^{(n,m)} = 1$, the nth SC is modulated/demodulated and coded/decoded using modulation and coding scheme m. Thus, the optimization problem can be transformed into:

$$\begin{aligned}\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}\right) &= \arg\max_{\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}} \eta\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}\right) = \\ &= \arg\max_{\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}} \frac{\sum_{m\in\mathcal{M}}\sum_{n\in\mathcal{N}} \Psi^{(n,m)} r^{(n,m)}}{P_{\mathrm{AC}} + \sum_{m\in\mathcal{M}}\sum_{n\in\mathcal{N}} \Psi^{(n,m)}\left(p_{\mathrm{T}}^{(n,m)} + p_{\mathrm{DC}}^{(n,m)}\right)},\end{aligned} \tag{2.8}$$

subject to:

$$\Psi^{(n,m)} \in \{0,1\} \qquad \forall n \in \mathcal{N},\ m \in \mathcal{M}, \tag{2.9}$$

$$p_{\mathrm{T}}^{(n,m)} \geq P_{\mathrm{MIN}}^{(n,m)} \qquad \forall n \in \mathcal{N},\ m \in \mathcal{M}, \tag{2.10}$$

$$\sum_{m\in\mathcal{M}} \Psi^{(n,m)} \leq 1 \qquad \forall n \in \mathcal{N}, \tag{2.11}$$

$$\sum_{m\in\mathcal{M}}\sum_{n\in\mathcal{N}} \Psi^{(n,m)} p_{\mathrm{T}}^{(n,m)} = P_{\mathrm{TOT}}, \tag{2.12}$$

where $p_{\mathrm{T}}^{(n,m)}$, $r^{(n,m)}$ is the power allocated and the data rate archived at SC n using modulation and coding scheme m, respectively. Moreover, the minimum required power for the use of modulation and coding scheme is $P_{\mathrm{MIN}}^{(n,m)}$. Constraints (2.9) and (2.11) guarantees that each SC can be modulated and encoded using only one modulation and coding scheme.

Although the optimization problem is transformed by introduction of matrix $\mathbf{\Psi}$, it still belongs to a class of convex-concave fractional programs. For non-linear fractional programming, there exist techniques which allow to transform the objective function into a parametrized concave function with parameter λ. The problem can be defined as:

$$\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}\right) = \arg\max_{\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}} F\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}, \lambda\right) = \arg\max_{\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}} R\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}\right) - \lambda^{\star} P\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}\right). \tag{2.13}$$

Let $\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}\right)$ be the optimal solution set in (2.13), and $\lambda^{\star} = \frac{R\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}\right)}{P\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}\right)}$. The following statements are equivalent [43]:

$$\begin{aligned} F\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}, \lambda\right) > 0 \Leftrightarrow \lambda < \lambda^{\star}, \\ F\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}, \lambda\right) = 0 \Leftrightarrow \lambda = \lambda^{\star}, \\ F\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}, \lambda\right) < 0 \Leftrightarrow \lambda > \lambda^{\star}. \end{aligned}$$

Solving problem (2.13) is equivalent to finding the root of non-linear align $F\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}, \lambda\right) = 0$. In order to find the root of (2.13), the Dinkelbach method can be applied, i.e., an iterative algorithm to find the λ value by solving the parametrized problem in each iteration. The algorithm converges to the optimal solution with a superlinear convergence rate. The detailed convergence analysis can be found in [43].

Dual problem

In order to solve MINLFP problems, the Generalized Benders Decomposition (GBD) method, the Hunagarian algorithm or heuristic methods can be used. Unfortunately, the computational complexity of these algorithms is usually high, e.g. GBD is adequate for problems with just a few variables and for problems (2.8)-(2.12), the complexity of exhaustive search is $\mathcal{O}\left(|\mathcal{M}|^{|\mathcal{N}|} |\mathcal{M}|\right)$. To reduce the computational complexity the binary values of matrix $\mathbf{\Psi}$ are relaxed to be real numbers. Thus, the optimization problem is transformed to:

$$\begin{aligned} \left(\mathbf{p}_{\mathrm{Tt}}^{\star}, \mathbf{\Psi}^{\star}\right) &= \arg\max_{\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}} \eta\left(\mathbf{p}_{\mathrm{Tt}}, \mathbf{\Psi}, \lambda^{\star}\right) = \\ &= \arg\max_{\mathbf{p}_{\mathrm{t}}, \mathbf{\Psi}} \sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)} r^{(n,m)} - \lambda^{\star} \left(P_{\mathrm{AC}} + \sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)} \left(p_{\mathrm{T}}^{(n,m)} + p_{\mathrm{DC}}^{(n,m)}\right)\right), \end{aligned} \tag{2.14}$$

subject to:

$$\Psi^{(n,m)} \in \mathbb{R} \qquad \forall n \in \mathcal{N},\ m \in \mathcal{M} \tag{2.15}$$

and (2.10)–(2.12). Introducing the Lagrangian multiplier Λ for equality constraint (2.12) and non-negative multipliers $\boldsymbol{\mu} = \left\{\mu^{(n,m)}\right\}$, $\forall n \in \mathcal{N},\ m \in \mathcal{M}$ for constraints (2.10), the Lagrangian function for the optimization problem can be written as:

$$\begin{aligned} \mathcal{L}\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}, \lambda, \Lambda, \boldsymbol{\mu}\right) = \sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)} r^{(n,m)} - \lambda \left(P_{\mathrm{AC}} + \sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)} \left(p_{\mathrm{T}}^{(n,m)} + p_{\mathrm{DC}}^{(n,m)}\right)\right) \\ - \Lambda \left(\sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)} p_{\mathrm{T}}^{(n,m)} - P_{\mathrm{TOT}}\right) + \sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \mu^{(n,m)} \left(p_{\mathrm{T}}^{(n,m)} - P_{\mathrm{MIN}}^{(n,m)}\right). \end{aligned} \tag{2.16}$$

The dual objective function is:

$$\mathcal{L}_{\mathrm{D}}\left(\lambda, \boldsymbol{\mu}\right) = \begin{cases} \max\limits_{\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}} \mathcal{L}\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}, \lambda, \Lambda, \boldsymbol{\mu}\right) \\ \text{s. t.} \quad (2.9) - (2.12) \end{cases}. \tag{2.17}$$

Then, the dual optimization problem is given by:

$$\left(\lambda^{\star}, \boldsymbol{\mu}^{\star}\right) = \arg\min_{\Lambda, \boldsymbol{\mu}} \mathcal{L}_{\mathrm{D}}\left(\Lambda, \boldsymbol{\mu}\right). \tag{2.18}$$

2.2.4 Solution of the optimization problem

After redefining the primal problem (2.14) to Lagrange function, and after defining the dual optimization problem, the necessary and sufficient KKT conditions can be used to solve the optimization problem:

$$\frac{\partial \mathcal{L}\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}, \lambda, \Lambda, \boldsymbol{\mu}\right)}{\partial p_{\mathrm{T}}^{(n,m)}} = 0, \tag{2.19}$$

$$\frac{\partial \mathcal{L}\left(\mathbf{p}_{\mathrm{T}}, \mathbf{\Psi}, \lambda, \Lambda, \boldsymbol{\mu}\right)}{\partial \Psi^{(n,m)}} = 0, \tag{2.20}$$

$$\Lambda \left(\sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)} p_{\mathrm{T}}^{(n,m)} - P_{\mathrm{TOT}} \right) = 0, \tag{2.21}$$

$$\mu^{(n,m)} \left(-p_{\mathrm{T}}^{(n,m)} + P_{\mathrm{MIN}}^{(n,m)} \right) = 0 \qquad \forall n \in \mathcal{N},\ m \in \mathcal{M}. \tag{2.22}$$

Let us solve the first condition for $p_{\mathrm{T}}^{(n,m)}$, and obtain the power allocation at the nth SC using modulation and coding scheme m, assuming $\Psi^{(n,m)} = 1$. For a given λ is derived as:

$$p_{\mathrm{T}}^{(n,m)^\star} = \left[\frac{\Delta f \rho^{(m)} \left(\beta\lambda \left(\rho^{(m)} - 1 \right) + 1 \right)}{\log(2) \left(\lambda + \Lambda - \mu^{(n,m)} \right)} - \frac{\Delta f N_0}{g^{(m)} \Gamma \left| h^{(n)} \right|^2} \right], \tag{2.23}$$

If $\Psi^{(n,m)} = 0$, the solution is $p_{\mathrm{T}}^{(n,m)^\star} = 0$. It can be observed that if $\rho^{(m)} = 0$ and $g^{(m)} = 0$ dB, the system applies uncoded scheme and the solution for the power allocation is the same as in the case of well-known water-filling algorithm. Similarly, solving the second condition, we obtain:

$$\zeta^{(n,m)} \triangleq \frac{\partial \mathcal{L}\left(\lambda, \boldsymbol{\mu}\right)}{\partial \Psi^{(n,m)}} = r^{(n,m)^\star} - \lambda \left(p_{\mathrm{T}}^{(n,m)^\star} + p_{\mathrm{DC}}^{(n,m)^\star} \right) - \Lambda p_{\mathrm{T}}^{(n,m)^\star}. \tag{2.24}$$

The subtrahend of variables ζ determine the cost (the sum of the transmit power and the power consumed by the BB processing) of the achieved throughput at the nth SC and for modulation and coding scheme m. Thus, the modulation and coding scheme can be simply selected by selecting the highest value of matrix $\boldsymbol{\zeta} = \left\{ \zeta^{(n,m)} \right\}$ for each SC. The closed-form solution for the modulation and coding scheme selection is defined as:

$$\Psi^{(n,m)^\star} = \begin{cases} 1 & \text{for} \quad m^\star = \arg\max_m \zeta^{(n,m)} \\ 0 & \text{for} \quad \text{otherwise} \end{cases}. \tag{2.25}$$

Let us now determine the Lagrange multipliers which fulfill constraints (2.10) and (2.12). The subgradient method could be used to find the optimal values of Λ and $\mu^{(n,m)}$, however, it is computationally complex for a large number of variables. Thus, the KKT conditions to solve the dual problem are used. Substituting (2.23) into (2.22), the closed-form for $\mu^{(n,m)}$ is derived:

$$\mu^{(n,m)^\star} = \lambda + \Lambda - \frac{\Delta f \rho^{(m)} \left(\beta\lambda \left(\rho^{(m)} - 1 \right) + 1 \right)}{\log(2) \left(P_{\mathrm{MIN}}^{(n,m)} + \frac{\Delta f N_0}{g^{(m)} \Gamma \left| h^{(n)} \right|^2} \right)}. \tag{2.26}$$

For Λ, the four possible cases are considered. First, when in the transmitter the total transmit power is not limited. In this case, the constraint (2.12) is not taken into account and $\Lambda^\star = 0$. Second, when the power allocated to each SC is higher than the minimum power required for the use of a specific encoder (without causing transmission outage at this SC), and (2.22) is inactive ($\mu^{(n,m)} = 0$, $\forall n \in \mathcal{N},\ m \in \mathcal{M}$). In this case, the optimal Λ is:

$$\Lambda^\star = \frac{\sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)^\star} \Delta f \rho^{(m)} \left(\beta\lambda \left(\rho^{(m)} - 1 \right) + 1 \right)}{\log(2) \left(P_{\mathrm{TOT}} + \sum_{m\in\mathcal{M}} \sum_{n\in\mathcal{N}} \Psi^{(n,m)^\star} \frac{\Delta f N_0}{g^{(m)} \Gamma \left| h^{(n)} \right|^2} \right)} - \lambda. \tag{2.27}$$

Algorithm 2 Proposed algorithm

initialization the maximum number of iteration I_{max} and the maximum tolerance ε
set $\mu^{(n,m)} = 0$, $\forall n, m$, $\lambda = \lambda_0$, $\Lambda = 0$ and the index of iteration $i = 0$
repeat
  Calculate $p_{\mathrm{T}}^{(n,m)^{\star}}$ using (2.23) and $\Psi^{(n,m)^{\star}}$ using (2.24) and (2.25) for a given λ
  if $p_{\mathrm{t}}^{(n,m)^{\star}} < P_{\mathrm{MIN}}^{(n,m)}$ **then**
    Calculate $\mu^{(n,m)}$ using (2.26)
  end if
  if P_{TOT} is not limited **then**
    $\Lambda = 0$
  else if $\sum\limits_{n\in\mathcal{N}} p_{\mathrm{t}}^{(n,m)^{\star}} \neq P_{\mathrm{TOT}}$ **then**
    Calculate Λ by equation (2.27) or (2.28) or using numercial method depending on the size of the set $\mathcal{V}$.
  end if
  $\lambda \leftarrow \frac{R(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}, \lambda)}{P(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}, \lambda)}$
  $i \leftarrow i + 1$
until $|F\left(\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}, \lambda\right)| \leq \varepsilon$ or $i = I_{\max}$
return $\mathbf{p}_{\mathrm{T}}^{\star}, \mathbf{\Psi}^{\star}$

The third case occurs when the power allocated to the nth SC is higher than $P_{\mathrm{MIN}}^{(n,m)}$ for the encoder m for at least one SC. By applying (2.23) and (2.26) to (2.21), the optimal Lagrange multiplier λ is given by:

$$\Lambda^{\star} = -\lambda + \frac{1}{\log(2)} \left(\frac{\sum\limits_{n,m\in\mathcal{N}/\mathcal{V}} \Psi^{(n,m)^{\star}} \Delta f \rho^{(m)} \left(\beta\lambda\left(\rho^{(m)} - 1\right) + 1\right)}{P_{\mathrm{tot}} - \sum\limits_{n,m\in\mathcal{V}} \Psi^{(n,m)^{\star}} P_{\mathrm{MIN}}^{(n,m)} + \sum\limits_{n,m\in\mathcal{N}/\mathcal{V}} \Psi^{(n,m)^{\star}} \frac{\Delta f N0}{g^{(m)}\Gamma\left|h^{(n)}\right|^2}} \right), \tag{2.28}$$

where $\mathcal{V} \subset \mathcal{N}$ is a set of indicates n and m for which μ is positive. It can be observed that if $\mathcal{V} = \emptyset$ the above equation reduces to (2.27). In the last case, the powers allocated by formula (2.23) at all SCs are lower than the power levels required to use modulation and coding schemes and (2.22) is active ($\forall n, m\, \mu^{(n,m)} > 0$). This may happen when the total transmit power limit is very low. In this case, the numerical methods have to be used to calculate λ value.

Based on the Dinkelbach method and equations (2.23)–(2.28) the proposed scheme is designed as Algorithm 2 presented above. In each iteration, the power allocation and modulation and coding scheme selection indicators for a given λ, Λ and $\mu^{(n,m)}$ are derived. Then, the values of Lagrange multipliers using the closed-form solution or numerical methods are updated, depending on the size of the subset $\mathcal{V}$. The algorithm finishes when one of the stop criterion is met.

2.2.5 Numerical results

In this subsection, results obtained by the proposed algorithm (Algorithm 2) are presented. The adaptive OFDM system uses $|\mathcal{M}| = 21$ AMC schemes. The Look-Up-Table (LUT), which contains the values of coding gain, coding rate and minimum SNR for the use of modulation and coding scheme for M-QAM ($\mathcal{M} \in \{4, 8, 16, 64, 256\}$) and for the Turbo Code (TC), Convolutional Code (CC), Punctured Convolutional Code (PCC) and for an uncoded scheme is used. Moreover, in order to maximize the EE the SC outage is allowed. The number of available SCs $|\mathcal{N}| = 256$, and the SCs distance is $\Delta f = 15$kHz (as in the LTE system). Other parameters are as follows: for the noise power spectral density the operational point in the temperature of 20°C is assumed, and that it is increased by the receiver noise figure of 10dB. Moreover, $P_{\mathrm{E}} = 10^{-5}$, $\beta = 5 \cdot 10^{-5}$, and $P_{\mathrm{AC}} = 0.1$ W as assumed in [22]. The channel model is Extended Pedestrian A.

Figure 2.4 illustrates the convergence of Algorithm 2 for various link distances. In this Figure, the normalized EE (energy efficiency over the maximum achieved EE value) versus the number of iterations is plotted. It can be observed that the energy efficiency converges to the maximum value within twelve iterations for all considered link distances.

Figure 2.5 illustrates the performance of Algorithm 2 compared to the reference methods. Because the EE results are presented against the link distance, the total transmit power is not fixed, assuming that it has to be sufficient to achieve the target BEP. The water-filling scheme allocates the transmit power using water-filling principle and chooses the modulation and coding scheme according to the SNR at each SC. The Shannon limit for EE is calculated as the Shannon channel-capacity over the total transmit power and the power of analog circuits as e.g. in [24, 44] (thus, neglecting the computational power). It can be observed that Algorithm 2 results in higher EE than the water-filling algorithm. Moreover, that for Algorithm 2, noticeably higher EE translates to slightly lower throughput when compared to the water-filling scheme. Figure 2.6 shows the total transmit power versus the link distance. It can be observed that Algorithm 2 reduces the total transmit power compared to the water-filling scheme.

Next, Algorithm 2 with adaptive modulation using only one (non-adaptive) coding technique (either CC, PCC or uncoded scheme) has been examined. In Figure 2.7, EE of such approaches versus the link distance can be observed. Note that EE for the Algorithm 2 is always higher than for the adaptive modulation techniques (with no coding adaptation). Considering results presented in Figure 2.5 and in Figure 2.7 it can be observed that AMC with computational awareness allows to increase EE significantly in wireless links.

Figure 2.8 compares EE versus the total transmit power for the considered schemes and for four example link distances. It can be observed that there exist the optimal point for the transmit power that maximizes EE. Moreover, Algorithm 2 achieves the best results for all values of the transmit power. In Figure 2.9 the throughput as a function of the total transmit power is plotted. For Algorithm 2, the achieved throughput is the highest compared to the water-filling scheme. The reason is that in case of the fixed transmit power the proposed algorithm maximizes the total

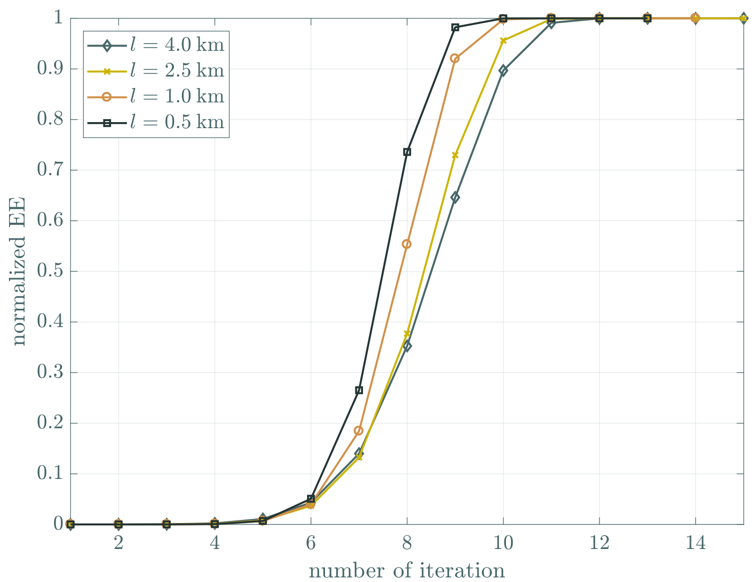

Figure 2.4: The convergence of Algorithm 2

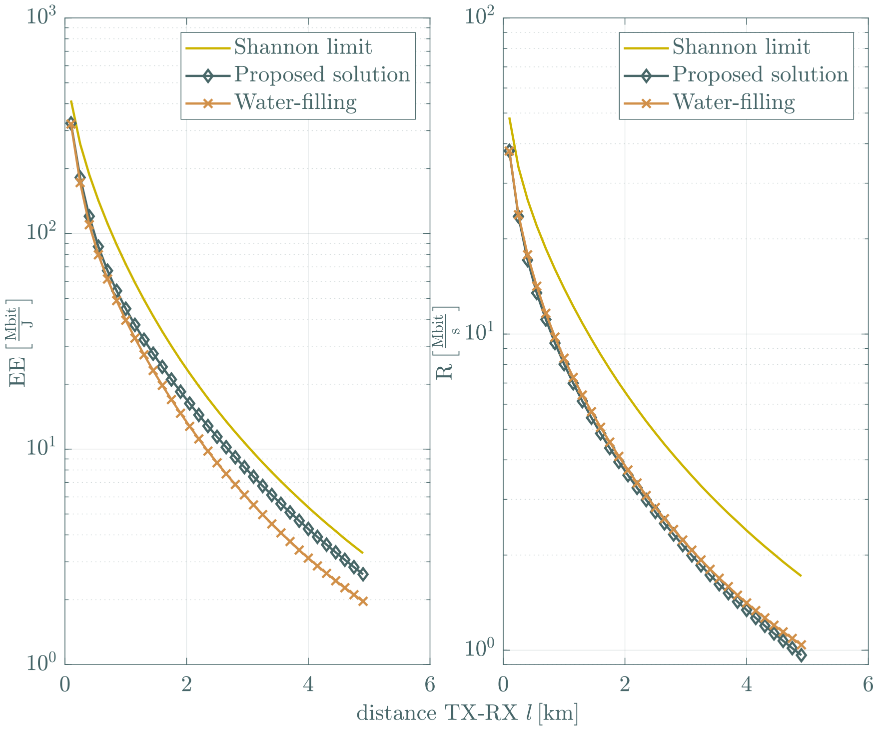

Figure 2.5: Energy efficiency (left) and throughput (right) versus the link distance.

throughput and minimizes the computational power.

2.3 Chapter summary and conclusions

In Chapter 2, the author of this thesis proposed the energy-efficient resource allocation algorithm for the OFDM wireless communication system using AMC techniques with computational aware-

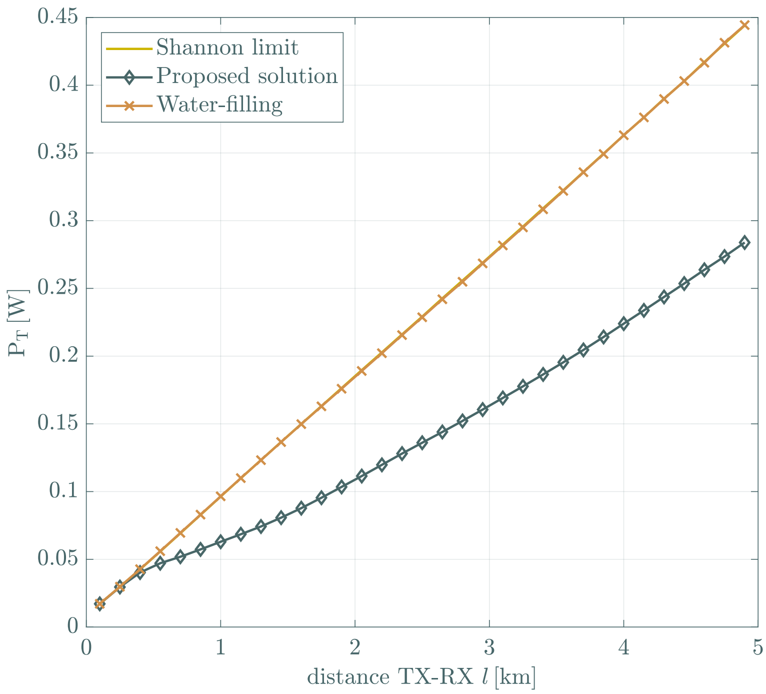

Figure 2.6: Total transmit power versus the link distance.

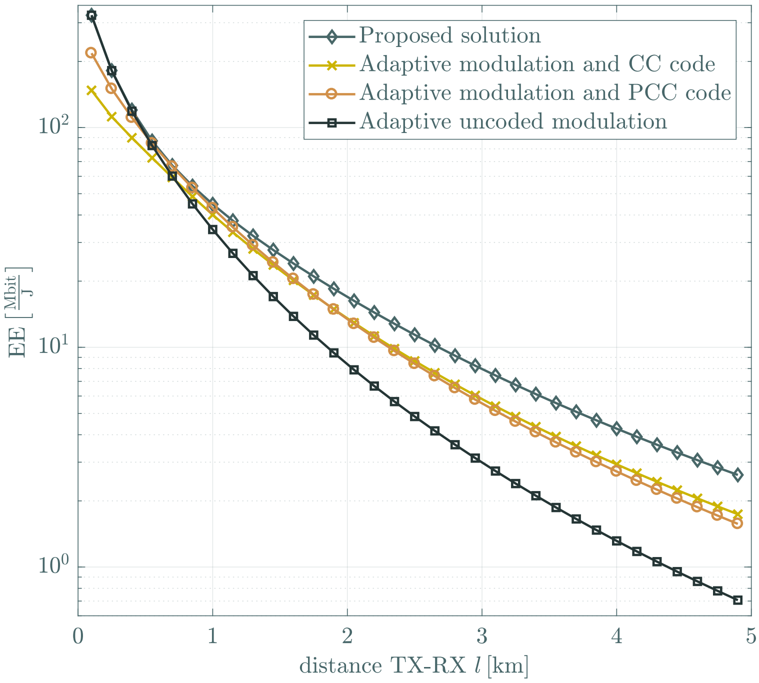

Figure 2.7: Energy efficiency versus the link distance.

ness. It means that the power consumption model contains not only the transmission power allocated to SCs and the static circuit power but also the power consumed by the baseband signal processing which changes dynamically according to the radio environment conditions. The energy efficiency is maximized by the adaptive transmit power allocation and modulation and coding scheme selection. For this reason the energy efficiency optimization problem belongs to a broader class of MINLFP programming problem what means that the optimization variables take continuous and discrete values. Therefore, the optimization problem has been transformed

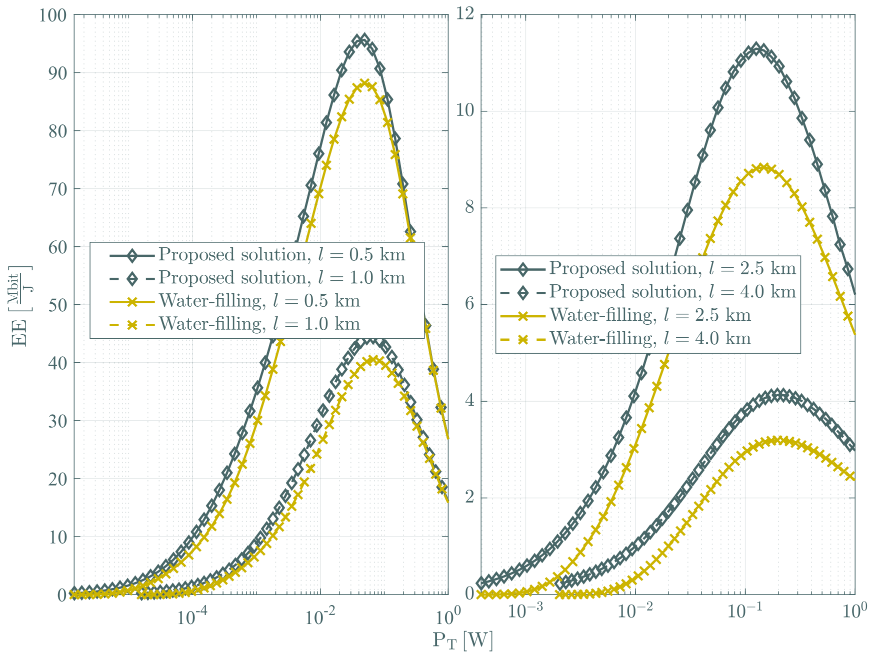

Figure 2.8: Energy efficiency versus the total transmit power.

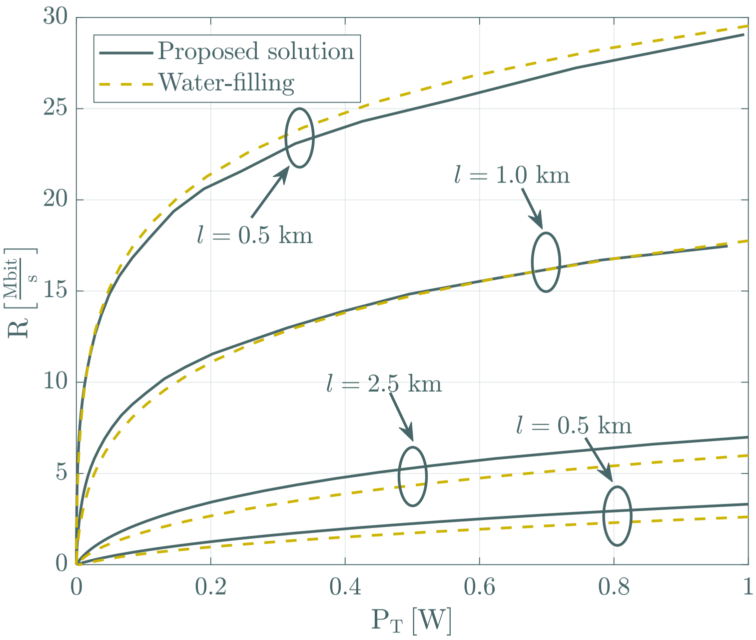

Figure 2.9: Throughput versus the total transmit power.

by introducing the decision matrix, applying the Dinkelbach method, and finally solved using dual decomposition method. For the transformed optimization problem, the closed-form solution for the power allocation and the encoder/decoder selection has been determined.

The solution has been evaluated by the computer simulations, and the results have been compared with other methods known from the literature. Simulation results show that the adaptive modulation and coding techniques allow for: increased energy efficiency, increased average throughput, reduced required transmit power and reduced total power consumption. Moreover, it has been observed that there exists the optimal point for the transmit power maximizing the energy efficiency. The gain in the energy efficiency of the proposed solution compared to the reference methods is between 10% and 15% depending on the scenario what can result in the reduction of the power consumption in OFDM wireless communication systems. Finally, the results show that the EE values obtained by the proposed algorithm are achieved with superlinear convergence.

Chapter 3

Energy efficiency in a multiuser OFDMA network

In this Chapter, the author of this thesis extends his considerations from a single link to a multiuser OFDMA network where a base station serves a number of users which share the bandwidth divided into subcarriers. In this case, the energy efficiency metric can be associated with the whole network or individual users, thus can be defined in different ways. In the literature, three main approaches to maximizing the energy efficiency metric can be distinguished:

(i) maximizing the energy efficiency of the whole network,

(ii) maximizing the sum of the users energy efficiency,

(iii) maximizing the minimum user's energy efficiency.

In the first approach, the energy efficiency is defined as the ratio of total throughput (the sum of users data rate) to the total power consumed in the network. It means that the channel coefficients of all users have to be available in one central entity. Therefore such an approach is mostly applied in the downlink scenario wherein the base station allocates the resources. The energy efficiency for the second and the third approach is defined by the sum of the ratio of data rate achieved by each user to the power consumed by it. Thus the energy efficiency is maximized individually for each user and the channel coefficient of other users are not required. Therefore these definitions are usually considered in the uplink transmission. Moreover, it is obvious that depending on the energy efficiency metric definition, the resource allocation and EE resulting from it can be different.

In Figure 3.1 and 3.2 the example of the downlink and uplink transmissions in the multiuser OFDMA network is presented, respectively. It can be observed that (in the contrast to the single link scenario) the available bandwidth is shared among many users in the network. It means that not only transmit power but the subcarrier assignment has to be determined as well. Moreover, for some systems, the modulation and coding schemes have to be determined for each user. Thus, more degrees of freedom can be distinguished compared to the single link scenario.

In this chapter, the author first (in Section 3.1) reviews the aspects of energy efficiency optimization (rate and power estimation, appropriate constraints and the optimization problem) in the context of a multiuser OFDMA network scenario. Then, in Section 3.2, he presents his original contribution to the solution of the problem of OFDMA resource allocation aiming at energy efficiency maximization, with computational awareness. Specifically, in Subsection 3.2.2, the considered system model is described, and the optimization problem is formulated. The necessary transformation of the optimization problem and the proposed solution are described in Subsection

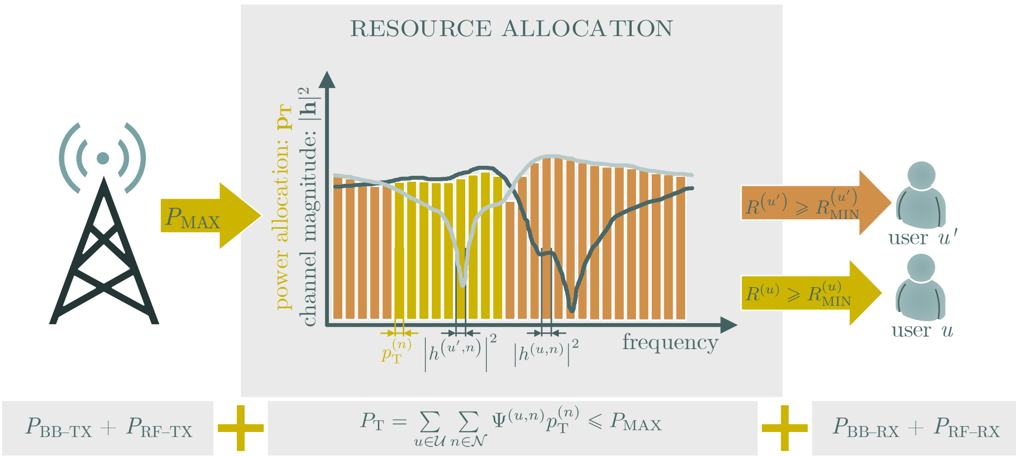

Figure 3.1: The multicell OFDMA downlink network, where $p_T^{(n)}$ determines the power allocated on SC n, $\Psi^{(u,n)}$ the binary variable determining if the subcarrier n is assigned to user u or not while the channel coefficients in the link between BS and users u and u' are defined by $h^{(u,n)}$ and $h^{(u',n)}$, respectively. The data rate achieved by user u and u' are denoted as $R^{(u)}$ and $R^{(u')}$ respectively. The variables related to the system constraints are denoted as P_{MAX}, $R^{(u)}_{\mathrm{MIN}}$ and $R^{(u')}_{\mathrm{MIN}}$ which define the maximum transmit power and the minimum data rate achieved by user u and u', respectively.

3.2.3. In Subsections 3.2.4 and 3.2.5, practical iterative algorithms for the EE resource allocation and MCS selection are presented respectively for the considered system model and problem formulation. The numerical results with detailed analysis are presented in Subsection 3.2.6. These experimental results are compared against the standard algorithms performance. The chapter summary and conclusions are provided in Section 3.3.

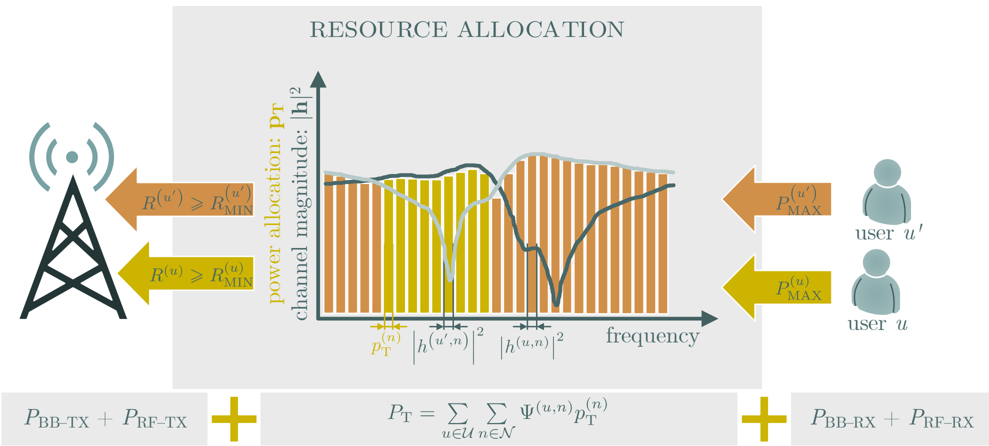

Figure 3.2: The multicell OFDMA uplink network, where $p_T^{(n)}$ determines the power allocated on SC $n \in \mathcal{N}$, $\Psi^{(u,n)}$ the binary variable determining if the subcarrier n is assigned to user u or not while the channel coefficients in the link between BS and users u and u' are defined by $h^{(u,n)}$ and $h^{(u',n)}$, respectively. The data rate achieved by user u and u' are denoted as $R^{(u)}$ and $R^{(u')}$ respectively. The variables related to the system constraints are denoted as $P^{(u)}_{\mathrm{MAX}}$, $P^{(u')}_{\mathrm{MAX}}$, $R^{(u)}_{\mathrm{MIN}}$ and $R^{(u')}_{\mathrm{MIN}}$ which define the maximum transmit power and the minimum data rate for u and u', respectively.

Table 3.1: The values of the power consumption parameters.

Papers	Scenario	Circuit power [W]	Power amplifier efficiency	$\beta\left[\frac{\mathrm{W}}{\mathrm{Mbit/s}}\right]$
Wang *et al.* [59]	downlink	0.01	38%	–
Xiong *et al.* [50]	uplink, downlink	$\{0.05, 10\}$	38%	–
Ye *et al.* [55]	uplink	0.1	38%	–
Bossy *et al.* [16]	downlink	0.1	100%	–
Ren *et al.* [54]	downlink	0.2	38%	–
Tham *et al.* [58]	downlink	1.0	38%	0.1
Wang *et al.* [53]	downlink	10	40%	0.1
D.W.K Ng *et al.* [61]	downlink	10	100%	0.1
Yang *et al.* [56]	downlink	$\{10, 30\}$	38%	$\{1, 2\}$
Xiong *et al.* [51]	downlink	$\{15, 30\}$	38%	0.2
D.W.K Ng *et al.* [62]	multicell downlink	10	20%	–

3.1 State of the art

3.1.1 Transmission rate estimation in a multiuser OFDMA network

In the case of the multiuser OFDMA network, the total throughput is the sum of the throughput for each user. The user's data rate is determined by the sum of data rate achieved on each subcarrier assigned to it. In the literature, all three approaches of the data rate estimation presented in Section 1.1 can be found:

(i) based on the Shannon formula considered among others in [50–57]. In [50–55] the subcarriers are considered independently (are not grouped into RBs), thus the resource allocation is determined per subcarrier. Whereas in [56, 57] the subcarriers are grouped into resource blocks as in some practical wireless communication systems, e.g., LTE.

(ii) estimated by the Shannon formula with scaling factors considered in [58, 59]. In [58] the Shannon formula is scaled by the factor dependent on a target bit error rate for an uncoded M-QAM modulation. In [59] the scaling factor is used to model the imperfect channel state information.

(iii) based on the error-rate function and the spectral efficiency of the applied MCS considered in [16] where the subcarriers are grouped into resource blocks and all RBs assigned to the same user must use the same modulation and coding scheme. In this case, the throughput results from the spectral efficiency of the applied MCS, effective SINR and the block-error rate which has been estimated by the complementary error function with two fitting parameters for each MCS. The values of the fitting parameters for the MCS used in the LTE standard have been provided in [16].

When grouping subcarriers into resource blocks, each RB includes multiple subcarriers subject to different channel gains, thus, an effective SNR mapping method should be applied to collect, and represent the channel state information. In [13, 14] one can find methods of channel-quality representation for the user's RBs. In [57, 60] the effective SINR over one RB has been obtained using the mean instantaneous capacity method which is based on the Shannon formula.

3.1.2 Estimation of the power consumption in a multiuser OFDMA network

In the multiuser OFDMA network, the total power consumption (similarly as in the single link scenario) consists of the transmit power and the power consumption of BB and RF processing at the transmitter and receiver. The total transmit power is equal to the sum of the users' transmission power. The users' transmission power is usually determined as the sum of the transmit power allocated to resources (subcarriers or RBs)s assigned to them. This definition works both for an uplink and a downlink scenario. As shown in Figures 3.1 and 3.2, the transmit power can be potentially allocated per subcarrier. While this is an additional degree of freedom, that can lead to a gain in the achievable data rate, it comes at a cost. The receiver must have the knowledge of the power allocated to each subcarrier to enable channel estimation and decoding. Therefore, the signalling overhead is much bigger than in a more practical scenario, e.g., in LTE where the transmit power is the same among all resource blocks assigned to one user [16].

In the case of the BB and RF processing, the power consumption model should be determined for each user independently (due to different characteristics of the end-user equipment). Thus, the receiver circuit power is the sum of the power consumed by the BB and RF processing at the end-users equipment in the downlink scenario. For example in [52], the power of the circuit is divided into the power consumed at the base station and the user equipment which is scaled with the number of subcarriers assigned in the base station to users. In the rest of the cited papers, the power consumed by circuits remains constant or is modeled as the linear function of the achieved data rate.

In Table 3.1 the values of the total fixed circuit power, power amplifier efficiency parameter and/or β parameter from a set of well established papers are provided. It can be observed that the power amplifier efficiency parameter in most cited papers hovers around 38% while the circuit power and β parameter oscillate much more. Moreover, in all cited papers, all parameters: the circuit power, the power amplifier efficiency and parameter β are assumed the same for all users in the network.

3.1.3 Constraints in a multiuser OFDMA network

It is obvious that each constraint of the system can cause reduction in maximal energy efficiency. Nevertheless, let us remember that the maximization of the energy efficiency does not ensure the network fulfils users Quality of Service (QoS) requirements. For example, Figure 3.3 shows the data rates and transmit powers of three users in the network[1]. Two of them are located close to the base station while the third is located at the edge of the cell. The resources (transmit power and subcarriers) have been allocated to maximize the energy efficiency of the whole network. It can be observed that none resources are allocated to the user at the edge of the cell. Thus, despite maximum energy efficiency is achieved, not all users are served. Therefore, in this case the minimum data rate constraints are required. In the literature, the following constraints for the energy efficiency optimization of the multiuser OFDMA network have been considered:

- the maximum transmission power constraint which has been considered in [50–55, 58, 59, 61, 62]. In the case of the downlink transmission this constraint ensures that the sum of transmission powers allocated in the base station is less than or equal to the maximum allowed value. Whereas, for the uplink transmission [50, 55] the maximum transmission power constraint concerns each user in the network. It means that the sum of transmit powers allocated on subcarriers for a given user has to be less than or equal to the maximum transmit power of its device. It is obvious that the maximum transmit power can vary among users as shown in Figures 3.1 and 3.2.

[1] Note that because in Section 3.1, the author of this thesis discusses the state of the art and general problems of EE optimization in a OFDMA network, in Figure 3.3, particular values on the axes are omitted. This is intentional to show the general relations between graph coordinates, abstracting from particular simulation scenarios.

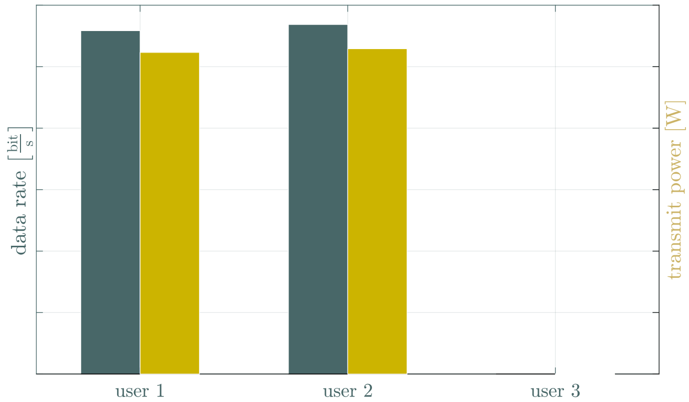

Figure 3.3: The data rates and transmit powers of three users in the network where two of the users are located close to the base station while the third is located at the edge of the cell. The case of EE maximization without additional constraints.

- the minimum data rate constraint considered in [50–53, 55, 59, 61, 62]. In both (downlink and uplink) scenario it means that the data rate of a given user has to be not smaller than assumed value. Moreover, this value can be different for each user as shown in Figures 3.1 and 3.2.
- the subcarrier/resource block allocation constraint examined in [50–55, 57, 59–61]. This constraint guarantees that a given subcarrier/resource block can be assigned to maximally one user, in order to avoid the inter-user interference. It is usually realized by introducing the auxiliary variables which take binary values making the optimization problem a MINLFP problem for which the techniques described in Section 1.4 are not sufficient. Therefore, in Section 3.1.4 the methods dealing with MINLP in the context of energy efficiency optimization are reviewed.
- the instantaneous proportional rate fairness constraint contemplated in [50, 54, 58] which ensures that each user would obtain a predetermined proportion of the system throughput in each resource-allocation determination [63].
- constraints resulting from system model considered in [16, 57, 60]. Such constraints usually are not described by the equation in the optimization problem because results from the considered system model, directly. For example in [16, 57, 60] the subcarriers are grouped into resource blocks and for each user, the same MCS over all its allocated RBs has to be used. Moreover, in [16] the transmit power is constant per RB for all RBs assigned to a given user.

3.1.4 Energy efficiency optimization in a multiuser OFDMA network

Let us note that in the context of a multiuser OFDMA network, not only the transmit power but also the subcarrier/resource blocks assignment has to be determined. The subcarriers or resource blocks assignment is usually represented by the binary variables (that can be equal to 1 if a subcarrier or resource block is assigned to a particular user or 0 if it is not), so that the optimization problems can be classified as MINLFP problems which are very difficult to solve by standard optimization techniques. Therefore, in this section the optimization techniques used to solve a MINLFP problem in the context of the energy efficient multiuser OFDMA network are presented.

In the most of the cited papers, the optimization procedure consists of at least two stages out of all presented below: (i) transmission power allocation, (ii) subcarriers/resource blocks assignment and/or (iii) modulation and coding scheme selection. The values of the optimization variables of the particular stage are usually determined while setting the values of the optimization variables for other stages as fixed. Such an approach can be realized by the primal decomposition technique which reformulates the problem into many maximization problems. For example, in the first stage, the values of the transmission power allocated at the subcarrier which maximize the energy efficiency are determined. In the second stage, based on these powers, the optimization is carried by changing subcarriers assignment and modulation and coding schemes. For continuous transmit power values, standard optimization techniques can be used as long as the problem is concave/convex. The more complex task is to determine the binary decision variables.

Various methods can be used to solve MINLFP problems [64], e.g., branch-and-bound [57, 60], outer approximation or generalized Bender's decomposition method. The drawback of these methods is their poor scalability, i.e., these are efficient only for small size problems. For example, in the branch-and-bound method the complexity increases exponentially as the problem size increases. Therefore, the suboptimal solutions which give the near-optimal results have been proposed in the literature. Here below, the author focuses on the most common method which can be applied to different system models. In this method, applied in [16, 52, 53, 61], the binary decision variables have been relaxed to be real numbers within interval $[0, 1]$ and then the Dinkelbach [43], dual decomposition method and KKT conditions [65] have been applied to determine the transmission power allocation. Moreover, in order to determine the decision variables of the subcarrier/resource block allocation for each subcarrier/resource block, the cost-benefit metric which is equal to the achieved throughput minus the transmit power multiplied by the parameter resulting from the Dinkelbach method are obtained. Thus, if this value is positive a given subcarrier should be allocated to the user but if it is negative the assignment of this subcarrier to the user is unprofitable from the EE point of view. It is obvious that if for a given subcarrier/resource block, more than one user has a positive value of the cost-benefit metric, this subcarrier should be allocated to the user with the highest cost-benefit metric. Then, these metrics are rounded to 0 or 1 to get an integer-valued solution. The presented suboptimal solution gives the near-optimal results with superlinear convergence.

While in minority, there are also other solution methods used in the literature. For example, in [57, 60], the branch-and-bound method has been applied to find optimal RB allocation. In [50], the brute force search has been applied to find optimal subcarrier assignment, but due to extremely high complexity near-optimal and suboptimal solution have been proposed as well. The suboptimal methods which are based on the energy efficiency transmit power estimation and subcarrier assignment resulting from spectral-efficient maximization have been designed in [54, 55]. Other suboptimal methods have been proposed in [51, 52, 59]. Nevertheless, the review of all proposed methods is not the goal of this chapter because these depend on the system model and do not have universal nature.

3.2 Optimization of EE in the Downlink LTE Transmission with computational awareness

In the remainder of this chapter, the author of this thesis investigates the energy-efficient resource allocation problem in the downlink of an OFDMA network with multiple users, and presents his original contribution to this field. An iterative algorithm is developed to maximize the overall energy efficiency of the downlink transmission by allocating the RBs and the transmit power, which is constant for all RBs assigned to a given user. Moreover, it is assumed that all RBs assigned to the same user must use the same MCS, as in the LTE or 5G specification. In this form, the optimization problem belongs to a broad class of problems called MINLFP, which is very difficult to solve analytically in the original form. Hence, in order to solve it, the author of this thesis proposes an iterative algorithm with fast convergence based on the Dinkelbach method. In each iteration, the solution for the power and resource blocks allocation is derived by the numerical method using the KKT multipliers and KKT conditions, while modulation and coding scheme, for each user, is obtained by the iterative algorithm. Simulation results show that despite the computational simplicity of the proposed solution, it achieves better results than the solutions known from the literature.

3.2.1 Main contribution over the existing methods

In the recent years, the energy efficiency problem has been widely investigated for wireless communication, including systems applying OFDMA. In the literature, one can find a lot of works dealing with energy-efficient resource allocation schemes for such networks. For example, in [66], the authors focus on the downlink energy-efficient transmission in OFDMA systems where the energy efficiency metric is defined as the ratio of Shannon capacity to the total power transmitted in the network. In that paper, flat fading channel is considered. Moreover, individual subcarriers are treated independently, and are not grouped into resource blocks, unlike in the most of contemporary wireless communications systems. The approach presented in that paper is an idealized case, which does not take limitations of the practical wireless communication systems into account. The same approach is taken in [53] and [50], where the authors consider maximization of the energy efficiency for the downlink (and uplink in [50]) transmission for frequency-selective channels. Zhanyang et al. in [56] propose an energy-efficient resource allocation scheme for the downlink in the LTE networks where subcarriers are grouped into resource blocks. However there, simplified method of collecting the channel information is considered. Furthermore, the system throughput is calculated using the Shannon formula what means that the resulting throughput is higher than that resulting from the use of a specific modulation and coding scheme. In [60] and [54], the energy efficiency optimization problem is divided into two subproblems: (i) RBs (or subcarriers) allocation and (ii) power control. It means that the process of subcarrier allocation is made only one and is not change in the power control phase. In this chapter, the author of this thesis proposes the joint resource blocks and power allocation algorithm with MCS selection for the allocated RBs.

The system model which the author of this thesis considers in this chapter, is the same as in [13] and [14]. However, contrarily to those papers, where the authors focus on throughput maximization, here below, the author defines and solves the problem of energy efficiency maximization. Moreover, here, the throughput is calculated based on the target BLER curves, and the spectral efficiency of given MCS. In contrast to the cited works, the author of this thesis takes limitations of the practical wireless communication systems into account, such as the fact that the allowable code rates take discrete values, and that subcarriers are grouped in resource blocks. It is also assumed that all RBs assigned to the same user must use the same MCS, as in the LTE or 5G specification. As mentioned, the optimization problem is an MINLFP problem, which cannot be solved analytically. In order to solve it, the author of this thesis proposes the iterative algorithm with fast convergence that maximizes the overall energy efficiency of the considered OFDM LTE/5G-like network.

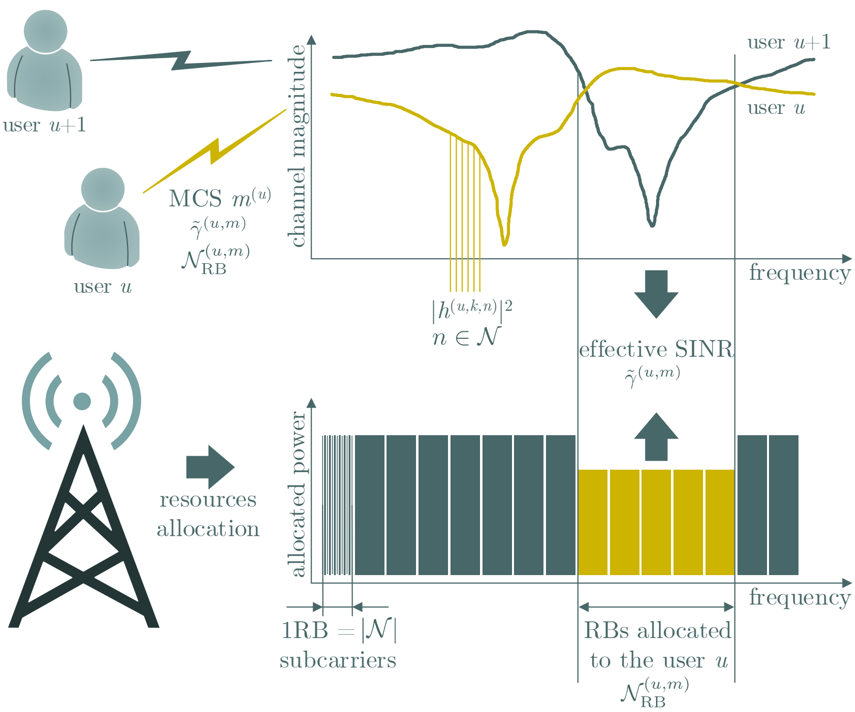

Figure 3.4: System model with MCS and power allocation for RBs of distinct users in the downlink.

3.2.2 System model and problem formulation

Let us consider the downlink transmission presented in Figure 3.4 where the set of users $\mathcal{U}$ share the set of $\mathcal{N}_{\mathrm{RB}}$ resource blocks, and each RB contains the set of $\mathcal{N}$ adjacent subcarriers. Moreover, let us assume that the users channels are reciprocal (the downlink channel has the same characteristic, as the uplink channel), and all RBs assigned to the same user in the downlink, in any given Transmission Time Interval (TTI) must use the same MCS (one from the set $\mathcal{M}$ available modulation and coding schemes), as in the LTE specification. Furthermore, all resource blocks assigned to the user, are transmitted with the same power, but the power between the users can vary. In the considered system model, the interference from and to the other system are not taken into account. Because each RB, assigned to the user, includes multiple subcarriers subject to different channel gains (attenuation), an SNR-mapping method should be applied to collect and represent the channel state information. One of such methods is Exponential Effective SINR Mapping (EESM).

In [13, 15], one can find other methods of channel-quality representation for the user's RBs. In the remainder of this thesis, the author will use the more accessible method to approximate effective SINR which is expressed as:

$$\tilde{\gamma}^{(u,m)} = \frac{\left|\mathcal{N}_{\mathrm{RB}}^{(u,m)}\right| |\mathcal{N}|}{\sum\limits_{k \in \mathcal{N}_{\mathrm{RB}}^{(u,m)}} \sum\limits_{n \in \mathcal{N}} \frac{N_0}{p_{\mathrm{T}}^{(u,m,k,n)} \left|h^{(u,k,n)}\right|^2}}, \tag{3.1}$$

where $\mathcal{N}_{\mathrm{RB}}^{u,m}$ and $\left|\mathcal{N}_{\mathrm{RB}}^{(u,m)}\right|$ is the set and the number of RBs assigned to user u who uses m-th modulation and coding scheme, respectively. Moreover, $p_{\mathrm{T}}^{(u,m,k,n)}$ is the power allocated to subcarrier n in RB k for user u and MCS m, and $h^{(u,k,n)}$ is the channel characteristic for this user at subcarrier n in RB k. The power spectral density of the white noise is denoted as N_0. In the above equations, it can be observed that RBs allocated to the users are dependent on the

Table 3.2: MCS parameters table

MCS index m	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$b^{(m)}$	0.187	0.308	0.466	0.742	1.171	1.852	3.057	4.498	7.247	10.845	16.723	25.714	38.311	59.211	95.875
$c^{(m)}$	0.044	0.045	0.054	0.066	0.091	0.141	0.234	0.275	0.461	0.632	0.911	1.355	2.461	3.551	5.445
$\gamma_{\mathrm{REQ}}^{(m)}$ [dB] [67]	-6.2790	-4.5350	-2.7910	-0.9301	1.1012	3.0802	5.2610	6.8614	8.9403	10.580	12.530	14.390	16.180	18.050	20.130

applied MCSs. From the energy efficiency perspective, this an important aspect. If we order the MCS indexes according to the bit-rates they provide, in the ascending order (the lower m the lower bit-rate) then, in the case of relatively high channel attenuation (low effective SNR) for a given RB, application of a high MCS index causes increase of the transmit power. As a result the energy efficiency can be reduced. In the typical approach, for many reasons [66]- [54], the system throughput is calculated using Shannon formula which does not take limitations of practical wireless communication systems into account. In the approach, the author depart from this ideal case, and calculates the system throughput as a real throughput resulting from the block-error rate and the spectral efficiency of the applied MCS. Consequently, in the considered system model, the throughput is defined as:

$$R = \sum_{u \in \mathcal{U}} \frac{\rho^{(m)} \left| \mathcal{N}_{\mathrm{RB}}^{(u,m)} \right| |\mathcal{N}|}{T} \left[1 - \mathrm{BLER}\left(m, \tilde{\gamma}^{(u,m)} \right) \right], \tag{3.2}$$

where m is MCS index for user u, $\rho^{(m)}$ is code rate in bits/symbol for MCS m, and T is the OFDM symbol duration. Moreover, BLER for RBs that are assigned to the user u and that use MCS m can be accurately predicted by [14]:

$$\mathrm{BLER}\left(m, \tilde{\gamma}^{(u,m)} \right) = 0.5 \cdot \mathrm{erfc}\left(\frac{\tilde{\gamma}^{(u,m)} - b^{(m)}}{\sqrt{2} \cdot c^{(m)}} \right), \tag{3.3}$$

where $\mathrm{erfc}(\cdot)$ is the complementary error function, and $b^{(m)}$ and $c^{(m)}$ are the fitting parameters for given MCS m whose values are shown in Table 3.2 and which were determined by authors using *Curve Fitting Toolbox* being part of MATLAB software.

In the considered system model, the total power consumption consists of two parts: variable transmission power P_{T} and constant circuit power P_{C}. Based on equation (3.1), the total transmit power is defined as:

$$P_{\mathrm{T}} = \sum_{u \in \mathcal{U}} \left| \mathcal{N}_{\mathrm{RB}}^{(u,m)} \right| |\mathcal{N}| \, p_{\mathrm{T}}^{(u,m,k,n)} = \sum_{u \in \mathcal{U}} \tilde{\gamma}^{(u,m)} \sum_{k \in \mathcal{N}_{\mathrm{RB}}^{(u,m)}} \sum_{n \in \mathcal{N}} \frac{N_0}{\left| h^{(u,k,n)} \right|^2}. \tag{3.4}$$

The circuit power P_{C} is the power required by all operations of transmitter circuitry, which is incurred by the radio frequency transceiver frontend and baseband processing.

The energy efficiency of the considered downlink transmission is defined as the ratio of the throughput to the total power consumed in the downlink, i.e. as the number of successfully transmitted information bits (satisfying the assumed BLER) per unit energy consumption (Joule):

$$\eta = \frac{R}{P} = \frac{R}{P_{\mathrm{C}} + P_{\mathrm{T}}} \left[\frac{\mathrm{bit}}{\mathrm{Joule}} \right]. \tag{3.5}$$

Thus, the optimization problem is defined as to find the MCS index for each user $\mathbf{m}^{\star} = \left\{ m^{(u)^{\star}} \right\}$, a set of RBs assigned to the users $\boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star} = \left\{ \mathcal{N}_{\mathrm{RB}}^{(u,m)^{\star}} \right\}$ and the value of effective SINR $\tilde{\boldsymbol{\gamma}}^{\star} = \left\{ \tilde{\gamma}^{(u,m)^{\star}} \right\}$ (depending on and resulting from the allocated transmit power $p_{\mathrm{T}}^{(u,m,k,n)}$) that maximize η:

$$\left(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star} \right) = \arg \max_{\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}} \eta \left(\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}} \right), \tag{3.6}$$

subject to:

$$\mathcal{N}_{\mathrm{RB}}^{(i,m)} \cap \mathcal{N}_{\mathrm{RB}}^{(j,m)} = \emptyset,\ i \neq j \qquad \forall i \in \mathcal{U},\ j \in \mathcal{U}, \tag{3.7}$$

$$\tilde{\gamma}^{(u,m)} \geq \gamma_{\mathrm{REQ}}^{(m)} \qquad \forall u \in \mathcal{U},\ m \in \mathcal{M}. \tag{3.8}$$

Constraint (3.7) guarantees that each RB is assigned to maximum one user. Moreover, constraint (3.8) guarantees achieving the minimum value of effective SINR $\gamma_{\mathrm{REQ}}^{(m)}$ for MCS m that assures required BLER.

3.2.3 Proposed solution

In the optimization problem, we deal with discrete values of the code rate and continuous values of the effective SINR. Furthermore, the RB that maximize energy efficiency to each user have to be assigned. Consequently, the optimization problem is MINLFP, and in the case of exhaustive search, its complexity is equal to $\mathcal{O}\left(|\mathcal{U}|^{|\mathcal{N}_{\mathrm{RB}}|}\,|\mathcal{M}|^{|\mathcal{U}|}\right)$. Moreover, in view of the ratio of two functions, the defined problem belongs to a broad class of convex-concave fractional problems. In practical communications systems, high complexity transceivers are less favorable, thus below, the author proposes the iterative algorithm with low complexity equal to $\mathcal{O}\left(|\mathcal{N}_{\mathrm{RB}}|\,|\mathcal{N}|\, i_{\mathrm{dink}}\right)$, (where i_{dink} is the number of iteration for Dinkelbach method), which achieves the higher energy efficiency than the solutions presented in the literature so far.

Transformation of the optimization problem

In order to solve the optimization problem, the objective function has been transformed into a more traceable form. In the first step of the transformation, the Dinkelbach method [43] for nonlinear fractional programming which then allows to determine the optimal value of effective SINR for each user and for a given set of the RBs is used. Thus, (3.6) is transformed into a new parametrized concave function with parameter λ, which is mathematically defined as:

$$\begin{aligned}(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star}) &= \arg \max_{\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}} F\left(\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}, \lambda^{\star}\right) = \\ &= \arg \max_{\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}} R\left(\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}\right) - \lambda^{\star} P\left(\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}\right).\end{aligned} \tag{3.9}$$

Let $(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star})$ be the optimal solution set in (3.9), and $\lambda^{\star} = \frac{R(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star})}{P(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star})}$. The following statements are equivalent:

$$\begin{aligned}F\left(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star}, \lambda\right) > 0 &\Leftrightarrow \lambda < \lambda^{\star}, \\ F\left(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star}, \lambda\right) = 0 &\Leftrightarrow \lambda = \lambda^{\star}, \\ F\left(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star}, \lambda\right) < 0 &\Leftrightarrow \lambda > \lambda^{\star}.\end{aligned}$$

Solving problem (3.9) is equivalent to finding the root of nonlinear equations $F\left(\tilde{\boldsymbol{\gamma}}^{\star}, \mathbf{m}^{\star}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^{\star}, \lambda^{\star}\right) = 0$. In order to find the root of (3.9), the Dinkelbach method can be applied, i.e., an iterative algorithm to find the λ value by solving the parameterized problem in each iteration. The algorithm using the Dinkelbach method converges to the optimal solution with a superlinear convergence rate. The detailed convergence analysis can be found in [43].

In the second step of the objective function transformation, let us introduce the decision matrix $\boldsymbol{\Psi}$ whose size is $|\mathcal{U}| \times |\mathcal{N}_{\mathrm{RB}}| \times |\mathcal{M}|$. The elements $\Psi^{(u,k,m)}$ of the decision matrix determine whether RB k is assigned to the user u, who uses MCS m. In this case, the system throughput and the total transmit power are represented as:

$$R = \frac{\rho^{(m)}\,|\mathcal{N}|}{T} \sum_{u \in \mathcal{U}} \sum_{k \in \mathcal{N}_{\mathrm{RB}}} \sum_{m \in \mathcal{M}} \Psi^{(u,k,m)} \left[1 - \mathrm{BLER}\left(m, \tilde{\gamma}^{(u,m)}\right)\right], \tag{3.10}$$

$$P_{\mathrm{T}} = \sum_{u \in \mathcal{U}} \tilde{\gamma}^{(u,m)} \sum_{k \in \mathcal{N}_{\mathrm{RB}}} \sum_{m \in \mathcal{M}} \Psi^{(u,k,m)} \sum_{n \in \mathcal{N}} \frac{N_0}{\left|h^{(u,k,n)}\right|^2}, \tag{3.11}$$

respectively. Finally, the values of decision matrix $\mathbf{\Psi}$ are equal to 0 or 1, but in order to reduce the computational complexity the binary values of matrix $\mathbf{\Psi}$ are temporary relaxed to be real numbers.

3.2.4 Energy efficient resource allocation algorithm

Here below, the author of this thesis proposes the energy efficient resources allocation algorithm with fast convergence. In order to determine the optimal value of effective SINR and the set of RBs for each user, the Lagrangian function:

$$\mathcal{L}\left(\tilde{\boldsymbol{\gamma}}, \mathbf{\Psi}, \lambda, \boldsymbol{\mu}\right) = R - \lambda\left(P_{\mathrm{C}} + P_{\mathrm{T}}\right) + \sum_{m \in \mathcal{M}} \sum_{u \in \mathcal{U}} \mu^{(u,m)} \left(\tilde{\gamma}^{(u,m)} - \gamma_{\mathrm{REQ}}^{(m)}\right), \tag{3.12}$$

and KKT conditions:

$$\frac{\partial \mathcal{L}\left(\tilde{\boldsymbol{\gamma}}, \mathbf{\Psi}, \lambda, \boldsymbol{\mu}\right)}{\partial \tilde{\gamma}^{(u,m)}} = 0, \tag{3.13}$$

$$\mu^{(u,m)} \left(-\tilde{\gamma}^{(u,m)} + \gamma_{\mathrm{REQ}}^{(m)}\right) = 0 \qquad \forall u \in \mathcal{U},\ m \in \mathcal{M} \tag{3.14}$$

are defined. The Lagrange multiplier which is responsible for fulfilling constraint (3.8) is denoted as $\mu^{(u,m)}$, $\forall u \in \mathcal{U}$, $m \in \mathcal{M}$, $\mu^{(u,m)} \geq 0$. Then, solving condition (3.13), the closed form solution of the effective SINR for user u, MCS m and for a given λ is derived as:

$$\tilde{\gamma}^{(u,m)^\star} = b^{(m)} + c^{(m)} \sqrt{-\log\left(\frac{\sqrt{\pi} c^{(m)} \lambda \sum\limits_{k \in \mathcal{N}_{\mathrm{RB}}} \Psi^{(u,k,m)} \sum\limits_{k \in \mathcal{N}} \frac{N_0}{|h_{u,k,n}|^2}}{\rho^{(m)} \left|\mathcal{N}_{\mathrm{RB}}^{(u,m)}\right| \left(1 + \mu^{(u,m)}\right)}\right)}. \tag{3.15}$$

Similarly, calculating derivative of (3.12) with respect to $\Psi^{(u,k,m)}$, obtaining:

$$\zeta^{(u,k,m)} \triangleq \frac{\rho^{(m)} |\mathcal{N}|}{T} \left[1 - 0.5\mathrm{erfc} \cdot \left(\frac{\tilde{\gamma}^{(u,m)^\star} - b^{(m)}}{\sqrt{2} \cdot c^{(m)}}\right)\right] - \lambda \sum_{k \in \mathcal{N}} \frac{\tilde{\gamma}^{(u,m)^\star} N_0}{\left|h^{(u,k,n)}\right|^2}. \tag{3.16}$$

It can be observed that the subtrahend of the above equation defines the cost of the achieved throughput for RB k, modulation and coding scheme m and for user u. Thus, if the value of variable $\zeta^{(u,k,m)}$ is positive, it means that the RB k should be allocated to the user u. It is obvious that in this solution, one RB can be allocated to more than one user, so the highest of $\zeta^{(u,k,m)}$ values for each RB and for each user, assuming that the users apply a given MCS have to be chosen. Consequently, the closed-form solution for the RBs allocation is defined as:

$$\Psi^{(u,k,m)^\star} = \begin{cases} 1 & \text{for} \quad (k^\star, u^\star) = \arg\max\limits_{k,u} \zeta^{(u,k,m)} \\ 0 & \text{for} \quad \text{otherwise} \end{cases}. \tag{3.17}$$

Based on the equations and transformations described in the previous subsection, let us propose the energy-efficient resource blocks and power allocation algorithm for a given λ and a set of modulation and coding schemes $\mathbf{m}$ which is designed as in Algorithm 3. In Algorithm 3, one can pay special attention to lines 4–6, which are responsible for finding the best RB when a user has not obtained any resource block to transmit its data. In this case, each RB is considered independently, i.e., it means that the number of RBs assigned to user u is equal 1 $\left(\left|\mathcal{N}_{\mathrm{RB}}^{(u,m)}\right| = 1\right)$, and that the optimal value of effective SINR for each RB is calculated according to the following equation:

$$\tilde{\gamma}^{(u,k,m)\star} = b^{(m)} + c^{(m)} \sqrt{-\log\left(\frac{\sqrt{\pi}c^{(m)}\lambda \sum_{k\in\mathcal{N}} \frac{N_0}{|h_{u,k,n}|^2}}{\rho^{(m)}\left(1+\mu^{(u,m)}\right)}\right)}. \tag{3.18}$$

Then, the RB, which is assigned to a user, is selected using equation (3.16) and (3.17) for $\tilde{\gamma}^{(u,m)\star} = \tilde{\gamma}^{(u,k,m)\star}$. If at least one RB is assigned to the user, the optimal value of effective SINR is determined using equation (3.15). This procedure is repeated until the sets of RBs allocated to the users achieve convergence, or the index of an iteration is equal the maximum number of iterations.

3.2.5 MCS selection algorithm

The iterative MCS selection algorithm is proposed below. Typically, the EE optimization is performed using the Shannon formula for the throughput definition, and then, a modulation and coding scheme is selected according to the value of the determined SINR value. This approach is an over-simplification of the real energy efficiency estimation problem in practical wireless communication systems. In the approach, the author of this thesis considers selection of each MCS based on the BLER curves. The first problem in the approach is that the code rates are discrete values in contrast to the standard approaches (where the Shannon formula is used) what causes that the mixed integer nonlinear fractional problem is also non-convex. Moreover, for each MCS, the set of RBs allocated to a user can be different, so the problem cannot separate into two subproblems: the RBs allocation problem and the MCS selection problem. As a consequence, the complexity of this problem is too high for practical applications. Hence, below in this chapter, the author of this thesis proposes iterative algorithm which is presented as Algorithm 4. It can be observed that for each MCS change, a new set of RBs assigned to the users and a value of parameter $\hat{\lambda}^{(u,m)}$ is determined using Algorithm 3. When all changes of MCS for all users are done, a new λ parameter

Algorithm 3 Resource blocks and power allocation

initialization the maximum number of iteration I_{RB}, the index of iteration $i_{\text{RB}} = 0$ and $\mathcal{N}_{\text{RB}}^{(u,m)} = \emptyset, \forall u \in \mathcal{U},\ m \in \mathcal{M}$
For a given λ and $\mathbf{m}$:
repeat
  if $\mathcal{N}_{\text{RB}}^{(u,m)} = \emptyset$ **then**
    Calculate $\tilde{\gamma}^{(u,k,m)\star}$ using equation (3.18) and $\Psi^{(u,k,m)\star}$ using equations (3.16) and (3.17) for $\tilde{\gamma}^{(u,m)\star} = \tilde{\gamma}^{(u,k,m)\star}$.
  else
    Calculate $\tilde{\gamma}^{(u,m)\star}$ using equation (3.15) and $\Psi^{(u,k,m)\star}$ using equations (3.16) and (3.17).
  end if
  if $\tilde{\gamma}^{(u,m)\star}$ or $\tilde{\gamma}^{(u,k,m)\star} \leq \gamma_{\text{REQ}}^{(m)}$ **then**
    Calculate $\mu^{(u,m)}$ using numerical method.
  end if
  $i_{\text{RB}} \leftarrow i_{\text{RB}} + 1$
until $\boldsymbol{\mathcal{N}}_{\text{RB}}$ converges or $i_{\text{RB}} = I_{\text{RB}}$
return $\lambda = \frac{R(\tilde{\boldsymbol{\gamma}}^\star, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\text{RB}}^\star)}{P(\tilde{\boldsymbol{\gamma}}^\star, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\text{RB}}^\star)}$

is determined by selecting the highest value of matrix $\hat{\boldsymbol{\lambda}}$ and the vector of MCS $\mathbf{m}$ is updated. Algorithm 4 finishes when one of the stop criteria is met.

3.2.6 Numerical results

In this section, computer simulation results obtained by the proposed optimization algorithm are presented. The tested system model consists of $|\mathcal{M}| = 15$ modulation and coding schemes which are defined in the LTE specification as the set of the number of available RB: $|\mathcal{N}_{\mathrm{RB}}| \in \{6, 15, 25, 50, 75, 100\}$. Moreover, in order to maximize the energy efficiency, the resource block is not necessarily assigned to any user. Each RB contains $|\mathcal{N}| = 12$ subcarriers, which are spaced by $\Delta f = 15$kHz from each other. Other parameters are as follows: for the noise power spectral density operational point in the temperature of 20°C is assumed, and that it is increased by the receiver noise figure of 10dB. Moreover, each user has to achieve the BLER lower than 10% and $P_{\mathrm{C}} = 0.1$W as assumed in [22]. The channel model is the Extended Pedestrian A.

In order to investigate the performance of the proposition, the results have been compared to the reference methods. The first method, which is called the *max-throughput*, the system throughput is maximized constrained by the maximum transmit power, which is determined by the proposed solution. In order to maximize the total throughput, the resource blocks are assigned to the users with the highest channel gain, and then, the optimal transmit power is obtained using the *water-filling* principle. Finally, the modulation and coding scheme is selected according to the effective SINR calculated by equation (3.1). The second reference scheme *Shannon EE*, which is based on the method found in [53], maximizes the energy efficiency of an OFDMA network by the power and subcarriers allocation, but without MCS selection. In order to fairly compare this reference methods with the author's proposition, the scheme presented in [53] was adapted to the system model and all subcarriers assigned to the user, are transmitted with the same power, but the power between the users can vary. After the subcarrier and power allocation the MCS is selected according to the effective SINR.

Figure 3.5 illustrates the convergence of the proposed algorithm for various cell radius l, the number of users $|\mathcal{U}|$ and for $|\mathcal{N}_{\mathrm{RB}}| = 100$ resource blocks. The energy efficiency determined by the proposed solution is normalized to the optimal one. The curves in this figure show the number of iterations resulting from Dinkelbach method equals $i_{\mathrm{dink}} = i_{\mathrm{RB}} + i_{\mathrm{MCS}}$, because this is the only unknown value in the set of $\mathcal{O}\left(|\mathcal{N}|\,|\mathcal{N}_{\mathrm{RB}}|\, i_{\mathrm{dink}}\right)$ values. It can be observed that EE figure converges

Algorithm 4 MCS selection

initialization the maximum number of iteration I_{MCS}, the index of iteration $i_{\mathrm{MCS}} = 0$, the maximum tolerance ε and $m^{(u)} = 0, \forall u \in \mathcal{U}$
repeat
  for $u := 1$ **to** $|\mathcal{U}|$ **do**
    for $m := 1$ **to** $|\mathcal{M}|$ **do**
      Use Algorithm 3 for a given λ and $\mathbf{m}$ to generate a new value of $\hat{\lambda}^{(u,m)}$ parameter and $\boldsymbol{\mathcal{N}}_{\mathrm{RB}}$
    end for
  end for
  Select a new MCS for one user according to: $m^{(u)^\star} \leftarrow \arg\max_{u,m} \hat{\boldsymbol{\lambda}}$.
  $\lambda \leftarrow \hat{\lambda}$ for $m^{(u)^\star}$
  $i_{\mathrm{MCS}} \leftarrow i_{\mathrm{MCS}} + 1$
until $F\left(\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}, \lambda\right) < \varepsilon$ **or** $i_{\mathrm{MCS}} = I_{\mathrm{MCS}}$
return $\left(\tilde{\boldsymbol{\gamma}}^\star, \mathbf{m}^\star, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}^*\right) \leftarrow \left(\tilde{\boldsymbol{\gamma}}, \mathbf{m}, \boldsymbol{\mathcal{N}}_{\mathrm{RB}}\right)$

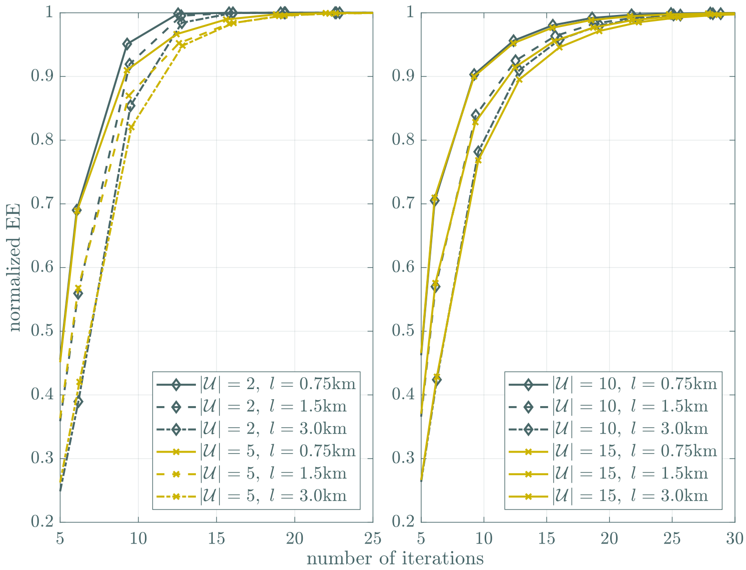

Figure 3.5: The convergence of the proposed algorithmic solution.

to the maximum value in 15 to 30 iterations depending on the system configuration.

In the next figures, the energy efficiency versus the number of available RBs is plotted. It can be seen in Figure 3.6 and Figure 3.7 that the algorithmic solution achieves better results than the results obtained by the max-throughput scheme and scheme proposed in [53] for all considered system configurations. Moreover, energy efficiency increases with the number of RBs. It means that the cost resulting from increasing of the transmit power is relatively small compared to the gains obtained by increasing the total throughput. Note that the difference between the proposed solution and the reference methods are lower for smaller cell radius because in such cases, the constant circuits power dominates over the total transmit power.

Figure 3.8 presents the energy efficiency as a function of the number of users. In this case, the system, where the users share $|\mathcal{N}_{\mathrm{RB}}| = 100$ resource blocks, and are located at the cell edge with radius 0.75 km and 3.0 km is considered. Here again, the proposed solution achieves better

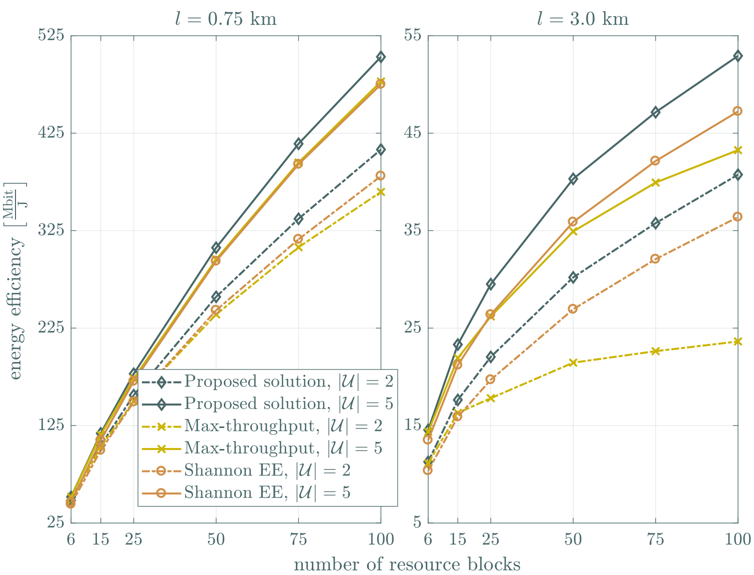

Figure 3.6: Energy efficiency versus the number of available RBs for $l = 0.75$km (left) and $l =$ 3.0km (right).

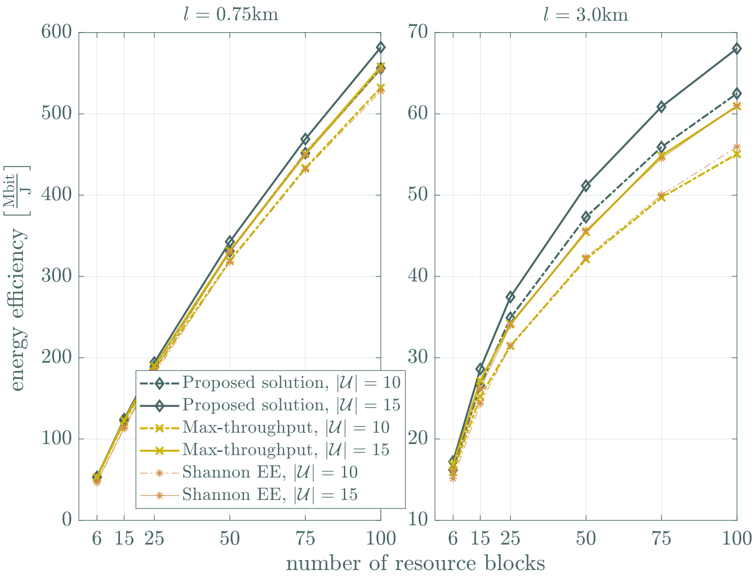

Figure 3.7: energy efficiency versus the number of available RBs for $l = 0.75$km (left) and $l = 3.0$km (right).

EE results than the reference methods. It is noticeable, that for the proposed solution and for the scheme proposed in [53], the energy efficiency increases with the number of users due to the multiuser diversity gain. However, for the max-throughput scheme, the energy efficiency can decrease because maximization of throughput can increase the total transmit power, and as a result can reduce the energy efficiency.

Figure 3.9 shows the energy efficiency as a function of cell radius. Again, it is assumed that all users are located at the cell edge. This figure confirms that the performance of the proposed algorithmic solution outperforms the another (reference) ones. It is also noticeable, that the energy efficiency decreases with the cell radius.

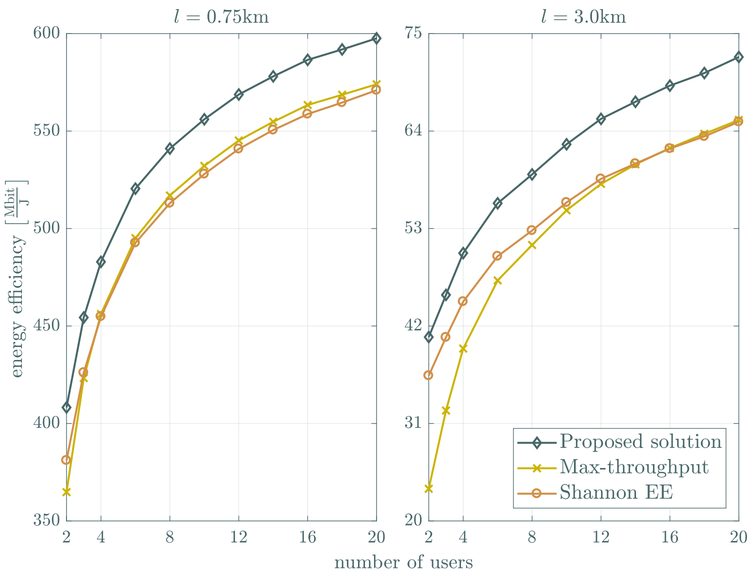

Figure 3.8: energy efficiency versus the number of users for $l = 0.75$km (left) and $l = 3.0$km (right).

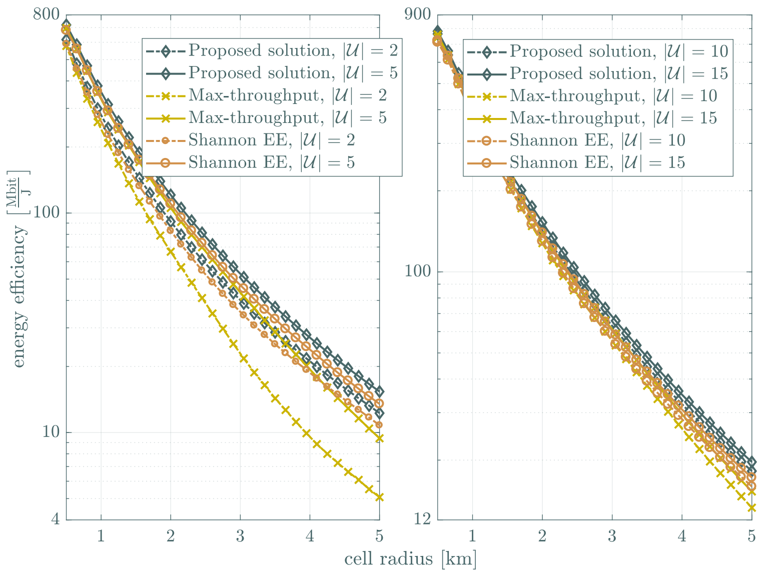

Figure 3.9: energy efficiency versus the cell radius.

3.3 Chapter summary and conclusions

In this chapter, the author of this thesis has analyzed the downlink energy-efficient transmission in an OFDMA (LTE-like) network. The EE metric has been defined as the sum throughput in the network over the network total energy consumption that includes the radio signal emission power as well as the signal processing power at all transmitters and receivers. (Again, accounting for the power consumed by necessary computations stands for the *computational awareness* in the network.) The throughput has been determined based on BLER, and the spectral efficiency for the considered modulation and coding schemes. Moreover, in the system model, the subcarriers are grouped in RBs. It means that the considered system takes the practical aspects of the wireless communication systems into account what is not a common approach in the literature particularly in the context of EE maximization. Due to the continuous values of the SNR and discrete values of the SE and code rates, the defined optimization problem is MINLFP problem. Moreover, because the modulation and coding scheme for each user has to be chosen from the finite set, the optimization is combinatorial. Therefore, the optimization problem is very difficult in the original form and cannot be solved analytically. Thus, the author of this thesis proposed the original algorithm which maximizes the energy efficiency by the joint power and RBs allocation based on the Dinkelbach method. Furthermore, the iterative algorithm for modulation and coding scheme has been proposed. The computational complexity of the proposed solution is equal to $\mathcal{O}\left(|\mathcal{N}_{\text{RB}}|\,|\mathcal{N}|\,i_{\text{dink}}\right)$ what compared to exhaustive search which complexity is equal to $\mathcal{O}\left(|\mathcal{U}|^{|\mathcal{N}_{\text{RB}}|}\,|\mathcal{M}|^{|\mathcal{U}|}\right)$ gives significant gain.

The proposed solution has been evaluated by the computer simulations. Simulation results show that the algorithm proposed by the author of this thesis achieves better results than the reference methods. The energy efficiency values obtained by the proposed solution are higher than obtained by the reference methods in all investigated scenarios. The gain in the energy efficiency of the proposed solution compared to the reference methods is between 10% and 60% depending on the scenario what can result in the reduction of the power consumption in the wireless communication systems applying it. Finally, due to low complexity of the proposed algorithm, it can be a good alternative to the methods which do not include practical complexity aspects in the system design.

Chapter 4

Energy efficiency in multiuser OFDMA relay networks

The use of relaying nodes is a promising a technique for increasing the energy efficiency of a radio communication network. In the literature, different scenarios of transmission supported by relay nodes can be distinguished. Figure 4.1 illustrates four transmission modes in the multiuser OFDMA relay network which can be found in the literature:

(i) direct transmission [68–71],

(ii) relayed transmission [68–73],

(iii) relayed transmission with direct link [74, 75],

(iv) relay beamforming [76].

Depending on the system model, the transmission mode is selected related to network conditions from the considered set of modes. The set of transmission modes can contain all transmission modes, several or one of them, e.g., direct transmission and relayed transmission. Another scenario commonly considered in the literature, is when the user pairs communicate with each other via the relay node as shown in Figure 4.2.

Nevertheless, irrespective of the scenario, in the case of the multiuser OFDMA relay network, the transmission is typically analyzed in two Time Slots (TSs). One use case, which is considered

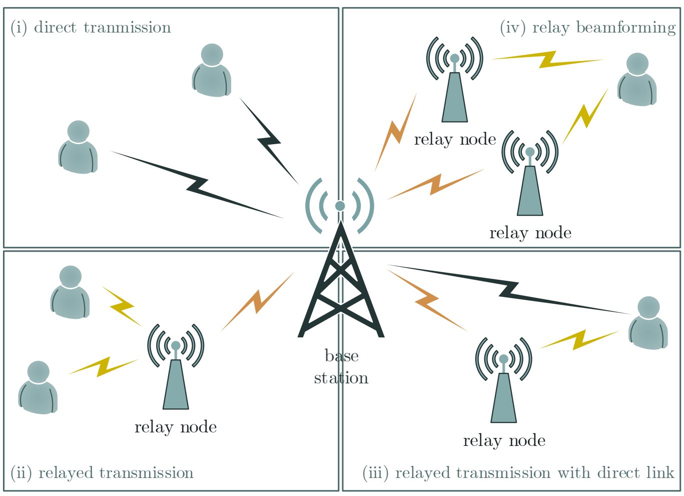

Figure 4.1: The transmission modes in the multiuser OFDMA relay network.

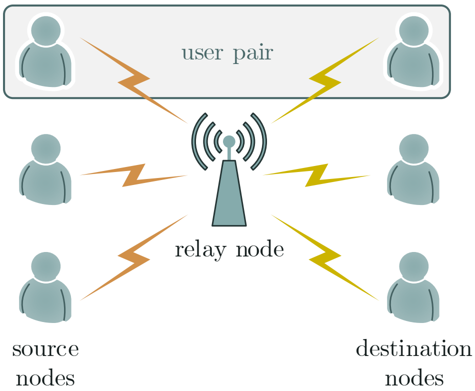

Figure 4.2: The scenario where three user pairs communicate in parallel via the relay node.

by the author of this thesis in his research is the relayed transmission with direct link. In such a case, in the first time slot, a transmitter sends data to be received by the relay and by the end-users. In the second time slot, the relay forwards the received data to their destination. Moreover, Amplify and Forward (AF) and the Decode and Forward (DF) relaying protocols are possible. The first one is based on amplification of the signal received by the relay, whereas the later on the demodulation and decoding of the received signal (resulting in noise and interference rejection) before further processing and transmission to the destination. Both protocols are elaborated in the next subsection.

The relayed transmission is considered as the promising technique for increasing the energy efficiency because the distance to end-user is divided into two or more shorter parts with lower channel attenuation. It allows reducing the transmit power while providing the same throughput or increasing the throughput for the same power allocation. Moreover, the smaller distances (better channel conditions) can result in less signal processing to be required for reliable communication, e.g., less complex channel coding and decoding is necessary. On the other hand, the cooperative transmission requires two time slots to deliver data to an end-user whereas the direct transmission only one. Moreover, similarly as base stations and end-user devices, the relay nodes consume the power related to receiving, processing and transmitting data. Thus, there are a few aspects which can impact the energy efficiency in the case of relay networks. These are summarized in Table 4.1 compared to the direct transmission.

In the context of the multiuser OFDMA relay network more degrees of freedom in the transmission flexibility can be distinguished than for a multiuser single-hop OFDMA network. In the literature the following degrees of freedom can be found:

- the transmission mode selection - if more than one of modes presented in Figure 4.1 are considered in the system, the transmission mode can be selected. Usually, in the system models from the literature, the direct transmission and the transmission with the help of the relay node are selectable. Moreover, two options of adaptability are possible. In the first the users are divided into groups, each with a pre-determined transmission mode [68–70]. In the second option the transmission modes are adaptively selected for every user related to the current channel conditions [71, 74, 76].

- the relay nodes selection - in the literature, two approaches are considered in the context of relay nodes selection. In the first approach the users are assigned to the relay nodes permanently [68, 69]. In the second approach the relay nodes are selected adaptively [70, 71, 74, 75]. The complexity of the first approach is lower than of the second one but the achieved

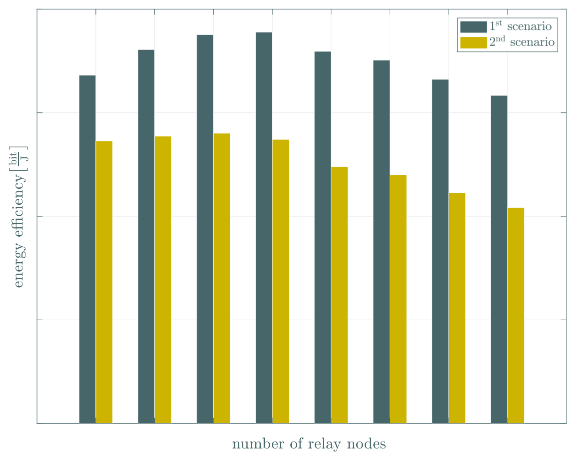

Figure 4.3: The energy efficiency against the number of the relay nodes.

energy efficiency can be lower. It results from the fact that in the adaptive relay selection more ways to transmit signal is possible. Finally, in the case of relay beamforming the relay nodes selection is extended to the set of relay nodes selection [76]. It means that more than one relay node can transmit data to one user.

- the subcarrier/resource block pairing - relies on matching subcarriers in the first and second time slot of the relaying transmission, which maximize the energy efficiency. The subcarrier pairing is realized in two possible ways: when the same [68, 69, 75, 77] or different [70–74, 76, 78–80] subcarriers are used in the first and second time slots. The first approach can be less efficient in terms of energy efficiency but less computationally complex than the second approach which reallocates resources in the second time slot. Nevertheless, the resource reallocation requires down-conversion of the signal to base band what may consume additional power.

- the localization and the number of relay nodes - these aspects are not usually determined during the optimization procedure but have a significant impact on the achieved energy efficiency. Let us remember that each relay node consumes power when it is turned on.

Table 4.1: The factors increasing or decreasing the energy efficiency of relayed and direct transmission

	Increasing EE	Decreasing EE
relayed transmission	• the distance to end-user is divided into two or more shorter parts with lower channel attenuation • reducing the transmit power while providing the same throughput or increasing the throughput for the same power allocation • less complex signal processing may be used • possibility of regenerating the signal in the relay nodes	• two time slots are required to deliver data to end-user • the relay nodes consume the power related to receiving, processing and transmitting data • more (than in the direct transmission) optimization variables which can cause more complex resource allocation algorithm
direct transmission	• one time slot is required to deliver data to end-user • less circuit power consumption than in the multiuser OFDMA relay transmission • less (than in the relayed transmission) optimization variables can reduce the complexity of resource allocation algorithm	• high transmit power for the long links • complex signal processing may be required for the long links

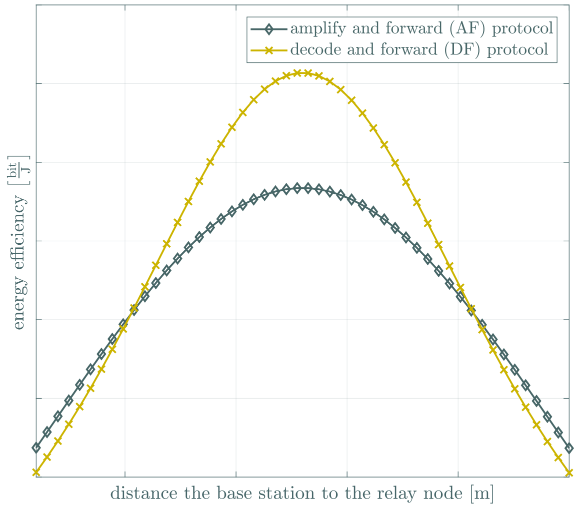

Figure 4.4: The energy efficiency against the distance form the base station to the relay node.

Thus, if the number of relay nodes is too high the power consumption can dominate over the potential profit resulting from applying the cooperative transmission. In Figure 4.3 the energy efficiency against the number of relay nodes for a sample scenarios is plotted [71, 74][1]. It can be observed that in both scenarios exist some number of the relay nodes in the network which maximize the energy efficiency. Below this value, the potential of the relayed transmission is not fully used while above this value the circuit powers dominate over the achieved profit. Moreover, if the relays are misplaced in the network, the benefit of using them may be negligible. An extreme case is when the relay node is located very close to the base station or the end-user. In such cases, the distance to the end-user is divided into a very short and long path with a length comparable to that of the direct link. Figure 4.4 illustrates the energy efficiency versus distance to the relay node from the base station for AF and DF relaying protocols. The relay is placed in between source and destination nodes of fixed positions. It can be observed that for both relaying protocols the highest energy efficiency is achieved when the relay divides the distance between the base station and end-user in half.

- the transmit power and subcarrier/resource block allocation - in this case, the transmission powers allocated on subcarriers and subcarriers assignment to the users are determined (similar to the multiuser OFDMA network or the single link).

In Figure 4.5 the trade-offs observed in the multiuser OFDMA relay network are presented. Let us observe that if the number of degrees of freedom increases the computational complexity of the resource allocation algorithms increases. On the other hand fewer number of degrees of freedom reduces the computational complexity of the algorithms at the cost of potentially decreased energy efficiency.

In this chapter, the author of this thesis examines multiuser OFDMA relay (two-hop) networks with all degrees of freedom listed above, and in the presence of interference originating from the fact that the same resources (subcarriers) can be used in the first and the second time slot of the relayed transmission. First, in Section 4.1 the author reviews the aspects of energy efficiency optimization (rate and power estimation, appropriate constraints and the optimization problem) for multiuser

[1]Note that because in this chapter introduction, the author of this thesis discusses the general issues of EE optimization in OFDMA relay networks, in Figure 4.3 and in the following one (Figure 4.4), particular values on the axes are omitted. This is intentional to show the general relations between graph coordinates, abstracting from particular simulation scenarios.

OFDMA relay networks with transmission flexibility. Then, in Section 4.2 he presents his original contribution to this field. Specifically, in Subsection 4.2.2, the considered multiuser DF relay interference network model and the problem of OFDMA resource allocation are presented for such a network, aiming at energy efficiency maximization, with computational awareness. Next, the author's original analytical and algorithmic solutions for the mentioned problem are presented. The steps in the transformation of the non-concave optimization problem are discussed in Subsection 4.2.3. In Subsection 4.2.4, the author of this thesis presents novel algorithmic solution to approach the optimal selection of the transmission mode (direct or relayed), transmission power, subcarriers and subcarriers-pairing. This is followed by the algorithm complexity analysis in Subsection 4.2.5. In Subsection 4.2.6, the computer simulation results are provided and compared against the performance of reference methods. The chapter is summarized and concluded in Section 4.3.

4.1 State of the art

4.1.1 Data rate estimation in a relay network

All the papers considered in this thesis, investigating a multiuser OFDMA relay network use the Shannon formula for the data rate estimation. This is in the contrast to the OFDM single link and multiuser OFDMA network, where other solutions were used as well. However, the specific usage of Shannon formula depends on the considered relaying protocol. Figure 4.6 illustrates the transmission with help of the relay node and the power consumption related to the amplify and forward and decode and forward relaying protocols. Let us note that if the direct link is not considered (e.g., it is in a deep fade), the SNR at the end-user device on subcarrier n aims to zero: $\gamma^{(u,n)} \to 0$. Such an assumption is commonly applied mainly due to the increase in the complexity of the optimization problem. Nevertheless, if the direct link is taken into account, it can cause the increase in the energy efficiency without any additional cost because the signal received by the end-user from the relay node, in the second time slot, is combined with the signal received from the base station in the first time slot, using e.g. the Maximum Ratio Combining (MRC) method, thus the SNR in the receiver increases, as well. In the context of the energy-efficient resource allocation the link data rate is described differently for each relaying protocol:

- the amplify and forward protocol wherein the signal received in the first time slot by a relay node is amplified and transmitted to the end-user in the second time slot. Thus, it can be observed that no time-consuming and energy-intensive signal processing is carried out. On the other hand, let us remember that the relay amplifies not only desired signal but all other received signals as well. The data rate of user u while using subcarrier pair (n, k), i.e., subcarrier n for transmission from BS and subcarrier k for transmission from the relay, and

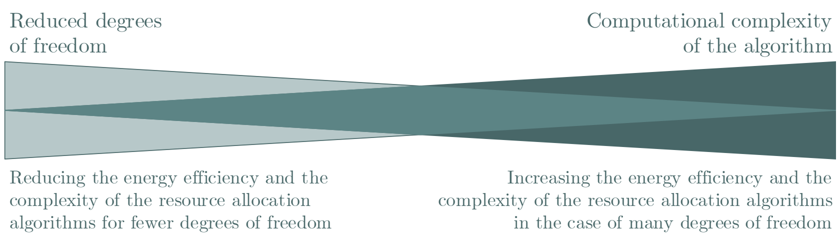

Figure 4.5: The trade-offs observed in the multiuser Orthogonal Frequency Division Multiple Access relay network.

applying MRC reception can be estimated by [81]:

$$r_{\mathrm{R}}^{(u,n,k)} = \frac{1}{2}\Delta f \log_2\left(1 + \frac{\gamma^{(\mathrm{RN},n)}\gamma^{(u,k)}}{1+\gamma^{(\mathrm{RN},n)}+\gamma^{(u,k)}} + \gamma^{(u,n)}\right), \tag{4.1}$$

where $\gamma^{(x,y)}$ determines the SNR value at the receiver x observed on subcarrier y as shown in Figure 4.6. Moreover, u denotes UE, and Relay Node (RN) denotes the relay node. Because of two-slot transmission the factor $\frac{1}{2}$ scales Shannon formula. Moreover, in some papers, e.g., [68–70], the authors have applied the approximation for high receiver's SNR values. Moreover, in [72, 77, 82] the data rate estimation of the AF relaying protocol in the interference networks can be found.

- the decode and forward protocol wherein the received by relay node data (in the first time slot) are decoded and then coded again and forwarded to end-user (in the second time slot). This approach can increase the total power consumption but the potential errors can be eliminated in the relay node and thus they are not propagated to the end-user. For DF relaying protocol the data rate of user u using subcarrier pair (n,k) may be expressed as [71, 73, 81, 83]:

$$r_{\mathrm{R}}^{(u,n,k)} = \frac{1}{2}\Delta f \min\left\{\begin{array}{l}\log_2\left(1+\gamma^{(\mathrm{RN},n)}+\gamma^{(u,n)}\right)\\ \log_2\left(1+\gamma^{(u,k)}\right)\end{array}\right\}. \tag{4.2}$$

The factor of $\frac{1}{2}$ in (4.2), similarly as in (4.1), accounts for the fact that two time slots are required. Moreover, in [78–80] the data rate estimation of the DF relaying protocol in the interference networks can be found.

Sometimes, the authors have consider AF relaying protocol instead of DF protocol because they think that DF relaying protocol requires more than two time slots due to the time-consuming signal processing. Finally, in Table 4.2 the pros and cons of the described relaying protocols are summarized.

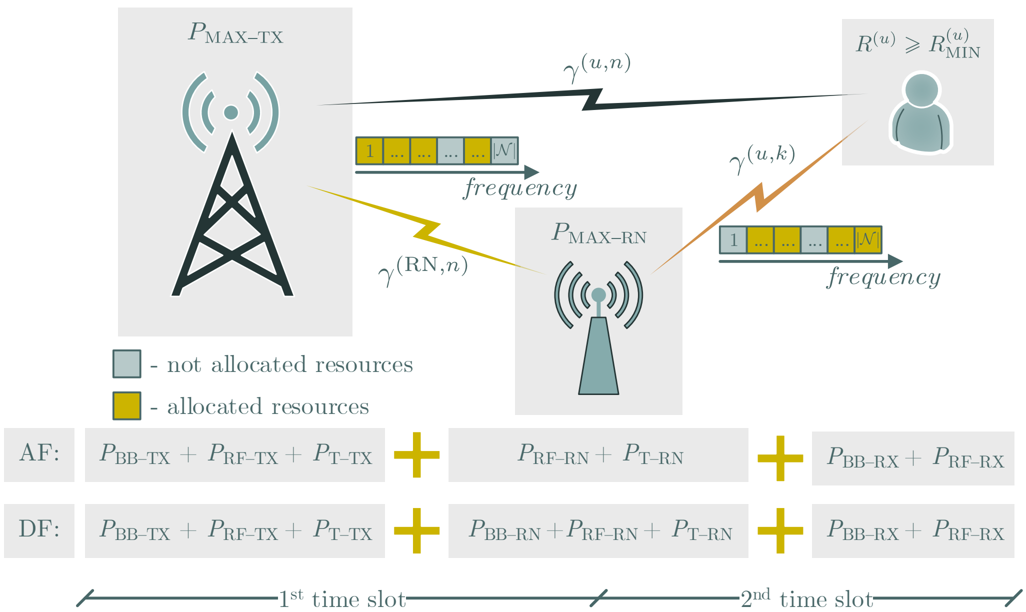

Figure 4.6: Transmission supported by the relay node, and the power consumption related to the amplify and forward and decode and forward relaying protocols, where $\gamma^{(x,y)}$ determines the SNR value at the receiver x observed on subcarrier y.

Table 4.2: Pros and cons of the relaying protocols

	Pros	Cons
amplify and forward	• no time-consuming and energy-intensive BB signal processing is carried out • two time slots are enough to deliver the data • the simple structure of the relay node	• the increase in the total power consumption resulting from RF signal processing in the relay node • the relay node amplifies not only desired signal but also other received signals (the potential errors can be propagated to the end-user) • the resource reallocation is limited and may require additional signal processing that increases the power consumption
decode and forward	• the potential errors can be eliminated in the relay node (are not propagated to the end-user) • the possibility to resource reallocation during the BB signal processing	• the increase in the total power consumption resulting from the BB and RF signal processing in the relay node • the time-consuming signal processing may require more than two time slots to deliver the data to end-user • the complex structure of the relay node

Table 4.3: The values of the power consumption parameters in the multiuser OFDMA relay networks.

Papers	Scenario	TX P_C [W]	RN P_C [W]	RX P_C [W]	TX PA efficiency	RN PA efficiency	$\beta \left[\frac{W}{Mbit/s}\right]$
Cheung *et al.* [68,69]	AF downlink	60	20	–	38%	20%	–
Loodaricheh *et al.* [70]	AF downlink	100	0.1	0.1	38%	100%	–
Lu *et al.* [75]	DF with DL downlink	0.05, 0.1, 0.2	–	–	50%	50%	0.38
Xiong *et al.* [76]	DF with DL downlink	0.2	–	–	38%	38%	0.01
Bossy *et al.* [71]	DF downlink	40	4	0.1	100%	100%	–
Singh *et al.* [73]	DF downlink	0.1	0.1	–	100%	100%	–
Bossy *et al.* [74]	DF downlink	40	4	0.1	100%	100%	0.01
Zappone *et al.* [83]	DF	–	–	0.01	100%	100%	–
Xiong *et al.* [85]	AF	0.025	–	0.025	40%	40%	–
Singh *et al.* [72,77]	AF	0.2	0.1	0.2	100%	100%	–
Singh *et al.* [78]	DF	–	0.025	0.025	100%	100%	–
Singh *et al.* [82]	AF	0.025	0.025	0.025	100%	100%	–
Singh *et al.* [79]	DF	0.01	–	0.01	100%	100%	–
Singh *et al.* [80]	DF	0.025	0.05	0.025	100%	100%	–

It can be observed that the equations (4.1) and (4.2) describe the data rate achieved by user u using a given subcarrier pair. Thus, in general, the total throughput in the multiuser OFDMA relay network within two time slots is equal to the sum of the data rate for all users links using subcarriers assigned to them, in one of the selected transmission modes or relaying protocols if they can be adaptively selected according to channel conditions. It means that the total throughput can contain the throughput of relayed transmission as well as the throughput of direct transmission. In order to avoid inter-user interference, typically it is assumed that the subcarriers pair can be assigned to the maximum one user among all transmission modes. Nevertheless, there are some paper where the same subcarrier can be used by more users [71, 74, 83, 84]. It may result in interference among signals transmitted to different users but if the channel attenuation values in the interfering links are relatively high, the interference may be small enough that the transmission will result in higher EE.

4.1.2 Total consumed power estimation in a relay network

Similar to the data rate estimation, the total consumed power depends on the relaying protocol:

- in the case of the AF relying protocol the signal received by relay node does not have to be downconverted to baseband, thus the total power consumption equals:

$$P = \underbrace{P_{\mathrm{T-TX}} + P_{\mathrm{T-RN}}}_{P_{\mathrm{T}}} + \underbrace{P_{\mathrm{BB-TX}} + P_{\mathrm{BB-RX}}}_{P_{\mathrm{BB}}} + \underbrace{P_{\mathrm{RF-TX}} + P_{\mathrm{RF-RN}} + P_{\mathrm{RF-RX}}}_{P_{\mathrm{RF}}}, \tag{4.3}$$

  as shown in Figure 4.6. It can be observed that the transmit power is the sum of transmission power allocated in the transmitter and relay node keeping in mind that these transmissions happen typically in two consecutive time slots. Moreover, the power consumption by the RF signal processing in the relay node $P_{\mathrm{RF-RN}}$ can be divided into receiving and transmitting part but in the literature, it is usually assumed to be one value.

- in the DF relaying protocol, the received signal is downconverted, decoded, coded and modulated, causing increased power consumption. Thus, the power consumption model contains in addition the power consumed by the BB processing in the relay node $P_{\mathrm{BB-RN}}$ resulting in the total power consumption:

$$P = \underbrace{P_{\mathrm{T-TX}} + P_{\mathrm{T-RN}}}_{P_{\mathrm{T}}} + \underbrace{P_{\mathrm{BB-TX}} + P_{\mathrm{BB-RN}} + P_{\mathrm{BB-RX}}}_{P_{\mathrm{BB}}} + \underbrace{P_{\mathrm{RF-TX}} + P_{\mathrm{RF-RN}} + P_{\mathrm{RF-RX}}}_{P_{\mathrm{RF}}}. \tag{4.4}$$

  Similarly to the power consumption by the RF signal processing in the relay node, the power consumed by the BB processing $P_{\mathrm{BB-RN}}$ can be divided into transmitting and receiving part but it is usually assumed to be one value. Moreover, $P_{\mathrm{BB-RN}}$ may depend on the complexity of the signal processing.

Depending on the considered past work, some elements of the models presented above are taken into account and some are omitted. Therefore, similarly as in the previous section in the case of multiuser OFDMA network, the values of the power consumption parameters used by various authors are collected in Table 4.3. It is obvious that due to the diversity of the relay nodes and end-user devices in the network the circuit power consumption can be different. Nevertheless, in all cited papers it is assumed that the circuit power consumption is the same among the end-user devices and relay nodes. Moreover, in some papers [75, 76] the circuit power has not been divided into power consumed by BS, relay node and end-user but has been summed in one value. Furthermore, it can be observed that in Table 4.3 the direction of transmission (downlink or uplink) is not specified for some papers. These authors consider transmission between pairs of users with help of the relay node as shown in Figure 4.2. If some value in Table 4.3 is not specified, it means that such an parameter has not been considered. If there is more than one value provided, it means that the authors have analyzed different scenarios.

4.1.3 Constraints in a multiuser OFDMA relay network

There is high number of potential degrees of freedom in the multiuser OFDMA relay network. Below the author summarizes the constraints considered in the related papers:

- the maximum transmit power constraint considered in [68–70, 72–80, 82]. In the context of practical wireless communication systems, the transmit power should be limited in each transmitter. Nevertheless, the common approach in the literature is to ensure that the sum of the power allocated in all transmitters does not exceed the maximum power budget of the whole system.

- the minimum data rate constraint which has been taken into account in [70, 72, 74, 77]. Due to two time slots that are required to deliver the data to the end-user in the relayed transmission mode, two approaches are considered in the context of the data rate constraints. In the first approach, the data rate is considered over two time slots. It means that in the direct transmission the data rate achieved by the user is summed over two time slots [74] or scaled by factor $\frac{1}{2}$ [70]. If the sum of the data rate achieved in the direct transmission mode is not scaled the factor $\frac{1}{2}$ is neglected for relayed transmission. Whereas, in the second approach the minimum data rate constraint ensures that the data rate achieved in the one time slot has to gather or equal to the assumed threshold, thus for the relayed transmission the data rate is scaled by the factor $\frac{1}{2}$ [72, 77, 82].

- the subcarrier assignment constraints which restrict each subcarrier to be used at most once in each time slot in order to avoid interference. In the contrast to the multiuser OFDMA network this constraint has two meanings in the context of relay network. On the one hand, it ensures that a single transmission mode, usually direct or relayed, is chosen for each user-subcarrier pair while on the other hand guarantees that each subcarrier is only allocated to at most one end-user. In this form, the subcarrier assignment constraints have been considered in [68–70, 76]. Nevertheless, in the literature exist papers [71, 74, 77] where the subcarrier can be utilized in the direct and relayed transmission mode simultaneously, but within one transmission mode, it can be utilized by one user. Such an approach can cause interference, however, the properly designed resource allocation algorithm can increase the energy efficiency compared to the network without inter-user interference. Moreover, in the scenario wherein the user pairs communicate with each other via relay node [72, 73, 75, 78–80] (Figure 4.2) or only the relayed transmission mode is considered [75], the subcarrier assignment constraints comes to guaranteeing that subcarrier or subcarrier pair is utilized by only one user.

- the proportional rate fairness constraint considered in [75, 76, 85]. It is defined in the same way as in the multiuser OFDMA network. Thus, each user would obtain a predetermined proportion of the system throughput in each resource-allocation determination.

4.1.4 Energy efficiency optimization in a multiuser OFDMA relay network

As presented in Figure 4.5, the complexity of the resource allocation algorithm increases with the number of the degree of freedom. Moreover, usually the originally defined optimization problem can not be solve by the standard optimization techniques and some transformations may be required. Thus, let us review the techniques/methods applied to solve the energy efficiency optimization problem in the multiuser OFDMA relay network:

- the Dinkelbach method known from the previous sections allows to transform the objective fractional function into a new parameterized concave function. Let us remember that the Dinkelbach method can be applied if the numerator of the objective function is concave while the denominator is convex or if the numerator is affine, the denominator does not have to be restricted in sign. The transformation of the objective function into the parameterized concave function has been applied in [68–74, 76–80, 82, 83, 85], thus in 15 out of 16 cited in this section papers, even when the numerator is non-concave. In this case other methods (described below) can be applied to transform the non-concave objective function into the series of concave functions.

- the epigraph method which is usually applied in the context of the decode and forward relaying protocol and the linearly rate-dependent circuit power consumption model. It can be observed that in equation (4.2) the $\min\{\cdot\}$ function is used to calculate the data rate for DF relaying protocol. From the optimization point of view it causes that the optimization problem belongs to the class of the max-min programming problem [71, 73, 78–81, 83]. Therefore, by applying the epigraph method the auxiliary variable is introduced replacing the $\min\{\cdot\}$ function. It requires two additional constraints to be created because the auxiliary variable has to be lower than or equal to the arguments of $\min\{\cdot\}$ function but on the other hand the standard optimization techniques can be applied after this transformation. In the case of the linearly, rate-dependent circuit power consumption the auxiliary variable is introduced making the denominator convex or affine [74].

- the SCA method transforms the non-convex/non-concave function into the series of convex/concave ones. The main idea of SCA method in the context of non-concave function is presented in Figure 4.7. The non-concave function $f(x)$ is locally approximated in i-th iteration by a concave function $\tilde{f}\left(x|x^{(i)}\right)$ that is equal to the approximated function for $x = x^{(i)}$ and not smaller in the rest of its range. The approximation is used to find new solution $x^{(i+1)}$. This procedure is repeated until the stop criteria are met. Because the approximation of the originally optimization problem is solved in each iteration, it is not guaranteed to obtain the global optimum. Nevertheless, due to convexity/concavity the convergence of the method is guaranteed. The SCA method is usually applied in the context of the system with inter-user interference wherein the function describing the users data rate is the source of the non-concavity [71, 72, 74, 77–80, 82, 83, 85]. In the literature two approaches to determine the approximation function can be found. In the first approach, the concrete approximation function together with replacing the optimization variables by equivalent ones is used. It means that the non-concave/non-convex function has to have a specific form that allows for approximation. This is commonly applied in the relayed transmission with the assumption that the direct link is not used [72, 77–80, 82]. The more universal method, based on the Difference of Concave/Convex (DC) programming, is considered in the second approach.

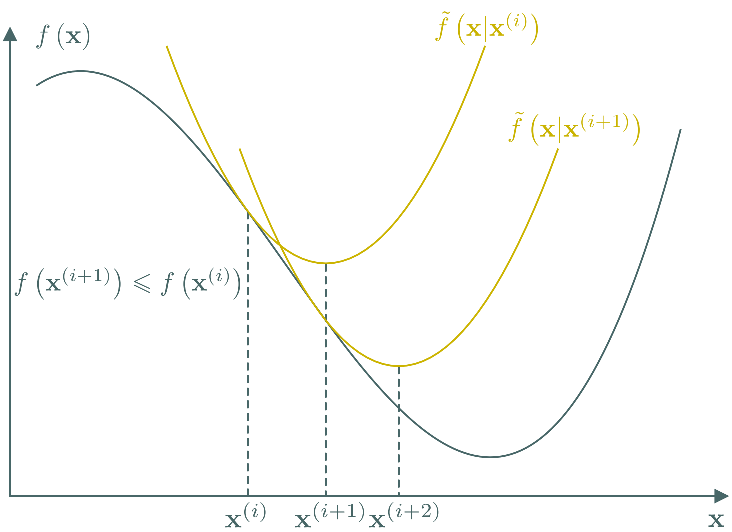

Figure 4.7: The illustration of the Successive Concave/Convex Approximation method.

Table 4.4: The optimization methods used depending on the system model.

	System model							Optimization methods					
	amplify and forward	decode and forward	pre-defined relay assignment	adaptive relay selection	subcarrier pairing	linearly rate-dependent power consumption model	inter-user interference	Dinkelbach method	epigraph method	SCA method	Hungarian algorithm	cost-benefit metric	other
Cheung *et. all* [68, 69]	×		×					×				×	
Loodaricheh *et. all* [70]	×			×	×			×			×	×	
Xiong *et. all* [76]		×		×		×							×
Bossy *et. all* [71]		×		×	×		×	×	×	×	×	×	
Bossy *et. all* [74]		×		×	×	×	×	×	×	×	×	×	
Lu *et. all* [75]		×		×		×							×
Singh *et. all* [77]	×		×				×	×	×				
Singh *et. all* [73]		×	×		×			×	×		×	×	
Singh *et. all* [72, 82]	×		×		×		×	×	×	×	×	×	
Singh *et. all* [78–80]		×	×		×		×	×	×	×	×	×	
Xiong *et. all* [85]	×		×				×						×

This requires the approximated non-concave/non-convex function to be a difference of concave/convex functions. Then, the subtrahend is approximated using the first order Taylor series at a given point achieving the difference of a concave/convex function and a linear function. This solution is typically used when the first one is not possible.

- the Hungarian algorithm that solves the assignment problem in polynomial time and is usually used in the context of the subcarrier pairing. It means that the Hungarian algorithm determines which subcarriers will be utilized as a pair in the first and second time slot, respectively. The input of the Hungarian algorithm is the $|\mathcal{N}| \times |\mathcal{N}|$ matrix with each element containing the cost of utilizing a given subcarrier pair in the first and second time slot. From the energy efficiency optimization point of view, it means that for each subcarrier pair, the user and relay node which maximize the energy efficiency have to be determined. Thus, actually, all possible combinations of the user-relay node pair for a given subcarriers pair should be checked. Hence the complexity of the resource allocation algorithm in the approach where the users are assigned to the pre-defined relay nodes is lower than in the approach with the adaptive assignment because fewer combinations have to be checked. The cost of utilizing a given subcarrier pair used by the user-relay node pair can be obtained by the cost-benefit metric in an analogical way as in the multiuser OFDMA network. In the context of computational complexity, the time complexity of the original algorithm is $\mathcal{O}\left(|\mathcal{N}|^4\right)$ [86] but it can be modified to achieve an $\mathcal{O}\left(|\mathcal{N}|^3\right)$ [87] running time. Thus, it can be observed that the subcarrier pairing together with adaptive relay selection causes the high computational complexity of the energy efficiency resource allocation algorithm.

Finally, Table 4.4 presents the optimization methods used depending on the scenario. It can be seen that with the increasing complexity of system model and the increase in the number of degrees of freedom, the number of optimization methods that have to be used grows. At the same time the computational complexity of the resource allocation algorithm rises.

4.2 Energy-efficient resource allocation in multiuser DF relay interference network with computational awareness

In this section, the author presents his original contribution to the field of design of energy-efficient resource allocation in multiuser DF relay interference network with computational awareness. He investigates joint subcarrier allocation, subcarriers pairing and power loading for optimized energy efficiency in multiuser and multicarrier downlink decode and forward relay interference networks with computational awareness, i.e., taking computations-related energy into account. In order to maximize EE of the network, the transmission mode is adapted to instantaneous channel conditions. For the benefit of spectral-efficiency, both direct- and relayed transmission is allowed to use the same SCs simultaneously. Linearly rate-dependent power consumption of signal processing is considered. The formulated optimization problem is the nonconvex fractional mixed binary-integer programming problem, which has Non-deterministic Polynomial-time (NP)-hard complexity. Hence, the author approximates the problem by the series of equivalent convex problems applying convex relaxation techniques such as a Successive Concave/Convex Approximation. Based on these transformations, the author develops an iterative algorithm exploiting the Dinkelbach method to tackle the nonlinear fractional programming problem which maximizes EE of the system. Moreover, in the considerations, the total transmission power constraint and the minimum required rate constraints have been included. Simulation results demonstrate the effectiveness of the proposed solution for future relay networks.

4.2.1 Main contribution over the existing methods

The energy-efficient resource allocation in OFDMA relay networks has been investigated in [68, 70, 75, 76, 88–90]. In [70], the authors have developed a joint relay selection, SC allocation, pairing, and power allocation algorithm for EE maximization in multiuser AF relay networks. Two groups of users have been considered: one is supposed to receive data directly from the BS in the first time slot, amplify, and forward data to the second group in the second TS. Thus, adaptive selection of the groups members has not been taken into account. Moreover, the authors assume that the direct-link channel, between BS and users belonging to the second group, is deeply fading. Furthermore, the power consumption model encompasses just the transmit power and the constant device on-off power without the power consumed by BB signal processing. Simplified system model is presented in [68]. In contrast to [70], the authors assume fixed relays locations in the network, and use of the same SCs in two TSs. Again, the power consumed by the BB processing has not been considered, the transmission mode has not been selected adaptively, and the direct-link interference between BS and a user has not been taken into account when the relaying mode is applied (direct and relayed transmission are not interfering). In [90], an energy-aware system has been considered for multiuser relay networks applying the AF protocol. Similarly to most other works, the covered region is divided into two areas, in each only one of the two transmission modes is served. Moreover, the power consumption of BB processing is not considered in the relay network, neither the interfering links between BS and a user in the relaying region. A more practical system presented in [75] assumes transmission via just one relay, and considers the BB signal-processing power. However, the convexity of the considered optimization problem is not proven, and the suboptimal solution is proposed. Furthermore, reuse of OFDM subcarriers in the second TS is not considered. In [76], multiple relay-aided OFDM systems are presented, where DF relay beamforming is employed. There, the BB-power-consumption model is included but the optimal solution and SCs reuse are not considered.

Optimization of EE in multiuser interference relay networks employing the AF or the DF protocol is considered in [78, 80, 91, 92]. In these works, non-cellular system is considered with multiple sources, destinations and one relay intermediating between them. There, SCs reuse can be applied in the relayed uplink when a relay can receive signals from multiple sources at the same SCs and in the relayed downlink, when a relay can transmit data to different destination receivers using the same SCs. Thus, interference occurs for users, what making the presented EE optimization problem nonconvex. Moreover, it is assumed that there is no interference channel in the direct link between sources and destinations, and the power consumption of BB processing is not included in the problem definition. Moreover, a specific case of SCA method has been applied to transform the optimization problem into a series of convex approximation functions which is not adequate in the considered case. In [93] similar scheme has been applied in the context of multicell network but the authors have consider multicell cluster with one relay-sharing for cell-edge users and the power consumed by BB-processing has been neglected.

In [83,84,94], the authors have proposed other methods to optimize EE metric in the interference networks. Nevertheless, the proposed method can not be applied in the considered system model in a direct way, because the authors have assumed the simplified model of the power consumption. In this case, the numerator is only nonconvex function while the denominator is affine, what simplifies the optimization problem transformation, significantly. In the considered case, the author takes the BB signal processing power depending on achieved rate into account, which causes that the numerator as well as the denominator of the objective function are nonconvex functions. Therefore, in order to solve the presented optimization problem, the additional transformations have to be done. Moreover, in [83, 84, 94], the authors have focused mainly on the power allocation algorithm while the optimal SC allocation and pairing (in the case of DF relay network) is usually neglected.

In this thesis, the author focuses on the EE optimization for the multiuser OFDMA downlink DF relay interference network. Here, BB-processing power consumption in taken into account, making the network management computationally-aware. The author proposes joint SCs pairing (SCs selection for the subsequent TSs), SCs and power allocation together with the transmission mode selection algorithm maximizing EE of the network. The novelty and the main contributions of the author of this thesis are as follows:

- In this thesis, the energy efficiency metric is optimized in the interference relay networks where the same subcarrier can be used by the base station and relay nodes causing the interference to the end-users. In the existing papers [68, 70, 75, 95] a given subcarrier can be assigned to only one user in direct or relayed transmission. Therefore in the considered system, three transmission modes can be chosen based on channel conditions. Apart from two standard modes: direct and relayed transmission using two TSs, the author considers the new approach where in the second TS (when a relay forwards data to an end-user), BS can simultaneously transmit the signal to another user using the same SC as the relay (what can increase spectral-efficiency). This causes intracell and intercell interference observed by the involved users. This also complicates the problem by making it nonconvex.

- In the considered model, one of the three mentioned transmission modes is adaptively selected for every user, in contrast to the common approach to EE optimization in relay networks [68, 70], where users are divided in groups, each with a pre-determined transmission mode. The common approach reduces the optimization complexity but is less efficient than proposed.

- In the considered system, the signal received by the end-user from the DF relay, in the second TS, is combined with the signal received from BS in the first TS, using MRC method, what increases the SINR. This effect is desired for EE, but it impedes the optimization problem, and past works [78, 80, 91] neglect it. The author of this thesis presents the optimization-problem solution by applying the SCA method to transform the problem to more tractable form.

- Moreover, the power consumption of BB processing has been taken into account. Although the power model, linearly dependent on the throughput, is known in the literature [23,75,76], it is usually neglected in relay networks due to non-convexity of the EE optimization problem. The author proposes transformation of the problem to find its solution.

4.2.2 System model and problem formulation

Let us consider the downlink transmission in a single-cell network with the set of DF relay nodes, denoted as $\mathcal{R}$. Each relay node works in the half-duplex mode i.e., the relay cannot receive and transmit data, simultaneously. In the considered network two sets of can be distinguish. The set $\mathcal{U}_{\mathrm{D}}$ denotes the users receiving data via direct transmission while $\mathcal{U}_{\mathrm{R}}$ denotes the users receiving data via relayed transmission with direct link. Moreover, the set of all users in the network is denoted by $\mathcal{U} = \mathcal{U}_{\mathrm{D}} \cup \mathcal{U}_{\mathrm{R}}$. The available bandwidth is divided into OFDM SC separated by Δf. The set of subcarrier is denoted as $\mathcal{N}$. As mentioned before the direct transmission required on TS to deliver data to end-user whereas the relayed transmission with direct link two TSs. In the first TS, base station transmits data received by the relays and by the UEs, while in the second time slot, the relays decode and forward the received data to their destinations. Moreover, in this model, the same subcarrier in the second TS of the direct and relayed transmission can be used, simultaneously. The example illustrating transmission in two TSs for the mentioned situation is presented in Figure 4.8. In the presented example, two end-users (denoted as u_{D} and u'_{D}) receive data directly from the base station, while one user u_{R} receives data from BS with the help of relay r. In the first TS, one can observe the standard case wherein data are transmitted to user u_{D} and to relay r using SC n' and n, respectively. Note that data received by the relay can be received by user u_{R} (in the first TS). In order not to cause too high interference, transmissions from BS to different users have to use different SCs ($n \neq n'$). However, in the second TS, both the relay and BS can use the same SC ($k = k'$) for signal transmission to user u_{R} and u'_{D}. This approach results in interference among signals transmitted to different users, but if the channel attenuation values in the interfering links are high it can increase spectral efficiency as well as energy efficiency.

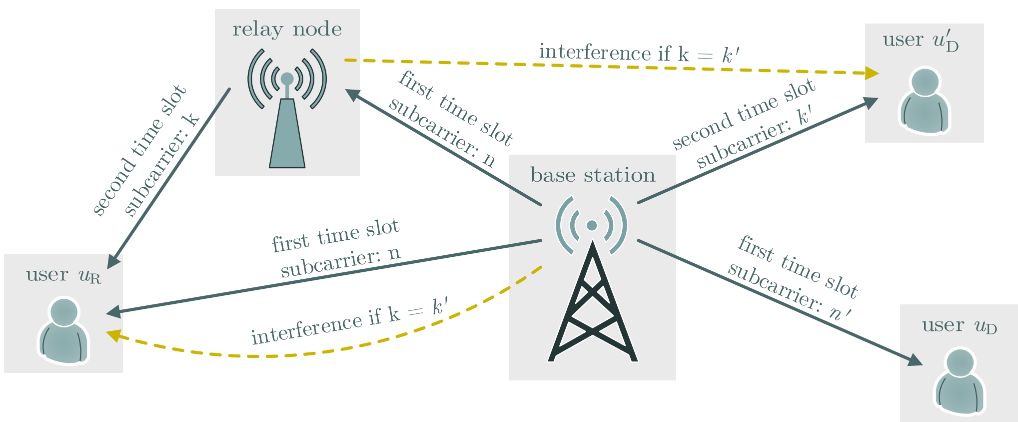

Figure 4.8: Exemplification of the relayed and direct transmission modes using two time slots and subcarriers: n, k, n' and k'.

Moreover, in contrast to the existing solutions [68, 70], in this system, the users are not grouped a priori, with pre-determined direct or relayed transmission. It means that each user adapts the transmission depending on the channel condition, to maximize EE of the network.

In the presented network model, the capacity of the relayed transmission link between base station and user u_{R} with the help of relay r, when using SC n in the first TS, and SC k in the second TS [95]:

$$r_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} = \min\left\{ r_{\mathrm{R,T1}}^{(r,n)}, r_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} \right\}, \tag{4.5}$$

where $r_{\mathrm{R,T1}}^{(r,n)}$ and $r_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}$ describe the involved links capacities between BS and the relay node r in the first TS given by:

$$r_{\mathrm{R,T1}}^{(r,n)} = \Delta f \log_2 \left(1 + \frac{\Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} p_{\mathrm{R,T1}}^{(n)} \left| h^{(r,n)} \right|^2}{\Delta f N_0} \right) \tag{4.6}$$

and between RN r and the end-user u_{R} in the second TS of the relayed transmission:

$$r_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} = \tag{4.7}$$
$$\Delta f \log_2 \left(1 + \frac{\Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} p_{\mathrm{R,T2}}^{(r,k)} \left| h^{(u_{\mathrm{R}},r,k)} \right|^2}{\Delta f N_0 + \sum\limits_{u_{\mathrm{D}} \in \mathcal{U}_{\mathrm{D}}} \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} p_{\mathrm{D,T2}}^{(k)} \left| h^{(u_{\mathrm{R}},k)} \right|^2} + \frac{\Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} p_{\mathrm{R,T1}}^{(n)} \left| h^{(u_{\mathrm{R}},n)} \right|^2}{\Delta f N_0} \right),$$

respectively, where $p_{\mathrm{R,T1}}^{(n)}$ and $p_{\mathrm{R,T2}}^{(r,k)}$ and determine the transmission powers allocated in the base station and relay node r on SCs n and k in the first and second TS of the relayed transmission while $p_{\mathrm{R,T1}}^{(n)}$ the transmission power allocated in the base station on SC k in the second TS of the direct transmission, respectively. The channel coefficients between the base station and RN r on subcarrier n and between relay node r and user u_{R} on SC k are given by $h^{(r,n)}$ and $h^{(u_{\mathrm{R}},r,k)}$ while between the base station and user u_{R} on SCs n and k by $h^{(u_{\mathrm{R}},n)}$ and $h^{(u_{\mathrm{R}},k)}$, respectively. The power spectral density of the white noise is denoted as N_0. The capacities of direct transmission in the first TS using subcarrier n and in the second TS using subcarrier k for the user u_{D}, are defined as:

$$r_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} = \Delta f \log_2 \left(1 + \frac{\Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} p_{\mathrm{D,T1}}^{(n)} \left| h^{(u_{\mathrm{D}},n)} \right|^2}{\Delta f N_0} \right), \tag{4.8}$$

$$r_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} = \Delta f \log_2 \left(1 + \frac{\Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} p_{\mathrm{D,T2}}^{(k)} \left| h^{(u_{\mathrm{D}},k)} \right|^2}{\Delta f N_0 + \sum\limits_{u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}} \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} p_{\mathrm{R,T2}}^{(r,k)} \left| h^{(u_{\mathrm{D}},r,k)} \right|^2} \right), \tag{4.9}$$

respectively, where $p_{\mathrm{D,T1}}^{(n)}$ determines the transmission power allocated in the base station on SC n in the time slot of the direct transmission. The channel coefficients between the RN r and user u_{D} on subcarrier k is given by $h^{(u_{\mathrm{D}},r,k)}$ while between the base station and user u_{D} on SCs n and k by $h^{(u_{\mathrm{D}},n)}$ and $h^{(u_{\mathrm{D}},k)}$, respectively. Finally, binary variables $\Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)}$ and $\Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$ determine whether SC n in the first TS or k in the second TS of direct transmission is assigned to user u_{D}, i.e., $\Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} = 1$ if SC n is assigned to user u_{D} in the first TS of direct transmission, otherwise $\Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} = 0$. The same rule applies to $\Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$. Moreover, $\Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} = 1$ when SC n selected in the first time slot is paired with SC k used in the second TS of the relayed transmission. Note that if $\Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} = 1$ it automatically means that $\Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} = 0$, because the utilization of the same SCs in relayed and direct transmission is allowed only in the second TS, thus in practice $\Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} = 1 - \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}$.

Thus, the sum-capacity of the considered network within two TSs for all links involving end-users in one of the selected transmission modes is expressed as:

$$R = \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}} \sum_{r\in\mathcal{R}} \sum_{n\in\mathcal{N}} \sum_{k\in\mathcal{N}} r_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} + \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{D}}} \sum_{n\in\mathcal{N}} \sum_{k\in\mathcal{N}} \left(r_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} + r_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} \right). \tag{4.10}$$

Let us now estimate the total power consumed in the network. In general, this power consists of the static power consumed by active circuits of devices, the dynamically changing transmit power, and the BB processing power consumption in the transmitters and receivers (dependent mostly on the modulation and coding schemes). The most common model of the BB processing power consumption is the linear model, wherein this power is directly proportional to the bit-rate (or capacity) of a link [23, 75, 76]. In considered model system this model has been applied as well. Moreover, the author deals with network where the technological advancement of each transmitter and receiver can be significantly different. For this reason, two independent proportionality factors: $\beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)}$ and $\beta_{\mathrm{D}}^{(u_{\mathrm{D}})}$, determining the power consumed by BB processing, in the relayed transmission for relay node r, end-user u_{R} and in the direct transmission for user u_{D} have been introduced. Thus, the total consumed power in the considered system is defined as:

$$\begin{aligned}
P = {} & P_{\mathrm{C}} + \sum_{r\in\mathcal{R}} P_{\mathrm{C}}^{(r)} + \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}} P_{\mathrm{C}}^{(u_{\mathrm{R}})} + \sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} P_{\mathrm{C}}^{(u_{\mathrm{D}})} \\
& + \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}} \sum_{r\in\mathcal{R}} \sum_{n\in\mathcal{N}} \sum_{k\in\mathcal{N}} \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \left(p_{\mathrm{R,T1}}^{(n)} + p_{\mathrm{R,T2}}^{(r,k)} + \beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)} r_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \right) \\
& + \sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} \sum_{n\in\mathcal{N}} \Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} \left(p_{\mathrm{D,T1}}^{(n)} + \beta_{\mathrm{D}}^{(u_{\mathrm{D}})} r_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} \right) + \sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} \sum_{k\in\mathcal{N}} \Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} \left(p_{\mathrm{D,T2}}^{(k)} + \beta_{\mathrm{D}}^{(u_{\mathrm{D}})} r_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} \right),
\end{aligned} \tag{4.11}$$

where $P_{\mathrm{C}}^{\mathrm{B}_l}$, $P_{\mathrm{C}}^{(r)}$, $P_{\mathrm{C}}^{(u_{\mathrm{R}})}$ and $P_{\mathrm{C}}^{(u_{\mathrm{D}})}$ are the constant powers consumed by the active circuits of BS, the relay node r and users' equipment respectively, when they are turned on.

The goal is to maximize the energy efficiency of the network defined by the ratio of the total throughput and total consumption power. The EE optimization problem amounts to finding such values of the transmit powers allocated to SCs and of the above-defined indicator variables $\mathbf{p}_{\mathrm{R}}^{\star} = \left\{ p_{\mathrm{R,T1}}^{(n)^\star}, p_{\mathrm{R,T2}}^{(r,k)^\star} \right\}$, $\mathbf{\Psi}_{\mathrm{R}}^{\star} = \left\{ \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)^\star} \right\}$ in the relayed transmission, and $\mathbf{p}_{\mathrm{D}}^{\star} = \left\{ p_{\mathrm{D,T1}}^{(n)^\star}, p_{\mathrm{D,T2}}^{(k)^\star} \right\}$, $\mathbf{\Psi}_{\mathrm{D}}^{\star} = \left\{ \Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)^\star}, \Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)^\star} \right\}$ in the direct transmission that maximize η, i.e.,

$$\left(\mathbf{p}_{\mathrm{R}}^{\star}, \mathbf{p}_{\mathrm{D}}^{\star}, \mathbf{\Psi}_{\mathrm{R}}^{\star}, \mathbf{\Psi}_{\mathrm{D}}^{\star} \right) = \arg \max_{\substack{\mathbf{p}_{\mathrm{R}}, \mathbf{p}_{\mathrm{D}} \\ \mathbf{\Psi}_{\mathrm{R}}, \mathbf{\Psi}_{\mathrm{D}}}} \eta \left(\mathbf{p}_{\mathrm{R}}, \mathbf{p}_{\mathrm{D}}, \mathbf{\Psi}_{\mathrm{R}}, \mathbf{\Psi}_{\mathrm{D}} \right), \tag{4.12}$$

subject to:

$$\sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} \Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} \leq 1 \qquad \forall n \in \mathcal{N}, \tag{4.13}$$

$$\sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} \Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} \leq 1 \qquad \forall k \in \mathcal{N}, \tag{4.14}$$

$$\sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}} \sum_{r\in\mathcal{R}} \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \leq 1 \qquad \forall n \in \mathcal{N},\ k \in \mathcal{N}, \tag{4.15}$$

$$\sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}} \sum_{r\in\mathcal{R}} \Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} < 1 \qquad \forall n \in \mathcal{N},\ k \in \mathcal{N}. \tag{4.16}$$

Constraints (4.13) and (4.14) restrict SCs n and k to be assigned to the maximum one user in a given BS, in the first and in the second TS of direct transmission, respectively. Likewise, constraint (4.15) guarantees that SCs n and k can be used by no more than one end-user and one relay node, in the relayed transmission for one BS. Constraint (4.16) ensures that SC n cannot be assigned at the same time to the direst and relayed transmission in the first TS at BS. Moreover, $\Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)}$, $\Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$ and $\Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}$ take only binary values: 0 or 1.

4.2.3 Transformation of the non-concave optimization problem

The optimization problem (4.12) is non-concave due to the fractional form of the objective function. However, it can be solved on condition that the numerator is concave or affine, and the denominator is convex, or vice versa. If the numerator is affine, the denominator does not have to be restricted in sign [43]. Unfortunately, in the considered case the numerator as well as the denominator of the objective function is non-convex. Moreover, the optimization problem belongs to a class of problems called MINLFP [65] problem what means that the optimization variables take both the continuous and the discrete values. Finally, inside the objective function, one can find $\min\{\cdot\}$ functions causing additional complication. Summarizing the above considerations, there does not exist any standard technique to solve the optimization problem. Thus, in order to solve it, some transformations of the objective function are needed.

Primal decomposition technique

In the first step of the optimization problem transformation, let us apply the primal decomposition technique. The primal decomposition can be applied when the problem has a coupling variable such that, when fixed to some value, the rest of the optimization problem decouples into several subproblems. Thus, let us decompose the objective problem to (4.12):

$$\left(\mathbf{p}_{\mathrm{R}}^{\star}, \mathbf{p}_{\mathrm{D}}^{\star}, \boldsymbol{\Psi}_{\mathrm{R}}^{\star}, \boldsymbol{\Psi}_{\mathrm{D}}^{\star}\right) = \arg \max_{\boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}} \arg \max_{\mathbf{p}_{\mathrm{R}}, \mathbf{p}_{\mathrm{D}}} \eta\left(\mathbf{p}_{\mathrm{R}}, \mathbf{p}_{\mathrm{D}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}\right), \tag{4.17}$$

subject to (4.13)–(4.16). Now, according to (4.17), the solution to the optimization problem comes down to solving a two-step maximization problem. In the first step, the optimal transmission powers $\mathbf{p}_{\mathrm{R}}^{\star}, \mathbf{p}_{\mathrm{D}}^{\star}$ are determined for fixed allocation variables and then base on them the subcarrier assignment problem can be solved.

Epigraph equivalent representation

Thus, the following transformations will be applied in order to determine the optimal transmission powers $\mathbf{p}_{\mathrm{R}}^{\star}, \mathbf{p}_{\mathrm{D}}^{\star}$. Let us introduce an auxiliary optimization variables: $\hat{p}_{\mathrm{D,T2}}^{(k)} = \ln\left(p_{\mathrm{D,T2}}^{(k)}\right)$, $\hat{p}_{\mathrm{R,T1}}^{(n)} = \ln\left(p_{\mathrm{R,T1}}^{(n)}\right)$ and $\hat{p}_{\mathrm{R,T2}}^{(r,k)} = \ln\left(p_{\mathrm{R,T2}}^{(r,k)}\right)$. Thus, from now, each previously defined variable with the circumflex determine the variables after substitution the auxiliary optimization variables e.g.:

$$\hat{r}_{\mathrm{R,T1}}^{(r,n)} = \Delta f \log_2\left(1 + \frac{\Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \mathrm{e}^{\hat{p}_{\mathrm{R,T1}}^{(n)}} \left|h^{(r,n)}\right|^2}{\Delta f N_0}\right). \tag{4.18}$$

In the next step of the (4.12) transformation, the $\min\{\cdot\}$ function in equation (4.5), is replaced by auxiliary variable $\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}$ for end-user u_{R}, relay node r and SCs (n,k). The introduced auxiliary variable has to be lower or equal to $\hat{r}_{\mathrm{R,T1}}^{(r,n)}$ and $\hat{r}_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}$, what implies two additional constraints in the optimization problem:

$$\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \leq \hat{r}_{\mathrm{R,T1}}^{(r,n)}, \tag{4.19}$$

$$\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \leq \hat{r}_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}. \tag{4.20}$$

Let note that a convex optimization problem is a problem where all of the constraints are convex functions, and the objective is a concave function if maximizing while constraint (4.19) is concave and constraint (4.20) is non-concave. Moreover, let us remember that $r_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$ given by equation (4.9) is is still non-concave, thus the standard techniques can not be used to solve the defined optimization problem. Nevertheless, in the next subsection, the sequential programming framework has been applied to transform introduced constrained to concave form.

Sequential concave optimization

The main idea of the Successive Concave/Convex Approximation is based on the approximation of the non-concave function by the series of concave ones. In this chapter, the SCA method in which the function has to be the difference of two convex functions is applied, i.e.,

$$f(\mathbf{x}) = f_1(\mathbf{x}) - f_2(\mathbf{x}). \tag{4.21}$$

Then, $f_2(\mathbf{x})$ is approximated the by linear function using the first-order Taylor series expansion at $\bar{\mathbf{x}}$:

$$f_2(\mathbf{x}) \leq f_2(\bar{\mathbf{x}}) + \frac{\partial f_2(\bar{\mathbf{x}})}{\partial \bar{\mathbf{x}}}(\mathbf{x} - \bar{\mathbf{x}}). \tag{4.22}$$

Note that constraints (4.19) and (4.20) as well as $r_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$ given by equation (4.9) with a modicum of algebra can be presented in a form of the difference of concave function:

$$\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} - \hat{r}_{\mathrm{R,T1}}^{(r,n)} \leq 0, \tag{4.23}$$

$$\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} + u_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} - \upsilon_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} \leq 0, \tag{4.24}$$

$$r_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} = u_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} - \upsilon_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}, \tag{4.25}$$

where

$$\begin{aligned} u_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} &= \Delta f N_0 \mathrm{e}^{\hat{p}_{\mathrm{R,T2}}^{(r,k)}} \left|h^{(u_{\mathrm{R}},r,k)}\right|^2 \\ &+ \left(\Delta f N_0 + \sum_{u_{\mathrm{D}} \in \mathcal{U}_{\mathrm{D}}} \mathrm{e}^{\hat{p}_{\mathrm{D,T2}}^{(k)}} \left|h^{(u_{\mathrm{R}},k)}\right|^2\right)\left(\Delta f N_0 + \mathrm{e}^{\hat{p}_{\mathrm{R,T1}}^{(n)}} \left|h^{(u_{\mathrm{R}},n)}\right|^2\right), \end{aligned} \tag{4.26}$$

$$\upsilon_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} = \Delta f N_0 \left(\Delta f N_0 + \sum_{u_{\mathrm{D}} \in \mathcal{U}_{\mathrm{D}}} \mathrm{e}^{\hat{p}_{\mathrm{D,T2}}^{(k)}} \left|h^{(u_{\mathrm{R}},k)}\right|^2\right), \tag{4.27}$$

$$u_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} = \Delta f N_0 + \sum_{u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}} \mathrm{e}^{\hat{p}_{\mathrm{R,T2}}^{(r,k)}} \left|h^{(u_{\mathrm{D}},r,k)}\right|^2 + \mathrm{e}^{\hat{p}_{\mathrm{D,T2}}^{(k)}} \left|h^{(u_{\mathrm{D}},k)}\right|^2, \tag{4.28}$$

$$\upsilon_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} = \Delta f N_0 + \sum_{u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}} \mathrm{e}^{\hat{p}_{\mathrm{R,T2}}^{(r,k)}} \left|h^{(u_{\mathrm{D}},r,k)}\right|^2. \tag{4.29}$$

Now, let us approximate the subtrahends of (4.23)–(4.25) by the first-order Taylor series expansion at $\bar{\mathbf{p}}_{\mathrm{R}} = \left\{\bar{p}_{\mathrm{R,T1}}^{(n)}, \bar{p}_{\mathrm{R,T2}}^{(r,k)}\right\}$ and $\bar{\mathbf{p}}_{\mathrm{D}} = \left\{\bar{p}_{\mathrm{D,T1}}^{(n)}, \bar{p}_{\mathrm{D,T2}}^{(k)}\right\}$ getting:

$$\Upsilon_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} - \tilde{r}_{\mathrm{R,T1}}^{(r,n)} \leq 0, \tag{4.30}$$

$$\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} + u_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} - \tilde{\upsilon}_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} \leq 0, \tag{4.31}$$

$$\tilde{r}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} = u_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} - \tilde{\upsilon}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}, \tag{4.32}$$

where $\tilde{v}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$ determines the linear approximations and is given by equation:

$$\tilde{r}_{\mathrm{R,T1}}^{(r,n)} = \frac{\partial r_{\mathrm{R,T1}}^{(r,n)} \Big|_{\hat{p}_{\mathrm{R,T1}}^{(n)}=\bar{p}_{\mathrm{R,T1}}^{(n)}}}{\partial \bar{p}_{\mathrm{R,T1}}^{(n)}} \left(\hat{p}_{\mathrm{R,T1}}^{(n)} - \bar{p}_{\mathrm{R,T1}}^{(n)}\right) + r_{\mathrm{R,T1}}^{(r,n)} \Big|_{\hat{p}_{\mathrm{R,T1}}^{(n)}=\bar{p}_{\mathrm{R,T2}}^{(r,k)}} \tag{4.33}$$

The rest approximations $\tilde{r}_{\mathrm{R,T1}}^{(r,n)}$ and $\tilde{v}_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}$ is obtained in the analogous way as in (4.33). Finally, the optimization problem (4.17) can be rewritten to the following form:

$$\left(\hat{\mathbf{p}}_{\mathrm{R}}^{\star}, \hat{\mathbf{p}}_{\mathrm{D}}^{\star}, \boldsymbol{\Upsilon}_{\mathrm{R}}^{\star}, \boldsymbol{\Psi}_{\mathrm{R}}^{\star}, \boldsymbol{\Psi}_{\mathrm{D}}^{\star}\right) = \arg \max_{\boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}} \arg \max_{\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}} \frac{R\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}\right)}{P\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}\right)}, \tag{4.34}$$

subject to (4.13)–(4.16) and (4.30)–(4.31). The vectors of variables maximizing the goal function are defined as: $\hat{\mathbf{p}}_{\mathrm{R}}^{\star} = \left\{\hat{p}_{\mathrm{R,T1}}^{(n)\star}, \hat{p}_{\mathrm{R,T2}}^{(r,k)\star}\right\}$, $\boldsymbol{\Upsilon}_{\mathrm{R}}^{\star} = \left\{\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)\star}\right\}$ in the relayed transmission, and $\hat{\mathbf{p}}_{\mathrm{D}}^{\star} = \left\{p_{\mathrm{D,T1}}^{(n)\star}, \hat{p}_{\mathrm{D,T2}}^{(k)\star}\right\}$ in the direct transmission while:

$$R\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}^{\star}, \boldsymbol{\Psi}_{\mathrm{D}}^{\star}\right) = \sum_{u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}} \sum_{r \in \mathcal{R}} \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{N}} \Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} + \sum_{u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{D}}} \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{N}} \left(r_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} + \tilde{r}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}\right) \tag{4.35}$$

and

$$\begin{aligned} P\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}^{\star}, \boldsymbol{\Psi}_{\mathrm{D}}^{\star}\right) &= P_{\mathrm{C}} + \sum_{r \in \mathcal{R}} P_{\mathrm{C}}^{(r)} + \sum_{u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}} P_{\mathrm{C}}^{(u_{\mathrm{R}})} + \sum_{u_{\mathrm{D}} \in \mathcal{U}_{\mathrm{D}}} P_{\mathrm{C}}^{(u_{\mathrm{D}})} \\ &+ \sum_{u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}} \sum_{r \in \mathcal{R}} \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{N}} \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \left(\mathrm{e}^{\hat{p}_{\mathrm{R,T1}}^{(n)}} + \mathrm{e}^{\hat{p}_{\mathrm{R,T2}}^{(r,k)}} + \beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)} \Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}\right) \\ &+ \sum_{u_{\mathrm{D}} \in \mathcal{U}_{\mathrm{D}}} \sum_{n \in \mathcal{N}} \Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} \left(p_{\mathrm{D,T1}}^{(n)} + \beta_{\mathrm{D}}^{(u_{\mathrm{D}})} r_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)}\right) + \sum_{u_{\mathrm{D}} \in \mathcal{U}_{\mathrm{D}}} \sum_{k \in \mathcal{N}} \Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} \left(\mathrm{e}^{\hat{p}_{\mathrm{D,T2}}^{(k)}} + \beta_{\mathrm{D}}^{(u_{\mathrm{D}})} \tilde{r}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}\right), \end{aligned} \tag{4.36}$$

determine the redefined throughput and total power consumption resulting from the application of the described transformations, respectively.

Dinkelbach method

Note that the numerator of the objective function of the optimization problem (4.34) is the sum of affine and concave functions while the denominator is the sum of constants, convex and convex function, thus the Dinkelbach method [43] can not be applied, theoretically. Nevertheless, in [23] the concavity of the optimization problem after applying the Dinkelbach method has been proven. Thus, let us transform the objective function into a new parametrized concave function by introducing parameter $\lambda^{\star}$, obtaining:

$$\begin{aligned} &\left(\hat{\mathbf{p}}_{\mathrm{R}}^{\star}, \hat{\mathbf{p}}_{\mathrm{D}}^{\star}, \boldsymbol{\Upsilon}_{\mathrm{R}}^{\star}, \boldsymbol{\Psi}_{\mathrm{R}}^{\star}, \boldsymbol{\Psi}_{\mathrm{D}}^{\star}\right) = \\ &\arg \max_{\boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}} \arg \max_{\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}} \left[R\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}\right) - \lambda^{\star} P\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}\right)\right], \end{aligned} \tag{4.37}$$

subject to (4.13)–(4.16) and (4.30)–(4.31), where $\lambda^{\star} = \frac{R(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}})}{P(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}})}$. Solving (4.37) is equivalent to finding the root of equation $R\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}\right) - \lambda^{\star} P\left(\hat{\mathbf{p}}_{\mathrm{R}}, \hat{\mathbf{p}}_{\mathrm{D}}, \boldsymbol{\Upsilon}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{R}}, \boldsymbol{\Psi}_{\mathrm{D}}\right) = 0$, what can be done using iterative Dinkelbach algorithm. Finally, it can be observed that optimization problem (4.37) is concave because the objective function is the summation of the concave terms and linear terms, thus it is concave by nature while all constraints are convex.

4.2.4 Proposed algorithmic solution

In order to maximize energy efficiency of the network, joint adaptive transmission mode selection, subcarrier pairing, subcarrier and power allocation algorithm is proposed. Because the indicator variables take binary values, the original optimization problem (4.12) belongs to MINLFP problems and the solution can be found using exhaustive search over all variables. Hence, the complexity of the optimization problem is high, particularly for a high number of users and SCs. Therefore, the optimization problem (4.37) has been decoupled (using primal decomposed technique) into transmission power allocation problem and subcarrier assignment problem.

Transmission power allocation problem solution

Note that the optimization problem (4.37) is a concave problem for the fixed subcarrier pairing and allocation and approximation at $\bar{\mathbf{p}}_{\mathrm{R}}$ and $\bar{\mathbf{p}}_{\mathrm{D}}$. Thus, let us define the transmission power allocation optimization problem as:

$$\left(\hat{\mathbf{p}}_{\mathrm{R}}^{\star},\hat{\mathbf{p}}_{\mathrm{D}}^{\star},\boldsymbol{\Upsilon}_{\mathrm{R}}^{\star}\right)=\arg\max_{\hat{\mathbf{p}}_{\mathrm{R}},\hat{\mathbf{p}}_{\mathrm{D}},\boldsymbol{\Upsilon}_{\mathrm{R}}}\left[R\left(\hat{\mathbf{p}}_{\mathrm{R}},\hat{\mathbf{p}}_{\mathrm{D}},\boldsymbol{\Upsilon}_{\mathrm{R}}\right)-\lambda^{\star}P\left(\hat{\mathbf{p}}_{\mathrm{R}},\hat{\mathbf{p}}_{\mathrm{D}},\boldsymbol{\Upsilon}_{\mathrm{R}}\right)\right] \tag{4.38}$$

subject to(4.30)–(4.31) which can be solved by applying a dual decomposition method. The Lagrangian function for (4.38) is given by:

$$\begin{aligned}\mathcal{L}\left(\hat{\mathbf{p}}_{\mathrm{R}},\hat{\mathbf{p}}_{\mathrm{D}},\boldsymbol{\Upsilon}_{\mathrm{R}},\lambda\boldsymbol{\mu}_{\mathrm{R}}\right)&=R\left(\hat{\mathbf{p}}_{\mathrm{R}},\hat{\mathbf{p}}_{\mathrm{D}},\boldsymbol{\Upsilon}_{\mathrm{R}}\right)-\lambda P\left(\hat{\mathbf{p}}_{\mathrm{R}},\hat{\mathbf{p}}_{\mathrm{D}},\boldsymbol{\Upsilon}_{\mathrm{R}}\right)\\&-\sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}}\sum_{r\in\mathcal{R}}\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{N}}\mu_{\mathrm{R,T1}}^{(u_{\mathrm{R}},r,n,k)}\left(\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}-\tilde{r}_{\mathrm{R,T1}}^{(r,n)}\right)\\&-\sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}}\sum_{r\in\mathcal{R}}\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{N}}\mu_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}\left(\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}+u_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}-\tilde{v}_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}\right),\end{aligned} \tag{4.39}$$

where and $\boldsymbol{\mu}_{\mathrm{R}}=\left\{\mu_{\mathrm{R,T1}}^{(u_{\mathrm{R}},r,n,k)},\mu_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}\right\}$ are the Lagrangian multipliers related to constraints (4.30) and (4.31). The dual optimization problem is to find:

$$\left(\boldsymbol{\mu}_{\mathrm{R}}^{\star}\right)=\arg\min_{\boldsymbol{\mu}_{\mathrm{R}}}\mathcal{L}_{\mathrm{D}}\left(\boldsymbol{\mu}_{\mathrm{R}}\right), \tag{4.40}$$

where $\mathcal{L}_{\mathrm{D}}\left(\boldsymbol{\mu}_{\mathrm{R}}\right)$ is the dual Lagrangian function defined as:

$$\mathcal{L}_{\mathrm{D}}\left(\boldsymbol{\mu}_{\mathrm{R}}\right)=\arg\max_{\substack{\mathbf{p}_{\mathrm{R}},\mathbf{p}_{\mathrm{D}}\\\boldsymbol{\Upsilon}_{\mathrm{R}},\boldsymbol{\mu}_{\mathrm{R}}}}\mathcal{L}\left(\hat{\mathbf{p}}_{\mathrm{R}},\hat{\mathbf{p}}_{\mathrm{D}},\boldsymbol{\Upsilon}_{\mathrm{R}},\boldsymbol{\mu}_{\mathrm{R}}\right) \tag{4.41}$$

The dual optimization problem (4.40) can be decomposed to a master problem and a subproblem, and it can be solved iteratively [70]. In the subproblem, for the initial values of the Lagrange multipliers, the optimization variables: $\hat{\mathbf{p}}_{\mathrm{R}}$, $\hat{\mathbf{p}}_{\mathrm{D}}$ and $\boldsymbol{\Upsilon}_{\mathrm{R}}$ are determined. After that, the Lagrangian multipliers $\boldsymbol{\mu}_{\mathrm{R}}$ are updated by solving the master problem. This procedure finishes when the convergence is reached and the KKT conditions are fulfilled.

Solution of the sub-problem

According to the KKT conditions, the optimal values of the transmit power and the auxiliary variables can be determined by taking the partial derivative of (4.39) with respect to $\hat{p}_{\mathrm{R,T1}}^{(n)}$, $\hat{p}_{\mathrm{R,T2}}^{(r,k)}$ and $\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}$ for the relayed transmission, $p_{\mathrm{D,T1}}^{(n)}$ and $\hat{p}_{\mathrm{D,T2}}^{(k)}$ for direct transmission and then, setting them to zero. Such system of equations can be iteratively solve by e.g. Newton method, thus let us define Jacobian for SC pair (n,k):

$$\mathbf{J}^{(n,k)}=\begin{bmatrix}\frac{\partial\mathcal{L}}{\partial\hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)}}\\\frac{\partial\mathcal{L}}{\partial\hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)}}\\\frac{\partial\mathcal{L}}{\partial\boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)}}\end{bmatrix}, \tag{4.42}$$

where $\hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)}$, $\hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)}$ and $\boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)}$ determine the vectors of the optimization variables for a given SC pair (n,k) and relay nodes $r \in \mathcal{R}$. Moreover, the Hessian matrix for SC pair (n,k) is given by:

$$\mathbf{H}^{(n,k)} = \begin{bmatrix} \frac{\partial^2 \mathcal{L}}{\partial^2 \hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)}} & \frac{\partial^2 \mathcal{L}}{\partial \hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)} \partial \hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)}} & \frac{\partial^2 \mathcal{L}}{\partial \hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)} \partial \boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)}} \\ \frac{\partial^2 \mathcal{L}}{\partial \hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)} \partial \hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)}} & \frac{\partial^2 \mathcal{L}}{\partial^2 \hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)}} & \frac{\partial^2 \mathcal{L}}{\partial \hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)} \partial \boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)}} \\ \frac{\partial^2 \mathcal{L}}{\partial \boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)} \partial \hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)}} & \frac{\partial^2 \mathcal{L}}{\partial \boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)} \partial \hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)}} & \frac{\partial^2 \mathcal{L}}{\partial^2 \boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)}} \end{bmatrix}. \tag{4.43}$$

According to the Newton method, the optimal values of the transmit powers and the auxiliary variables in $i_{\mathrm{newt}}+1$ iteration can be calculated by:

$$\begin{bmatrix} \hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)^\star}(i_{\mathrm{newt}}+1) \\ \hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)^\star}(i_{\mathrm{newt}}+1) \\ \boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)^\star}(i_{\mathrm{newt}}+1) \end{bmatrix} = \begin{bmatrix} \hat{\mathbf{p}}_{\mathrm{R}}^{(n,k)^\star}(i_{\mathrm{newt}}) \\ \hat{\mathbf{p}}_{\mathrm{D}}^{(n,k)^\star}(i_{\mathrm{newt}}) \\ \boldsymbol{\Upsilon}_{\mathrm{R}}^{(n,k)^\star}(i_{\mathrm{newt}}) \end{bmatrix} - \left(\mathbf{H}^{(n,k)}\right)^{-1} \mathbf{J}^{(n,k)}, \tag{4.44}$$

This iterative procedure is repeated until the stop criteria are met. Note, that the optimal values for a given SC pair (n,k) can be obtained for each pair, independently. It allows to parallelize the calculations and decrease their time.

Solution of the Master Problem

In master problem, the sub-gradient method [96] is used to update the Lagrange multipliers using equations (4.45) and (4.46), where $\boldsymbol{\tau}_{\mathrm{R}} = \left\{\tau_{\mathrm{R,T1}}^{(u_{\mathrm{R}},r,n,k)}, \tau_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}\right\}$, are the positive step-values in the iterative algorithm, while i_{sub} is the iteration number. Positive constant step size parameters are used in this chapter which are optimized to obtain fast convergence rate. The convergence proof of the sub-gradient method for constant step size is given in [97].

$$\mu_{\mathrm{R,T1}}^{(u_{\mathrm{R}},r,n,k)}(i_{\mathrm{sub}}+1) = \left[\mu_{\mathrm{R,T1}}^{(u_{\mathrm{R}},r,n,k)}(i_{\mathrm{sub}}) + \tau_{\mathrm{R,T1}}^{(u_{\mathrm{R}},r,n,k)}(i_{\mathrm{sub}})\left(\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)^\star} - \tilde{r}_{\mathrm{R,T1}}^{(r,n)^\star}\right)\right]^+, \tag{4.45}$$

$$\begin{aligned} &\mu_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}(i_{\mathrm{sub}}+1) = \\ &\quad \left[\mu_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}(i_{\mathrm{sub}}) + \tau_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}(i_{\mathrm{sub}})\left(\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)^\star} + u_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)^\star} - \tilde{v}_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)^\star}\right)\right]^+ \end{aligned} \tag{4.46}$$

for all $n \in \mathcal{N}$, $k \in \mathcal{N}$, $r \in \mathcal{R}$ and $u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}$.

Subcarrier assignment problem solution

Now, based on the optimal values of the transmit powers and the auxiliary variables, the SC paring and allocation optimization problem can be defined:

$$\begin{aligned} (\boldsymbol{\Psi}_{\mathrm{R}}^\star, \boldsymbol{\Psi}_{\mathrm{D}}^\star) = \arg\max_{\boldsymbol{\Psi}_{\mathrm{R}},\boldsymbol{\Psi}_{\mathrm{D}}} \mathcal{C}\left(\hat{\mathbf{p}}_{\mathrm{R}}^\star, \hat{\mathbf{p}}_{\mathrm{D}}^\star, \boldsymbol{\Upsilon}_{\mathrm{R}}^\star, \boldsymbol{\mu}_{\mathrm{R}}^\star\right) + \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}} \sum_{r\in\mathcal{R}} \sum_{n\in\mathcal{N}} \sum_{k\in\mathcal{N}} \Psi_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \mathcal{D}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} \\ + \sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} \sum_{n\in\mathcal{N}} \Psi_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} \mathcal{D}_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} + \sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} \sum_{k\in\mathcal{N}} \Psi_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} \mathcal{D}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} \end{aligned} \tag{4.47}$$

subject to: (4.13)–(4.16), where $\mathcal{D}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}$, $\mathcal{D}_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)}$ and $\mathcal{D}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$ are given by:

$$\mathcal{D}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} = \Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)^\star} - \lambda\left(\mathrm{e}^{\hat{p}_{\mathrm{R,T1}}^{(n)^\star}} + \mathrm{e}^{\hat{p}_{\mathrm{R,T2}}^{(r,k)^\star}} + \beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)} \Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)^\star}\right), \tag{4.48}$$

$$\mathcal{D}_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} = r_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)^\star} - \lambda\left(p_{\mathrm{D,T1}}^{(n)^\star} + \beta_{\mathrm{D}}^{(u_{\mathrm{D}})} r_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)^\star}\right) \tag{4.49}$$

$$\mathcal{D}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} = \tilde{r}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)^\star} - \lambda\left(\mathrm{e}^{\hat{p}_{\mathrm{D,T2}}^{(k)^\star}} + \beta_{\mathrm{D}}^{(u_{\mathrm{D}})}\tilde{r}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)^\star}\right) \tag{4.50}$$

Moreover, function $\mathcal{C}\left(\hat{\mathbf{p}}_{\mathrm{R}}^\star, \hat{\mathbf{p}}_{\mathrm{D}}^\star, \boldsymbol{\Upsilon}_{\mathrm{R}}^\star, \boldsymbol{\mu}_{\mathrm{R}}^\star\right)$ is defined by the following formula:

$$\begin{aligned}\mathcal{C}\left(\hat{\mathbf{p}}_{\mathrm{R}}^\star, \hat{\mathbf{p}}_{\mathrm{D}}^\star, \boldsymbol{\Upsilon}_{\mathrm{R}}^\star, \boldsymbol{\mu}_{\mathrm{R}}^\star\right) &= -\lambda\left(P_{\mathrm{C}} + \sum_{r\in\mathcal{R}} P_{\mathrm{C}}^{(r)} + \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}} P_{\mathrm{C}}^{(u_{\mathrm{R}})} + \sum_{u_{\mathrm{D}}\in\mathcal{U}_{\mathrm{D}}} P_{\mathrm{C}}^{(u_{\mathrm{D}})}\right) \\ &- \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}}\sum_{r\in\mathcal{R}}\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{N}} \mu_{\mathrm{R,T1}}^{(u_{\mathrm{R}},r,n,k)}\left(\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} - \tilde{r}_{\mathrm{R,T1}}^{(r,n)}\right) \\ &- \sum_{u_{\mathrm{R}}\in\mathcal{U}_{\mathrm{R}}}\sum_{r\in\mathcal{R}}\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{N}} \mu_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}\left(\Upsilon_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} + u_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)} - \tilde{v}_{\mathrm{R,T2}}^{(u_{\mathrm{R}},r,n,k)}\right)\end{aligned} \tag{4.51}$$

It can be observed that the subtrahends of (4.48)–(4.50) define the cost of the throughput achieved on SC pair n and k for user u_{R} in the relayed transmission and for user u_{D} in the direct transmission, respectively. Hence, if the values of $\mathcal{D}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}$, $\mathcal{D}_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)}$ or $\mathcal{D}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}$ are negative, using SCs n and k is not beneficial from the energy efficiency point of view. Moreover, note that $\mathcal{C}\left(\hat{\mathbf{p}}_{\mathrm{R}}^\star, \hat{\mathbf{p}}_{\mathrm{D}}^\star, \boldsymbol{\Upsilon}_{\mathrm{R}}^\star, \boldsymbol{\mu}_{\mathrm{R}}^\star\right)$ does not depend on the subcarrier pairing and allocation, and thus, it can be neglected.

In the following, the author of this thesis proposes the novel, optimal SCs pairing, SCs and power allocation, and the transmission mode selection scheme that maximizes EE of the network. In order to maximize the energy efficiency metric, for each subcarrier pair (n, k), the optimal users and relay nodes (optimal means for whom allocating SC pair (n, k) would cause the highest increase in EE) are determined.

- For the case when the relayed transmission and the direct transmission use the same subcarrier during the second time slot, the optimal users-pair $(u_{\mathrm{D},1}^\star, u_{\mathrm{R},1}^\star)$ and relay $r_1^\star$ for SC pair (n, k) can be found:

$$\forall n, k \qquad \left(r_1^\star, u_{\mathrm{D},1}^\star, u_{\mathrm{R},1}^\star\right) = \max_{r,u_{\mathrm{D}},u_{\mathrm{R}}} \boldsymbol{\mathcal{D}}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} + \boldsymbol{\mathcal{D}}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}. \tag{4.52}$$

- For the relayed mode, when each SC can be used only once in each time slot to avoid interference, the optimal user $u_{\mathrm{R},2}^\star$ and relay $r_2^\star$ can be found using formula:

$$\forall n, k \qquad \left(r_2^\star, u_{\mathrm{R},2}^\star\right) = \max_{r,u_{\mathrm{R}}} \boldsymbol{\mathcal{D}}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}\Bigg|_{\mathrm{e}^{\hat{p}_{\mathrm{D,T2}}^{(k)^\star}}=0}. \tag{4.53}$$

- For the direct, the optimal users in the first and in the second time slot can be found:

$$\forall n \qquad u_{\mathrm{D},2}^\star = \max_{u_{\mathrm{D}}} \boldsymbol{\mathcal{D}}_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)}, \tag{4.54}$$

$$\forall k \qquad u_{\mathrm{D},3}^\star = \max_{u_{\mathrm{D}}} \boldsymbol{\mathcal{D}}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}\Bigg|_{\substack{\mathrm{e}^{\hat{p}_{\mathrm{R,T1}}^{(n)^\star}}=0 \\ \mathrm{e}^{\hat{p}_{\mathrm{R,T2}}^{(r,k)^\star}}=0}}, \tag{4.55}$$

where $\boldsymbol{\mathcal{D}}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)} = \left\{\mathcal{D}_{\mathrm{R}}^{(u_{\mathrm{R}},r,n,k)}\right\}$ for $r \in \mathcal{R}$ and $u_{\mathrm{R}} \in \mathcal{U}_{\mathrm{R}}$, $\boldsymbol{\mathcal{D}}_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)} = \left\{\mathcal{D}_{\mathrm{D,T1}}^{(u_{\mathrm{D}},n)}\right\}$ and $\boldsymbol{\mathcal{D}}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)} = \left\{\mathcal{D}_{\mathrm{D,T2}}^{(u_{\mathrm{D}},k)}\right\}$ for $u_{\mathrm{D}} \in \mathcal{U}_{\mathrm{D}}$. Now, based on above equations, the optimal transmission mode for SC pair (n, k) which maximizes energy efficiency can be selected in a simple way:

$$\Omega(n,k) = \max\left\{\mathcal{D}_{\mathrm{R}}^{\left(u_{\mathrm{R},1}^\star,r_1^\star,n,k\right)} + \mathcal{D}_{\mathrm{D,T2}}^{\left(u_{\mathrm{D},1}^\star,k\right)}, \mathcal{D}_{\mathrm{R}}^{\left(u_{\mathrm{R},2}^\star,r_2^\star,n,k\right)}, \mathcal{D}_{\mathrm{D,T1}}^{(u_{\mathrm{D},2},n)} + \mathcal{D}_{\mathrm{D,T2}}^{\left(u_{\mathrm{D},3}^\star,k\right)}\right\}. \tag{4.56}$$

Thus, if $\Omega(n,k) = \mathcal{D}_{\mathrm{R}}^{\left(u_{\mathrm{R},1}^\star,r_1^\star,n,k\right)} + \mathcal{D}_{\mathrm{D,T2}}^{\left(u_{\mathrm{D},1}^\star,k\right)}$, the relayed and direct transmission is selected, wherein the same SC at the same time can be used. If $\Omega(n,k) = \mathcal{D}_{\mathrm{R}}^{\left(u_{\mathrm{R},2}^\star,r_2^\star,n,k\right)}$ the relayed mode without interference is selected, while $\Omega(n,k) = \mathcal{D}_{\mathrm{D,T1}}^{(u_{\mathrm{D},2},n)} + \mathcal{D}_{\mathrm{D,T2}}^{\left(u_{\mathrm{D},3}^\star,k\right)}$ implies that the direct transmission is

Algorithm 5 Iterative EE-maximizing Algorithm

1: Set the maximum numbers of iterations I_{dink}, I_{newt} and convergence tolerance ϵ.
2: Initialize the iteration counter $i_{\text{dink}} = 0$, parameter $\lambda = \lambda_0$.
3: Initialize $\hat{\mathbf{p}}_{\text{R}}$, $\hat{\mathbf{p}}_{\text{D}}$, $\bar{\mathbf{p}}_{\text{R}}$, $\bar{\mathbf{p}}_{\text{D}}$, $\boldsymbol{\Upsilon}_{\text{R}}$, $\boldsymbol{\mu}_{\text{R}}$ and step size $\boldsymbol{\tau}_{\text{R}}$
4: **repeat**
5: Initialize the iteration counter $i_{\text{newt}} = 0$.
6: **repeat**
7: Update $\hat{\mathbf{p}}_{\text{R}}$, $\hat{\mathbf{p}}_{\text{D}}$ and $\boldsymbol{\Upsilon}_{\text{R}}$ using (4.44).
8: Update $\boldsymbol{\mu}_{\text{D}}$ using (4.45)–(4.46).
9: Set $i_{\text{newt}} \leftarrow i_{\text{newt}} + 1$.
10: **until** convergence to get the optimal solutions $\hat{\mathbf{p}}^{\star}_{\text{R}}$, $\hat{\mathbf{p}}^{\star}_{\text{D}}$ and $\boldsymbol{\Upsilon}^{\star}_{\text{R}}$ or $i_{\text{newt}} > I_{\text{newt}}$
11: Set $\bar{\mathbf{p}}_{\text{R}} \leftarrow \hat{\mathbf{p}}^{\star}_{\text{R}}$, $\bar{\mathbf{p}}_{\text{D}} \leftarrow \hat{\mathbf{p}}^{\star}_{\text{D}}$.
12: Update $\boldsymbol{\Psi}_{\text{R}}$ and $\boldsymbol{\Psi}_{\text{D}}$ using (4.52)–(4.56).
13: Update $\lambda = \frac{R(\hat{\mathbf{p}}^{\star}_{\text{R}}, \hat{\mathbf{p}}^{\star}_{\text{D}}, \boldsymbol{\Upsilon}^{\star}_{\text{R}}, \boldsymbol{\Psi}^{\star}_{\text{R}}, \boldsymbol{\Psi}^{\star}_{\text{D}})}{P(\hat{\mathbf{p}}^{\star}_{\text{R}}, \hat{\mathbf{p}}^{\star}_{\text{D}}, \boldsymbol{\Upsilon}^{\star}_{\text{R}}, \boldsymbol{\Psi}^{\star}_{\text{R}}, \boldsymbol{\Psi}^{\star}_{\text{D}})}$.
14: Set $i_{\text{dink}} \leftarrow i_{\text{dink}} + 1$.
15: **until** convergence or $i_{\text{dink}} > I_{\text{dink}}$
16: Set $\boldsymbol{\Psi}_{\text{R}} \leftarrow \boldsymbol{\Psi}^{\star}_{\text{R}}$, $\boldsymbol{\Psi}_{\text{D}} \leftarrow \boldsymbol{\Psi}^{\star}_{\text{D}}$ and $\lambda^{\star} \leftarrow \lambda$.

the best solution for the EE optimization. Finally, the SC pairing and allocation can be determined by introducing $|\mathcal{N}| \times |\mathcal{N}|$ matrices $\boldsymbol{\Omega} = \{\Omega(n,k)\}$, $\boldsymbol{\Theta} = \{0,1\}$ and applying Hungarian method [86], where $\boldsymbol{\Omega}$ is a matrix of the SC allocation costs while $\boldsymbol{\Theta}$ is a decision matrix. If, as the result of the Hungarian algorithm, $\Theta(n,k) = 1$ for $\Omega(n,k) = \mathcal{D}_{\text{R}}^{\left(u^{\star}_{\text{R},1}, r^{\star}_1, n, k\right)} + \mathcal{D}_{\text{D,T2}}^{\left(u^{\star}_{\text{D},1}, k\right)}$ it means that SC n is assigned to user $u^{\star}_{\text{R},1}$ in the first TS of relayed transmission while SC k to user $u^{\star}_{\text{R},1}$ who receives data with the help of relay $r^{\star}_1$ and to user $u^{\star}_{\text{D},1}$ using direct transmission in the second time slot, so that $\Psi_{\text{R}}^{\left(u^{\star}_{\text{R},1}, r^{\star}_1, n, k\right)^{\star}} = 1$ and $\Psi_{\text{D,T2}}^{\left(u^{s}_{\text{D},1} tar, k\right)^{\star}} = 1$. Analogously, if $\Theta(n,k) = 1$ for $\Omega(n,k) = \mathcal{D}_{\text{R}}^{\left(u^{\star}_{\text{R},2}, r^{\star}_2, n, k\right)}$ variable $\Psi_{\text{R}}^{\left(u^{\star}_{\text{R},2}, r^{\star}_2, n, k\right)^{\star}} = 1$, and when $\Theta(n,k) = 1$ for $\Omega(n,k) = \mathcal{D}_{\text{D,T1}}^{\left(u_{\text{D},2}, n\right)} + \mathcal{D}_{\text{D,T2}}^{\left(u^{\star}_{\text{D},3}, k\right)}$ it means that $\Psi_{\text{D,T1}}^{\left(u^{s}_{\text{D},2} tar, n\right)^{\star}} = 1$ and $\Psi_{\text{D,T2}}^{\left(u^{s}_{\text{D},3} tar, k\right)^{\star}} = 1$.

Finally, let us formulate the novel proposed scheme that optimally allocates the resources in the multiuser downlink DF relay interference network with computational awareness, i.e., incorporating the BB-processing-related power in the power-consumption model. The EE-maximizing procedure is summarized in Algorithm 5. In the first steps of the proposed scheme, the maximum numbers of iterations I_{dink} and I_{newt} for two loops in the algorithm are set, and a set of variables is initialized. Then, for a given value of parameter λ, the transmission power variables $\hat{\mathbf{p}}_{\text{R}}$, $\hat{\mathbf{p}}_{\text{D}}$ and $\boldsymbol{\Upsilon}_{\text{R}}$ are updated using equations (4.44). Next, based on these values the Lagrangian multipliers $\boldsymbol{\mu}_{\text{R}}$ are updated using (4.45)–(4.46). In the next step, the approximation of the transmission power variables $\bar{\mathbf{p}}_{\text{R}}$ and $\bar{\mathbf{p}}_{\text{D}}$ are updated and the SC paring and allocation problem is solved by update $\boldsymbol{\Psi}_{\text{R}}$ and $\boldsymbol{\Phi}_{\text{D}}$ using (4.52)–(4.56). This procedure is repeated until the convergence of parameter λ is achieved or the iteration counter reaches I_{dink}.

4.2.5 Complexity analysis

The computational complexity of the proposed algorithm is $\mathcal{O}\left(i_{\text{newt}} i_{\text{dink}} |\mathcal{N}|^2 |\mathcal{K}| \left(|\mathcal{U}_{\text{R}}| + |\mathcal{U}_{\text{D}}|\right)^2 + i_{\text{dink}} |\mathcal{N}|^3\right)$, where the mean values of i_{newt} and i_{dink} are presented in Figure 4.9 and Figure 4.10. In Figure 4.9, the number of iteration of Newton i_{newt} and Dinkelbach i_{dink} algorithm as a function of the number of combinations equal to $|\mathcal{N}|^2 |\mathcal{K}| \left(|\mathcal{U}_{\text{R}}| + |\mathcal{U}_{\text{D}}|\right)^2$ is plotted. It can be observed that the number of iterations of the Netwon algorithm increases with the number of combinations, while the number of iterations of the Dinkelbach algorithm is independent on the number of combinations. Figure 4.10 shows the EE metric which is normalized to the maximum value of the energy efficiency for $I_{\mathrm{newt}} = 1000$ versus the number of iterations of Dinkelbach algorithm for the different values of the maximum number of iteration of the Newton method I_{newt}. Note that for value of $I_{\mathrm{newt}} \geq 5$ the proposed algorithm reaches the maximum values of EE in 8 iterations of the Dinkelbach method. It means that the maximum number of the Netwon method can be limited and the same results will be determined. This relatively high complexity results from the number of combinations which have to examined in order to solve the SC pairing and allocation problem. For each subcarrier pair (n, k) and for each combination of users and relay nodes (what gives $|\mathcal{N}|^2 |\mathcal{K}| (|\mathcal{U}_{\mathrm{R}}| + |\mathcal{U}_{\mathrm{D}}|)^2$ combinations), the transmission powers are determined in i_{newt} iterations. Then, based on the optimal power allocation, the Hungarian algorithm with $\mathcal{O}\left(|\mathcal{N}|^3\right)$ complexity is applied to find the optimal SC pair in allocation. This procedure is repeated i_{dink} times to achieve the convergence of parameter λ or the maximum number of iterations I_{dink}.

Although, the complexity of the proposed solution is relatively high, particularly for a large network, note the following: (i) equations (4.48) - (4.50) can be calculated independently for each combination, thus this procedure can be parallelized, (ii) the main goal here is to show the upper bound of the energy efficiency in the presented scheme, therefore all combinations are considered. The future work is to propose a suboptimal (practical) solution, e.g., by assigning the users to specific predicted relays and transmission modes based on channel conditions or other heuristic rules resulting from practical application of the proposed solution.

4.2.6 Simulation results

In this section, numerical and simulation results are presented that allow to compare the performance of the proposed algorithm with reference scheme. In the reference method (known from the literature), wherein direct or relayed transmission modes but without interference can be selected in response to channel conditions. In one of them, data are transmitted to the end-users directly

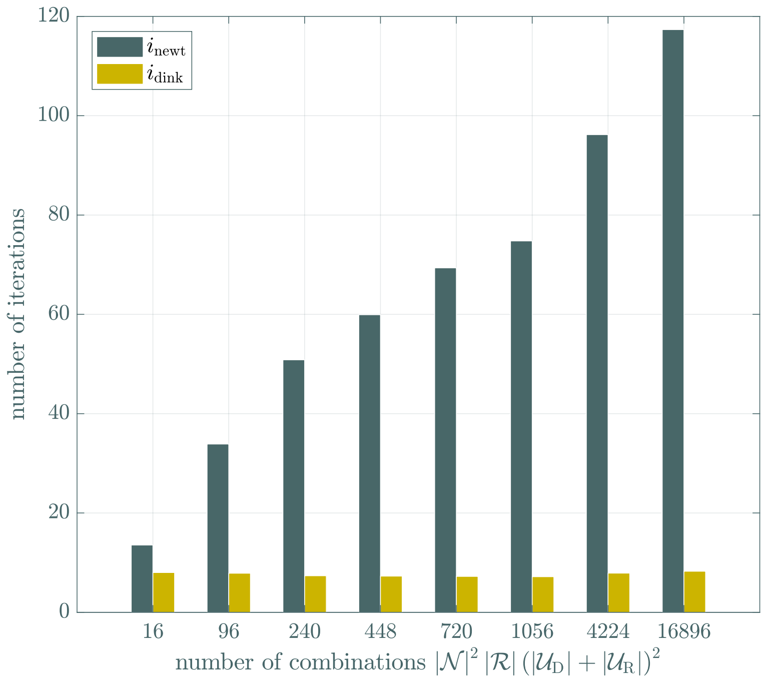

Figure 4.9: The mean number of iterations of the Newton and Dinkelbach method vs. number of combinations.

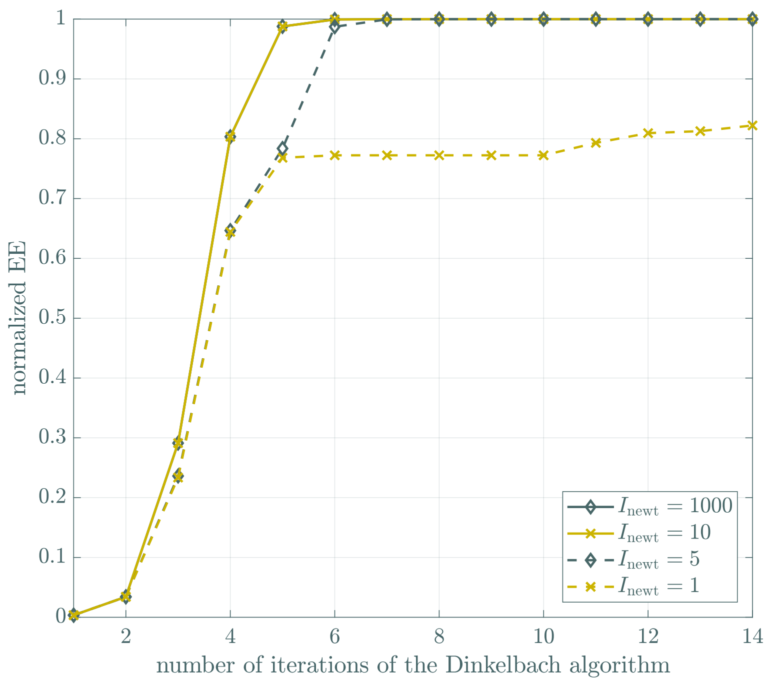

Figure 4.10: The normalized energy efficiency metric as a function of number of iterations of the Dinkelbach method.

Table 4.5: Simulation parameters.

Simulation parameter	Value
Center frequency	3.5 GHz
SC bandwidth, Δf	15 kHz
Noise power spectral density, N_0	-174 dBm/Hz
Static power consumption of the BS, P_C	40 W
Static power consumption of each relay, $P_\mathrm{C}^{(r)}$ $\forall r \in \mathcal{R}$	4 W
Static power consumption of each user, $P_\mathrm{C}^{(u_\mathrm{R})}$ $\forall u_\mathrm{R} \in \mathcal{U}_\mathrm{R}$ and $P_\mathrm{C}^{(u_\mathrm{R})}$ $\forall u_\mathrm{D} \in \mathcal{U}_\mathrm{D}$ [70]	0.1 W
Factor of the power consumed by BB signal processing, $\beta_\mathrm{R}^{(u_\mathrm{R},r)}$ $\forall r \in \mathcal{R}$, $u_\mathrm{R} \in \mathcal{U}_\mathrm{R}$ and $\beta_\mathrm{D}^{(u_\mathrm{D})}$ $\forall u_\mathrm{D} \in \mathcal{U}_\mathrm{D}$	0.01
Convergence tolerance, ϵ	10^{-8}
Cell radius	2 km
Channel model	Extended Pedestrian A
Number of channel realizations	1500

from BS both in the first and in the second TS. In the other, the user receives data via relay, so only one user is supported in the first and the second TS (there is no interference between users). It means that, in the second TS, the relay node and base station can not transmit data at the same SC. Moreover, in the reference method, and the BB-processing power is not taken into account in the optimization procedure, however, it is included in the EE metric calculation.

The author of this thesis considers single-cell network with BS in the center of the cell and users randomly located with 2-D uniform distribution. The relays are located in the carefully selected points in the cell. Their location-randomization significantly increases the time of the simulations, while not providing any additional value to results and conclusions. Nevertheless, the model can be readily extended to random location of relays. The simulation parameters are summarized in Table 4.5.

Now, let us show the cases, wherein in the second TS, the same SCs are assigned to the users for the direct and the relayed transmission. The results showing the transmission mode selection depending on the user location are presented in Figure 4.11. In this figure, for each channel realization two users have been randomly localized in the cell and they are plotted if the same SC in the second TS is used by them. The relay, for this illustrating example, is located 1.75 km from BS. Observe that EE optimization implies that the users which receive data directly from base station are concentrated in the center of the cell while the users receiving data via relay node are located closer to the relay. This is because significant channels attenuations in the interfering links result in the negligible signal distortion, and the use of the same SC at the same time can be possible. Presumably, a higher number of relays can increase the number of users working in the relayed transmission mode (reusing SCs in the second TS) and consequently, can increase EE significantly.

In Figure 4.12 average energy efficiency of the proposed and reference schemes and the sum of subcarriers which have been used simultaneously by the base station and the relay node in the second time slot, for 10 thousand channel realizations are plotted versus the number of relays. In this case, the results have been generated for $|\mathcal{N}| = 1$, $|\mathcal{U}_{\mathrm{R}}|+|\mathcal{U}_{\mathrm{D}}| = 2$ and in the case where the total transmission power is unlimited and the minimum rate is not provided. Note that for each number of relay nodes the energy efficiency of the proposed scheme achieves higher values compared to the reference scheme. Moreover, the profit in energy efficiency metric between proposed and reference scheme increases with the number of relay nodes in the cell because there is more possibility to find the channel conditions when the same subcarrier can be used by BS and relay node in the second TS, simultaneously. Finally, it can be observed that, in the beginning, the energy efficiency increases with the number of relay nodes then achieves the maximum value for the 6-th relay in the network and after that decrease. It results from dominating the static power consumed by the relay nodes over the throughput which they can provide.

In Figure 4.13, the network EE and the sum-throughput in the single-cell are presented. They have been obtained for $|\mathcal{R}| = 8$ relays and $|\mathcal{N}| = 1$, $|\mathcal{U}_{\mathrm{R}}| + |\mathcal{U}_{\mathrm{D}}| = 6$ users in the system. In

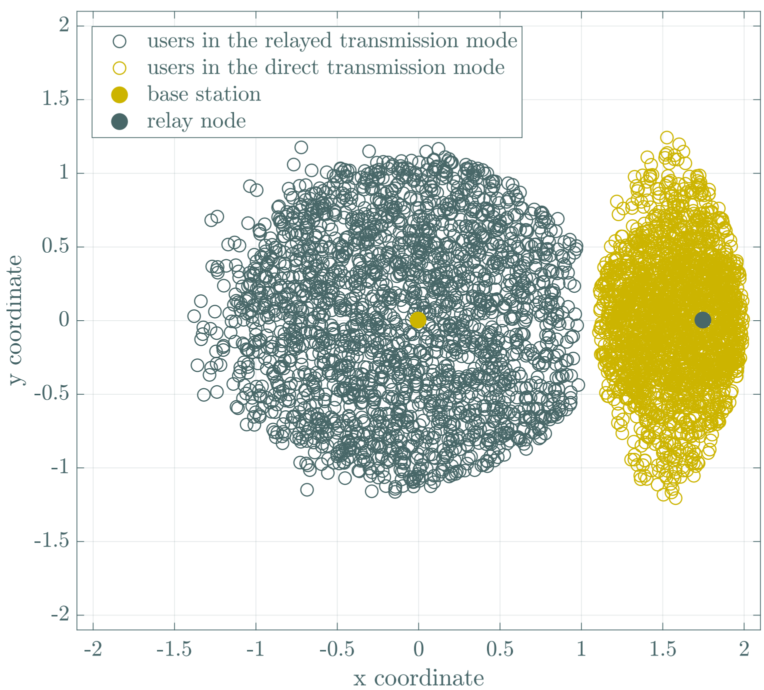

Figure 4.11: The cases when the same subcarriers are obtained for the direct and the relayed transmission in the second time slot.

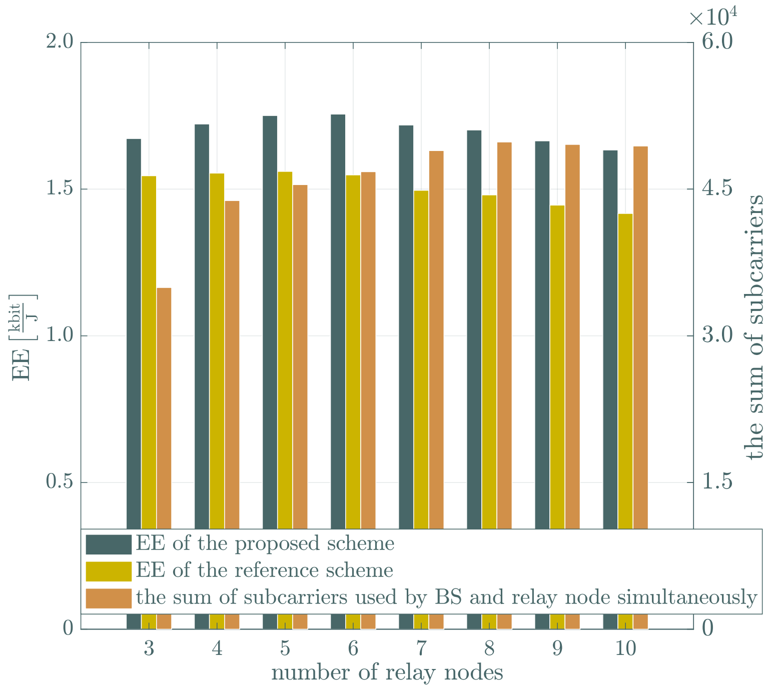

Figure 4.12: The energy efficiency of the proposed and reference schemes and the sum of SCs which have been used simultaneously by BS and the relay node in the second TS.

Figure 4.13, it can be observed that EE as well as throughput for the proposed scheme achieve higher values than the reference method. It can be also noticed that for a small number of SCs, the results are similar in both schemes because in this case, the probability of experiencing the channel conditions that allow to apply the mode re-using the SCs in the second TS is relatively low. Both energy efficiency and the sum-throughput increase with the number of SCs. In Figure 4.14, the mean of SCs used in each of the transmission modes versus the total number of SCs

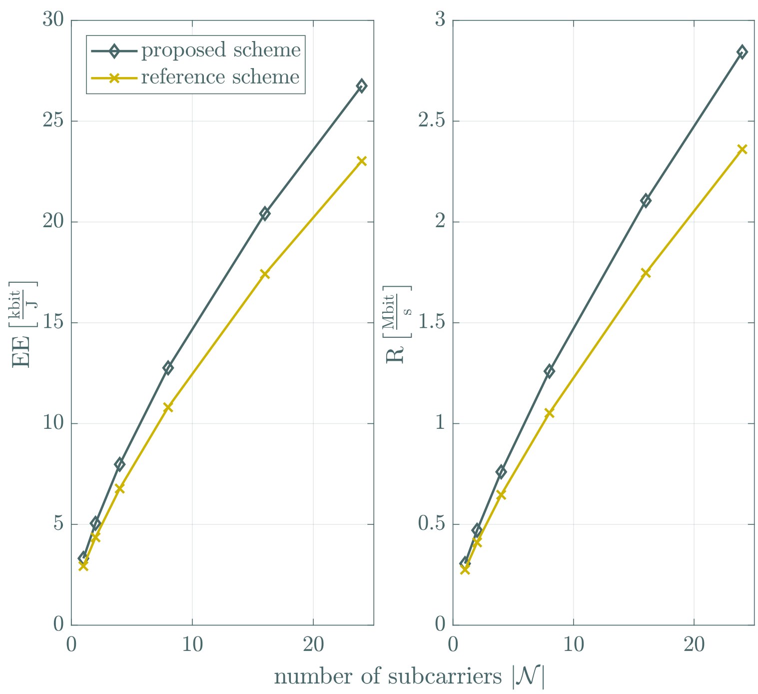

Figure 4.13: The energy efficiency and sum-throughput versus the number of subcarriers.

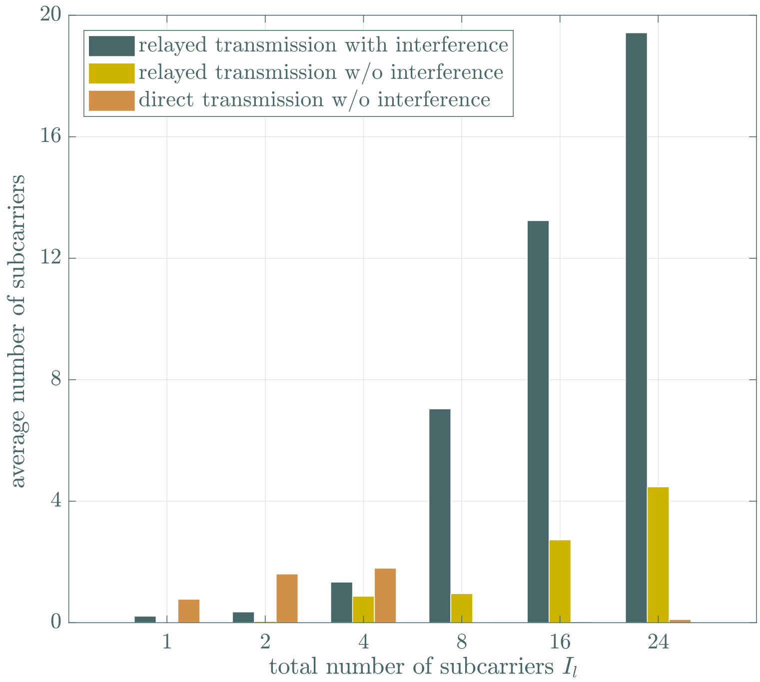

Figure 4.14: The mean of subcarriers used in a given transmission mode versus the total number of subcarriers.

is shown for $|\mathcal{R}| = 8$ and $|\mathcal{U}_\mathrm{R}| + |\mathcal{U}_\mathrm{D}| = 4$ in the system without the minimum rate constraint and total transmission power constraint. Observe that most of SCs are used in the mode wherein the BS and relay node used the same subcarrier in the second time slot (called in the figure as "relayed transmission with interference") because from the EE point of view it is the most beneficial approach.

The next results presented in Figure 4.15 show the impact of the number of users on energy

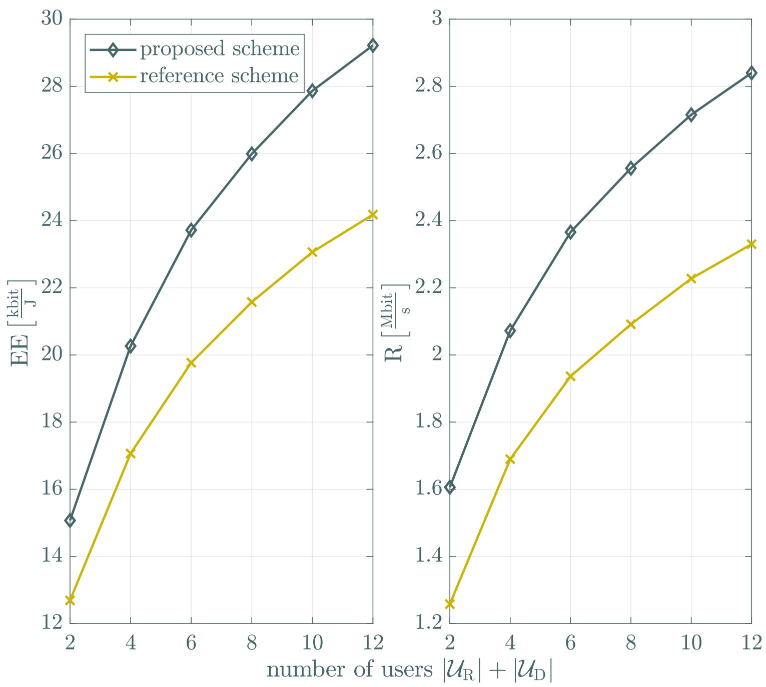

Figure 4.15: The energy efficiency and throughput versus the number of users.

efficiency and the sum-throughput in the system with $|\mathcal{N}| = 16$ and $|\mathcal{R}| = 8$. Here, again energy efficiency and sum-throughput are higher when the proposed energy efficiency maximization scheme is applied than in the reference method. Moreover, EE increases with the number of users due to the multiuser diversity gain. It can be also observed that the gap between the proposed scheme and reference method increases with the number of users for both metrics. The reason for that is shown in Figure 4.16 where the mean of subcarriers used in a given transmission mode as a function of the number of users is shown. In this figure, one can observe that the number of subcarriers which are applied in "relayed transmission with interference" increases with the number of users.

In Figure 4.17, the energy efficiency and the power consumption of the baseband processing as a function of factors $\beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)}$ and $\beta_{\mathrm{D}}^{(u_{\mathrm{D}})}$ for $|\mathcal{U}_{\mathrm{R}}| + |\mathcal{U}_{\mathrm{D}}| = 4$ and $|\mathcal{U}_{\mathrm{R}}| + |\mathcal{U}_{\mathrm{D}}| = 8$ are plotted. In this case, the author assumed that the factors of the power consumption of the baseband processing is the same in whole network, thus $\beta = \beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)} = \beta_{\mathrm{D}}^{(u_{\mathrm{D}})}$ for all l, k, m, n. It can be observed that the energy efficiency decreases when the power consumption of the BB processing increases. Moreover, power consumption of the baseband processing has the huge impact on the energy efficiency metric. Therefore, taking the power consumed by the BB processing into account is an important aspect of energy efficiency optimization.

4.3 Chapter summary and conclusions

In this chapter, the author of the thesis has analysed and solved the problem of energy-efficient resource allocation in multiuser downlink DF relay interference network with computational awareness. In the considered system model, the same subcarrier can be used by the base station and by the relay nodes, causing interference to end users. However, this subcarriers-reuse increases the energy efficiency of the network by increasing its spectral efficiency. The computational awareness refers to incorporating the power of BB processing in the power-consumption model, which becomes an issue in the future relay-opportunistic massive-communication networks. The formu-

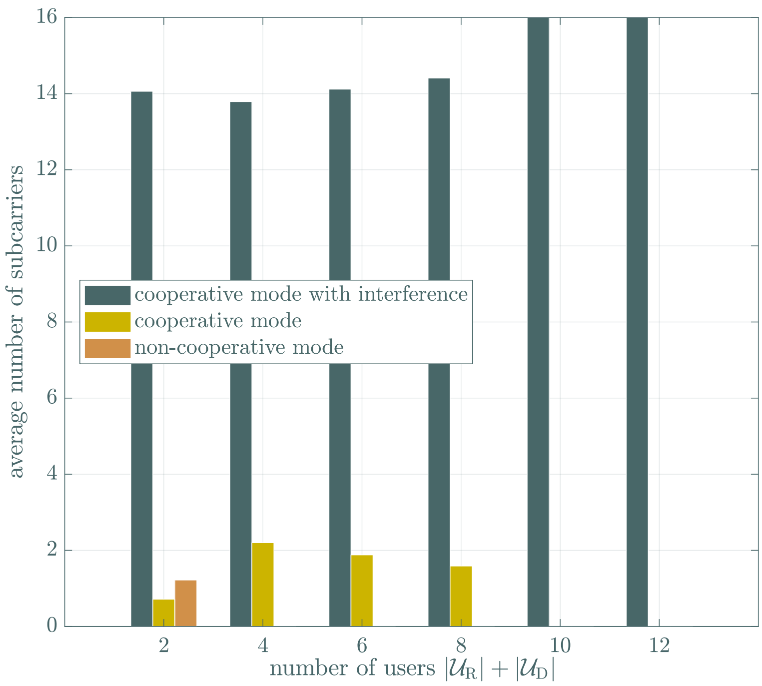

Figure 4.16: The mean of subcarriers used in a given transmission mode versus the number of users.

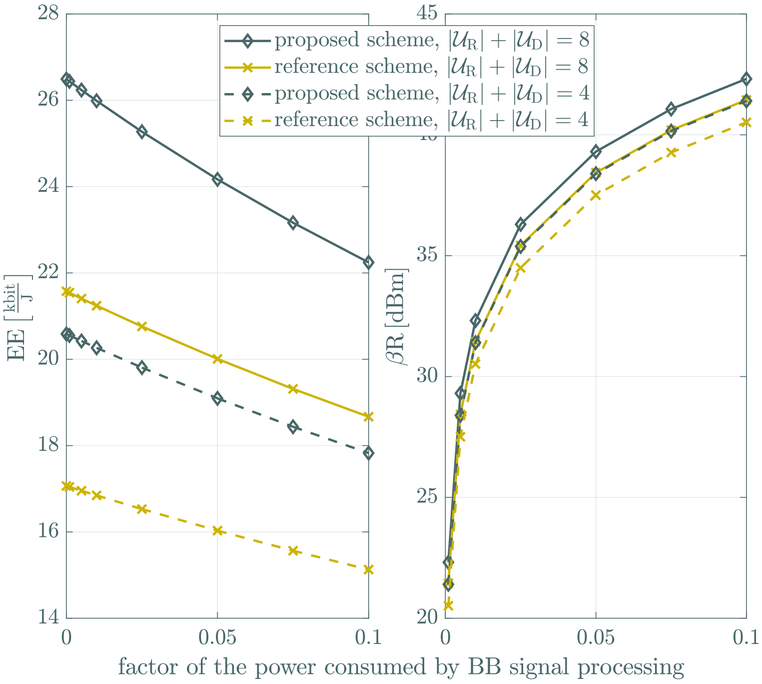

Figure 4.17: The energy efficiency and the power consumption of BB processing as a function of the factors $\beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)}$ and $\beta_{\mathrm{D}}^{(u_{\mathrm{D}})}$ assuming that $\beta = \beta_{\mathrm{R}}^{(u_{\mathrm{R}},r)} = \beta_{\mathrm{D}}^{(u_{\mathrm{D}})}$ for all k, m, n.

lated optimization problem is a non-concave fractional and mixed binary integer programming problem which is NP-hard to solve in its original form. Thus, the author of this thesis proposed a mechanism to transform such problem into the series of concave ones which can be solved by standard optimization techniques. Firstly, the primal decomposition technique has been applied to decouple the optimization problem into two-step maximization problem. Then, the epigraph and SCA methods have been employed to transform optimization problem to the form required by the *Dinkelbach* method which has been the last step of the optimization problem transformation. The joint subcarrier pairing, SC and power allocation with transmission mode selection algorithm, maximizing the energy efficiency metric of the network has been proposed. In order to obtain the optimal transmit power- and subcarrier allocation, a computationally efficient scheme basing on dual decomposition method has also been proposed. Moreover, the optimal SC pairing has been developed via Hungarian method. Finally, the proposed solution has been investigated by computer simulations and compared with the other existing competitive scheme. Simulation results show that it is possible to increase the energy efficiency of the network when subcarrier reusing is allowed. Although mutual interference is caused by parallel transmissions of the base station and relays nodes the resultant spectral efficiency is higher than in a single transmitter case. As a result, achievable EE is higher.

Chapter 5

Practical aspects of the energy-efficient resource allocation in OFDM/OFDMA links and networks

Followed by Chapters 2, 3 and 4, that presented optimal and algorithmic solutions for resource allocation in various scenarios, in this chapter, the author of this thesis addresses practical aspects of the energy-efficient resource allocation in OFDM/OFDMA radio communication links and networks. He addresses the issues of practical implementation of the algorithms, limitations of technologies and design trade-offs that are faced.

It is well known that the drawback of the OFDM technique is relatively high variations of the time-domain signal envelope and high PAPR. This in turn causes signal energy spilling (that might be called *energy waste* and negatively contributes to the transmitter EE) over the adjacent bands after the signal is amplified in the RF front-end, i.e. in PA. The severity of this phenomena depends on the particular design and used equipment, e.g. on the number of subcarriers, the class of PA and other techniques used to combat the non-linear distortions caused by the signal clipping. Thus, these design methods and equipment must be considered for the overall energy efficiency in links and networks. The discussion on practical design aspects of the RF front-end for energy-efficiency is presented in Section 5.1.

The author of this thesis is also aware of practical obstacles, limitations and degrees of freedom in finding the EE optimum for resource allocation in the networks considered in the preceding chapters. Therefore, in Section 5.2, he discusses practicality of the optimized solutions, identifies necessary design trade-offs, and tries to formulate a set of recommendations for the practical energy-efficient design of the future radiocommunication OFDM links and networks.

5.1 Impact of practical RF front-end on OFDM energy efficiency

An important topic that is typically overlooked while optimizing resources allocation for OFDM-based networks is the nonlinearity of OFDM transceivers. All works on adaptive resource allocation mentioned in the state-of-the art in Chapters 1–4 consider OFDM transceivers as linear systems resulting in, e.g., linear increase of the consumed power with the allocated power and no influence of power allocation on the interference power for this link. However, while this model can be used for high-throughput systems it cannot be used when the transceiver is optimized for low energy consumption. This is mainly caused by nonlinear characteristic of any practical power amplifier [98]. The operating point of a power amplifier, called "back-off" is the difference between the PA clipping power and the mean transmit power (in decibels, i.e., in the logarithmic scale). When high back-off is used, the nonlinear distortion can be negligible at the cost of low power amplifier efficiency. When trying to maximize the PA efficiency, thus, emitting the maximal part of the PA input power as a useful waveform, low back-off has to be used, and high nonlinear distortion is expected. Note that the power amplifier efficiency is not a fixed value [34]. It depends not only on the power back-off but also on the amplifier architecture (defined by its class) [99] or even on the methods of powering it. One of the heavily investigated scheme that can allow for the amplifier increased energy efficiency is envelope tracking, whose aim is to adjust the PA supply voltage according to the envelope of the transmitted signal [100]. Even if the PA energy consumption is reliably modeled, the nonlinearity of the supply voltage should be considered while powering a transceiver from batteries. The battery capacity decreases non-linearly with the energy consumption of PA [101].

The nonlinear PA input-output (AM/AM and AM/PM) characteristic has even stronger influence on the transmitted OFDM signal and its distortion. As a result of nonlinear processing, all utilized OFDM subcarriers, undergo intermodulation. New power components appear in the PA output signal spectrum at frequencies being linear combination of the input signal subcarrier frequencies. This is also visible as a Gaussian noise-like distortion at the occupied subcarriers [102]. The effect depends not only on the chosen PA back-off but also on the PA characterstics or on the properties of the OFDM signal being amplified. There are tens of different models of nonlinear PA ranging from some complicated Volterra-series, through polynomial representation with or without memory, to a simple clipper having linear AM/AM characteristic in a given range of input power and saturation above this range [103]. It has been shown in [104] that a PA of clipper-like characteristic guarantees the highest Signal to Noise and Distortion power Ratio (SNDR). Even if the PA characteristic is not like this, it is common to utilize Digital Pre-Distortion (DPD) (being a nonlinear signal processing unit applied before the OFDM signal enters PA) [105], so that the effective joint characteristic of DPD and PA is clipper-like.

While DPD minimizes the nonlinear distortion power, there is also an input OFDM waveform feature that plays an important role. Note that minimum distortion power at the PA output is obtained for a signal of constant envelope, e.g., Minimum Shift Keying signal. In the case of an OFDM signal, a sample for each time instance is a sum of many subcarriers modulated by typically uncorrelated complex data symbols. As there may be tens or hundreds of subcarriers, central limit theorem applies, resulting in OFDM signal samples being approximated by the complex Gaussian distribution [106]. This causes the instantaneous signal envelope to fluctuate significantly. This is typically measured for an OFDM symbol using Peak to Average Power Ratio (PAPR) metric that is the ratio of peak sample power to mean sample power. Observe that while both PAPR and PA back-off are defined in relation to the mean signal power, PAPR higher than the back-off for clipper PA means that some OFDM signal samples are clipped. As typical PAPR for OFDM symbol is greater than 6 dB, it means that PA can output signal of mean power up to 25% of its maximal rated power not to observe distortions. Such a scheme would be highly ineffective in terms of EE. For this reason, a number of signal processing algorithms have been elaborated that reduce PAPR of an OFDM signal [107] or even directly the induced distortion being aware of the PA characteristics [108, 109]. On the other hand, recent investigations have shown that the nonlinear "distortion" can be used to improve reception quality [110]. Last but not least, the above described Gaussian signal approximation is valid for the appropriately high number of subcarriers of possibly equal power. It has been shown that the PAPR distribution changes if the utilized subcarriers do not constitute a single block in frequency [111], or have varying power [112]. The ultimate example is an OFDM transmitter modulating a single subcarrier resulting in PAPR of

0 dB.

All these models and signal processing blocks should be considered at the stage of resources allocation for OFDM links or networks. However, even for simplified OFDM transceiver nonlinearity modeling, there is a limited number of papers that consider it in resources allocation algorithms. In [113], power allocation in an OFDM-based cognitive radio is considered, in order to maximize secondary user rate. The in-band and out-of-band distortion is calculated for the 3rd order polynomial nonlinearity. However, the model does not consider variation in allocated power among subcarriers, neither frequency-specific character of nonlinear distortion. Similar model and optimization is used in [114] for Generalized Frequency Division Multiplexing. As such, the same limitation of the results validity is observed. A clipper nonlinerity model is considered for optimization of power allocation in an OFDM-based link with relay. However, again there is no frequency-selectivity of the utilized distortion model, neither the number of utilized subcarriers influences the results. The optimization variable is the total allocated power, and equal power is allocated to each subcarrier.

The above discussion shows that there are still unsolved problems in resources allocation for energy efficient OFDM-based transmission. One of these is the front-end *nonlinearity-aware* optimization.

5.2 Practical OFDM system design trade-offs and recommendations for energy efficiency

As discussed in the previous sections, the role of computational awareness in OFDM/OFDMA resource allocation optimization for the expected energy efficiency of future radio communication systems cannot be overestimated, and has been emphasized in a number of recent papers. However, there are some limitations of the wireless systems or costs related to EE maximization, that can prevent the optimal solution to be achieved or makes it not profitable.

EE maximization versus optimization complexity

Power consumption associated with the implementation of the optimization algorithms to achieve maximal energy efficiency can be significant. The definition of optimization problem and its constraints are becoming more and more complex in order to reflect complex relation between different factors, e.g., influence of coding/decoding schemes on the transceiver power consumption. At the same time, the more complex problem results typically in more advanced optimization methods that need to be applied to find the global optimum. The resource allocation optimization methods, e.g., a combination of Dinkelbach method, SCA, Hungarian method, etc., can be significantly computationally complex, requiring many iterations to be employed. Moreover, these problems do not scale well with increasing problem size, e.g., number of considered users or subcarriers. As such, obtaining of a global EE maximum might be impossible in full-size networks in real time. Even if possible, this can bring so much energy consumption for computation of a solution, that it becomes impractical. Algorithms complexity and required computational resources (the cost) must be balanced with the performance improvement (the profit) that comes with exploiting the optimization algorithms. A suboptimal solution may achieve the EE performance close to the optimal at significantly lower computational time or energy. It can be achieved by utilizing a natural property of the SCA, Dinkelbach etc. algorithms, being iterativeness. The algorithms can be terminated after fewer iterations, reducing computational complexity proportionally to the savings in number of iterations. Another option, related to the numerical optimization methods, is proper definition of a starting point. By setting it close to the final solution, e.g., by using some simplified models or historical knowledge, fast convergence can be achieved.

EE maximization versus information availability and signaling overhead

Even if the EE optimization algorithm results in globally optimal solution, it is optimal only for the considered system model, being inherently imperfect. The most common source will be delayed or quantized channel- and network-state information required by the optimization algorithm. Finding the proper balance between EE maximization and provisioning of accurate input knowledge is one of the main trade-offs for the deployment of EE OFDM networks. First, this information can be inaccurate or outdated at source since it is based on (inevitably imperfect) estimation of the channel coefficients in the presence of noise using, typically, pilot signals from past symbol periods. Moreover, this information is typically quantized in order to reduce the required throughput of the control channel, e.g., to send it periodically from a UE performing channel estimation to a BS allocating resources. Last but not least, it may not be available in full at all network nodes, i.e., transmission of all channel coefficients of a given link to all other network nodes or to a central resource management unit, in order to coordinate inter-BS interference, would be associated with impractically high signalling overhead and potentially significant delay. Even if the optimal solution is calculated on time in the central resource management unit, the decision should be distributed among all controlled BSs within very tight latency budget.

Therefore, an optimization using reduced (but representative) information of links qualities should be considered, accepting reduced EE. The second option is to use hierarchical or distributed optimization, that performs delay and control link-demanding optimization locally at a single base station. This allows for prompt reaction to mobile radio channel changes, limiting control messages between BSs. The hierarchical optimization means that local decisions are supported by global, but slowly-varying coordination among BSs.

EE maximization versus available degrees of freedom

A limitation in achieving high energy efficiency may be a particular radio communication standard or a radio architecture with a limited number of degrees of freedom. For example, only one MCS might be available (allowed by system recommendations) for a given OFDM symbol or resource block (as in LTE or 5G system standard) or a fixed power per RB will be emitted. Moreover, the power-consumption of the wireless transceiver may be invariant of the resources allocation, e.g., the power consumed by a class A power amplifier may be independent of the transmitted signal or base-band power consumption may not scale linearly with the transmission rate. In such cases the potential EE gain by optimization can be limited, making the total signaling and computing overhead not justified. In the practical design of energy-efficient OFDM-based communication networks one has to assess (by simulations or measurements) whether the energy efficiency improvement achieved by the EE optimization algorithms is high enough and worth the computational and signaling costs.

This problem cannot be solved differently than by enabling additional degrees of freedom by redesigning transceivers or adding amendments to standards.

5.3 Chapter summary and conclusions

In this chapter, the practical aspects of energy-efficient resource allocation in OFDM/OFDMA links and networks were discussed. First, the author of this thesis considered the impact of practical RF front-end on energy-efficient resource allocation algorithms. Then, the drawbacks of the OFDM technique such as high PAPR, nonlinear PA characteristic and signal distortions were analyzed with respect to their impact on energy efficiency. Moreover, the trade-offs between EE maximization and typical limitations of wireless communication systems were considered. The author discussed the optimization complexity, information availability and signaling overhead as well as available degrees of freedom in the context of the energy efficiency maximization and provided recommendations for future energy-efficient OFDM networks design.

Thus, this chapter presented the author's view on the design of the energy-efficient resource allocation algorithms considering practical obstacles, limitations and degrees of freedom in finding the EE optimum for resource allocation in OFDM/OFDMA links and networks.

Chapter 6

Conclusion

Based on the theoretical research, analysed optimization problems, proposed analytical and algorithmic solutions, as well as experimental evaluations (based on computer simulations) conducted by the author of this thesis, the following conclusions can be drawn.

The maximization of the energy efficiency metric defined as the ratio of the achieved data rate to the power consumption is not a trivial issue. This is because enhanced capacity and service quality in modern wireless systems come at the expense of increased computational complexity of radio devices, and is related to more and more advanced signal processing (coding, decoding, modulation, equalization and other techniques). The power associated with the computational complexity of signal processing, apart and beyond the transmission power is a considerable part of the total power consumption. Thus, modern, energy efficient massive radio communication systems and networks are required to be *computationally aware*. Furthermore, diversification of the wireless communication systems, different hardware implementations of the applied algorithms as well as the practical limitations of these systems significantly complicate the EE optimization problem.

To address these issues structurally, the author of this thesis has identified three scenarios that he has investigated in depth. The author discusses the increasingly complex systems, starting from (i) the single OFDM link, (ii) the OFDMA single-hop network to (iii) the multi-hop relay OFDMA interference network. In each case, the author elaborates on the transmission rate estimation, power consumption modelling, existing optimization constraints, the optimization problem statement and the problem solutions. Specifically, in the power-consumption modelling, the author includes the signal-processing (and related computing) power. Moreover, in each investigated scenario, the author of this thesis proposed novel solutions and original algorithms for energy-efficient resource allocation which allow to increase the energy efficiency compared to the existing solutions.

The adaptive modulation and coding selection together with adaptive transmit power allocation obtained by the dedicated algorithm can increase the energy efficiency of the system without significant loss of the link throughput. The OFDM technique allows for the adaptive adjustment of transmission parameters allocated to subcarriers or resource blocks in response to the channel instantaneous conditions. Contrarily to the existing approaches that use AMC for the throughput maximization or the transmit power minimization, the author of this thesis has designed the algorithm with fast convergence for energy-efficient resource allocation in the system which applies adaptive modulation and coding and is computationally aware, i.e., the algorithm accounts for the transceiver computation-power consumption. Simulation results show that the adaptive modulation and coding techniques allow for: increased energy efficiency, increased average throughput, reduced required transmit power and reduced total power consumption. Moreover, there exists the optimal point for the transmit power maximizing the energy efficiency of a given OFDM link.

The maximization of the energy efficiency of an OFDMA radio network which takes the practical constraints of wireless communication systems into account is computationally complex and nontrivial. The limitations such as that the transmit power for all RBs assigned to a given user has to be constant, and that all RBs assigned to the same user must use the same MCS make the optimization problem combinatorial and the global optimum is very difficult to determined. Moreover, the data rate in a real wireless system results from the applied MCS and the error rate function, and thus, it is problematic to be estimated for the EE metric, in particular, when MCS depends on other parameters such as the applied coding, parameters of encoder/decoder, the length of the packet etc. In this thesis, the author has proposed the the iterative algorithm with fast convergence for energy-efficient resource allocation in the OFDMA system with practical limitations mentioned above. In each iteration, the solution for the multiuser power and resource blocks allocation is derived while modulation and coding scheme, for each user, is obtained by another embedded iterative algorithm proposed by the author. Simulation results show that despite the computational simplicity of the proposed algorithmic solution, it achieves higher energy efficiency, than the solutions from the existing literature, where the data rate is estimated by the Shannon formula. It means that the accuracy in the system modelling has a huge impact on the energy efficiency metric maximization.

The reuse of subcarriers in a multiuser OFDMA decode and forward relay network with embedded computational awareness can increase the energy efficiency in these networks. The author of this thesis has investigated the multiuser OFDMA network, in which the end-users can receive the signal via relay nodes operating in the decode and forward mode, or directly from the base station. Moreover, in the scenario considered by the author, the same subcarrier (or multiple subcarriers) can be (re)used in the second time slot of relaying, simultaneously in the direct and relayed transmission. This approach results in interference among signals transmitted to different users, but if the channel attenuation values in the interfering links are high, it increases both the spectral efficiency and the energy efficiency. In the considered model, the linearly rate-dependent power consumption of signal processing is considered. The author developed the iterative algorithm to tackle the nonlinear fractional programming problem which maximizes energy efficiency of the investigated system. Simulation results demonstrate the effectiveness of the proposed solution for future relay networks. The energy-efficient resource allocation in OFDM/OFDMA links and networks with computational awareness faces a number of practical limitations. This calls for the proper design and engineering of these systems accounting for OFDM/OFDMA technology imperfections. The author of this thesis elaborated on the ways of considering RF front-end imperfections (nonlinearities) for the EE optimization. Moreover, he discussed the design tradeoffs, and formulated recommendations for the energy-efficiency maximization accounting for the optimization complexity, required information availability, signalling overhead and the available degrees of freedom in OFDM/OFDMA resource allocation.

The author believes that the above conclusions allow to claim that the thesis of the dissertation has been proved, i.e., that there exist new methods for the energy efficiency maximization in the OFDM/OFDMA systems with computational awareness. Some of these new methods have been proposed and evaluated in this dissertation.

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