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Radio Resource Management for Quality of Experience Optimization in Wireless Networks

Master of Science Thesis

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Gestão de Recursos de Rádio para Otimização da Qualidade de Experiência em Sistemas Sem Fio

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RADIO RESOURCE MANAGEMENT FOR QUALITY OF EXPERIENCE OPTIMIZATION IN WIRELESS NETWORKS

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Contents

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Abstract

A new generation of wireless networks, the 5th Generation (5G), is predicted for beyond 2020. For the 5G, it is foreseen an emerging huge number of services based on Machine-Type Communications (MTCs) in different fields, such as, health care, smart metering and security. Each one of them requiring different throughput rates, latency, processing capacity, energy efficiency, etc.

Independently of the service type, the customers still need to get satisfied, which is imposing a shift of paradigm towards incorporating the user as the most important factor in wireless network management. This shift of paradigm drove the creation of the Quality of Experience (QoE) concept, which describes the service quality subjectively perceived by the users. QoE is generally evaluated by a Mean Opinion Score (MOS) ranging from 1 to 5.

In this context, QoE concepts can be considered with different objectives, such as, increasing battery life, optimizing handover decision, enhancing access network selection and improving Radio Resource Allocation (RRA). Regarding the RRA, in this master's thesis we consider QoE requirements when managing the limited available resources of a communication system, such as frequency spectrum and transmit power. More specifically, we study a radio resource assignment and power allocation problem that aims at maximizing the minimum MOS of the users in a system subject to attaining a minimum number of satisfied users.

Initially, we formulate a new optimization problem taking into account constraints on the total transmit power and on the fraction of users that must be satisfied, which is an important topic from an operator's point of view. The referred problem is non-linear and hard to solve. However, we get to transform it into a simpler form, a Mixed Integer Linear Problem (MILP), that can be optimally solved using standard numerical optimization methods. Due to the complexity of obtaining the optimal solution, we propose a heuristic solution to this problem, called Power and Resource Allocation Based on Quality of Experience (PRABE). We evaluate the proposed method by means of simulations and the obtained results show that it outperforms some existing algorithms, as well as it performs close to the optimal solution.

Keywords: Quality of Experience, Minimum Mean Opinion Score Maximization, Radio Resource Allocation, Power Allocation.

Resumo

Uma nova geração de sistemas de comunicações sem fio, 5ª Geração (5G), é prevista para 2020. Para a 5G, é esperado o surgimento de diversos serviços baseados em comunicações máquina à máquina em diferentes áreas, como assistência médica, segurança e redes de medição inteligente. Cada um com diferentes requerimentos de taxa de transmissão, latência, capacidade de processamento, eficiência energética, etc.

Independente do serviço, os clientes precisam ficar satisfeitos. Isto está impondo uma mudança de paradigmas em direção à priorização do usuário como fator mais importante no gerenciamento de redes sem fio. Com esta mudança, criou-se o conceito de qualidade de experiência (do inglês, *Quality of Experience (QoE)*), que descreve de forma subjetiva como o serviço é percebido pelo usuário. A QoE normalmente é avaliada por uma nota entre 1 e 5, chamada nota média de opinião (do inglês, *Mean Opinion Score (MOS)*).

Neste contexto, conceitos de QoE podem ser considerados com diferentes objetivos, como: aumentar a vida útil de baterias, melhorar a seleção para acesso à rede e aprimorar a alocação dos recursos de rádio (do inglês, *Radio Resource Allocation (RRA)*). Com relação à RRA, nesta dissertação consideram-se requerimentos de QoE na gestão dos recursos disponíveis em um sistema de comunicações sem fio, como espectro de frequência e potência de transmissão. Mais especificamente, estuda-se um problema de assinalamento de recursos de rádio e de alocação de potência que objetiva maximizar a mínima MOS do sistema sujeito a satisfazer um número mínimo de usuários pré-estabelecido.

Inicialmente, formula-se um novo problema de otimização considerando restrições quanto à potência de transmissão e quanto à fração de usuários que deve ser satisfeita, o que é um importante tópico do ponto de vista das operadoras. Este é um problema não linear e de difícil solução. Ele é então reformulado como um problema linear inteiro e misto, que pode ser resolvido de forma ótima usando algoritmos conhecidos de otimização. Devido à complexidade da solução ótima obtida, propõe-se uma heurística chamada em inglês de *Power and Resource Allocation Based on Quality of Experience (PRABE)*. O método proposto é avaliado por meio de simulações e os resultados obtidos mostram que sua performance é superior à de outros existentes, sendo próxima à da ótima.

Palavras-Chave: Qualidade de Experiência, Maximização da Mínima MOS, Alocação de Recursos de Rádio, Alocação de Potência.

List of Figures

List of Tables

List of Algorithms

Nomenclature

Acronyms

The abbreviations and acronyms used throughout this thesis are listed here. The meaning of each abbreviation or acronym is indicated once, when it first appears in the text.

2G	2nd Generation
3G	3rd Generation
3GPP	3rd Generation Partnership Project
4G	4th Generation
5G	5th Generation
AWGN	Additive White Gaussian Noise
BB	Branch and Bound
BER	Bit Error Rate
BLER	BLock Error Rate
BS	Base Station
CQI	Channel Quality Indicator
CSI	Channel State Information
eNB	Evolved Node B
EPA	Equal Power Allocation
EPC	Evolved Packet Core
EPS	Evolved Packet System
E-UTRAN	Evolved Universal Terrestrial Radio Access Network
IID	Independent and Identically Distributed
IP	Internet Protocol
ITU	International Telecommunication Union
LTE	Long Term Evolution

LTE-A	LTE-Advanced
MCS	Modulation and Coding Scheme
MILP	Mixed Integer Linear Problem
MIMO	Multiple Input Multiple Output
MME	Mobility Management Entity
MOS	Mean Opinion Score
MTC	Machine-Type Communication
OFDMA	Orthogonal Frequency Division Multiple Access
OFDM	Orthogonal Frequency Division Multiplexing
P-GW	Packet Data Network Gateway
PRABE	Power and Resource Allocation Based on Quality of Experience
QAM	Quadrature Amplitude Modulation
QoE	Quality of Experience
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RB	Resource Block
RRA	Radio Resource Allocation
RRM	Radio Resource Management
S-GW	Serving Gateway
SISO	Single Input Single Output
SNR	Signal to Noise Ratio
TDMA	Time Division Multiple Access
TTI	Transmission Time Interval
UE	User Equipment
VoIP	Voice over IP
ZMCSCG	Zero Mean Circularly Symmetric Complex Gaussian

Notations

The following notation is used throughout this thesis. We use uppercase and lowercase boldface to denote matrices and vectors, respectively. Plain letters are used for scalars. Other notational conventions are summarized as follows:

$\lvert \cdot \rvert$	-	Absolute value of a scalar or the cardinality of a set
$\mathbf{A} \odot \mathbf{B}$	-	Hadamard product between matrices $\mathbf{A}$ and $\mathbf{B}$
$\mathbf{A} \otimes \mathbf{B}$	-	Kronecker product between matrices $\mathbf{A}$ and $\mathbf{B}$
$\mathbf{A} * \mathbf{B}$	-	Khatri-Rao product between matrices $\mathbf{A}$ and $\mathbf{B}$
$\bigcup_{s\in\mathcal{S}} \mathcal{U}_s$	-	Set operation that represents the union of the sets $\mathcal{U}_s, \forall s \in \mathcal{S}$
$\bigcap_{s\in\mathcal{S}} \mathcal{U}_s$	-	Set operation that represents the intersection of the sets $\mathcal{U}_s, \forall s \in \mathcal{S}$
$u(a, b)$	-	Step function, which returns 1 if $a \geq b$ or 0 otherwise
$\text{vec}\{\mathbf{A}\}$	-	Linear transformation which converts the matrix $\mathbf{A}$ into a column vector
$\mathbf{0}_U$	-	Column vector of length U composed of 0's
$\mathbf{1}_U$	-	Column vector of length U composed of 1's
$\mathbf{I}_U$	-	Identity matrix with dimension $U \times U$

Symbols

We summarize here the symbols that are used in the considered system modeling of this thesis.

$f(\cdot)$	-	Link adaptation function
$f^{-1}(\cdot)$	-	Inverse of link adaptation function
$h_{u,k}$	-	Complex channel coefficient between the eNB and the UE u over the RB k
$\hat{h}_{u,k}$	-	Estimated channel between the eNB and the UE u over the RB k
K	-	Total number of RBs
$\mathcal{K}$	-	Set of RBs
$m_{u,k}$	-	Selected MCS associated to UE u in RB k
M	-	Total number of MCSs
$\mathcal{M}$	-	Set of MCSs
n_s	-	Target MOS value of service plan s
$p_{u,k}$	-	Power used by the eNB to transmit to UE u through the RB k
$p_{u,k,m}$	-	Minimum transmit power required by UE u to use RB k with MCS m
$\underline{\mathbf{P}}$	-	Multi-dimensional array arranging the elements $p_{u,k,m}$
$\mathbf{P}^{(2)}$	-	Mode-2 unfolding of $\underline{\mathbf{P}}$
P_{t}	-	Total transmit power
$q_{u,s}$	-	Binary operator assuming the value 1 if UE u subscribes the service plan s, or 0, otherwise
$\mathbf{Q}$	-	Matrix arranging the elements $q_{u,s}$
R_u	-	Total throughput of UE u
$\widetilde{r}_{u,k}$	-	Achievable throughput of UE u transmitting on RB k
$\widetilde{\mathbf{R}}$	-	Matrix arranging the elements $\widetilde{r}_{u,k}$
$r_{u,k,m}$	-	Achievable throughput of UE u transmitting on RB k and using MCS m
$\underline{\mathbf{R}}$	-	Multi-dimensional array arranging the elements $r_{u,k,m}$
$\mathbf{R}^{(2)}$	-	Mode-2 unfolding of $\underline{\mathbf{R}}$
S	-	Total number of subscription plans
$\mathcal{S}$	-	Set of subscription plans

t	-	System minimum MOS
U	-	Total number of UEs
$\mathcal{U}$	-	Set of UEs
U_s	-	Total number of subscribers of service plan s
$\mathcal{U}_s$	-	Set of subscribers of service plan s
$\mathbf{w}$	-	Vector arranging the variables of optimal solution
$\widetilde{x}_{u,k}$	-	Assignment index indicating whether the RB k is allocated to UE u
$\widetilde{\mathbf{X}}$	-	Matrix arranging the elements $\widetilde{x}_{u,k}$
$x_{u,k,m}$	-	Assignment index indicating whether the RB k is allocated to UE u using the MCS m
$\underline{\mathbf{X}}$	-	Multi-dimensional array arranging the elements $x_{u,k,m}$
$\mathbf{X}^{(2)}$	-	Mode-2 unfolding of $\underline{\mathbf{X}}$
$x^{(2)}$	-	Element of $\mathbf{X}^{(2)}$
α_s	-	Satisfaction factor of service plan s
$\hat{\gamma}_{u,k}$	-	Estimated instantaneous SNR of UE u on RB k
$\hat{\gamma}_{u,k,m}$	-	Minimum estimated SNR that the eNB needs to transmit the information to UE u in the RB k using the m^{th} MCS and guaranteeing the desirable value of BLER
η	-	Channel estimation error
ξ	-	Degradation of the channel estimation
$\boldsymbol{\rho}$	-	Matrix arranging the elements ρ_u
ρ_u	-	Binary operator assuming the value 1 if user u is satisfied or 0, otherwise
σ^2	-	Average AWGN power
τ_u	-	MOS of UE u
$\phi(\cdot)$	-	Function mapping rate into a MOS value
$\phi^{-1}(\cdot)$	-	Inverse function of $\phi(\cdot)$, it maps MOS values into corresponding required rate values
φ_s	-	Minimum number of UEs that should be satisfied for service plan s
$\boldsymbol{\varphi}$	-	Matrix arranging the elements φ_u
ψ_u	-	Required transmit rate for the UE u to be satisfied
$\boldsymbol{\psi}$	-	Matrix arranging the elements ψ_s

Chapter 1

Introduction

This is an introductory chapter where we present the motivation and scope of this master's thesis in Section 1.1. After that, we present the state of the art of Quality of Experience (QoE)-aware Radio Resource Allocation (RRA) methods in Section 1.2. The studied open problems and the main contributions are stated in Section 1.3. Finally, the thesis organization and the main scientific production during the Master course are presented in Sections 1.4 and 1.5, respectively.

1.1 Thesis Scope and Motivation

Different forecasts predict for beyond 2020 a new generation of wireless communications, the 5$^{\text{th}}$ Generation (5G) [1–3]. For the 5G, it is foreseen a 1000 times higher mobile data volume per unit area and a 10 to 100 times higher user data rate [2], as well as an emerging huge number of services based on Machine-Type Communications (MTCs) in different fields, such as, health care, smart metering and security.

In terms of Quality of Service (QoS), this diverse set of devices will ask for the support of an evenly diverse range of communication requirements related to throughput, latency, and packet loss ratio, among others. In this context, it will be difficult to define optimal throughput or latency values, because these will change from service to service. Therefore, the operators will increasingly need to focus on delivering high-quality service experience, independently of technical requirements.

This leads us to the concept of QoE, which is defined in [4] as the overall acceptability of an application or service, as perceived subjectively by the end-user. It is generally evaluated by a Mean Opinion Score (MOS) ranging from 1 to 5 [5].

The overall goal of QoE management is to optimize end-user QoE (end-user perspective), while making efficient use of network resources [6]. In order to successfully manage QoE for a specific application, it is necessary to understand and identify multiple factors affecting it (subjective and objectively) and how they impact QoE. Resulting QoE models dictate the parameters to be monitored and measured. In [7], a survey breaks down the overall process of QoE management into three general steps: QoE modeling, measurement and optimization.

QoE Modeling

Regarding the QoE modeling, its main objective is, given a set of conditions, to make QoE estimations. For this, first of all, it is necessary to identify the influencing factors, which, in [8], are grouped into four multidimensional spaces: Application (application configuration-related factors), Resource (network/system related factors, e.g., throughput, bandwidth, etc), Context (user's environment, e.g., location, time of day, movement, etc.) and User (characteristics of a human user, e.g., gender, age, education background, etc.).

The majority of works have been focused on identifying the relationship between QoE and the network/system related factors. For this purpose, quality assessments are deployed. The main idea is to expose users to a specific service, where they need to rate the quality of the service. The rates are then averaged into MOS. The details are specified in [9].

Nevertheless, there is still not a consensus on this topic. For example, in [10], it is formulated that QoS and QoE are connected through an exponential relationship, called IQX hypothesis, whereas, in [11], it is inferred that, especially for Voice over IP (VoIP) and mobile broadband scenarios, the users' experience follows logarithmic laws.

QoE Measurement

The main challenges in the QoE measurement are related to 3 questions [7]: what to collect? Where to collect? And when to collect?

Firstly, one needs to determine which data to acquire. This decision depends on the service type been monitored and on the QoE model adopted to convert the influencing factors into MOS.

Secondly, one needs to decide where to collect the data, which can be within the network, at the client side, or both. According to [12], the best way to obtain an accurate QoE assessment is to combine reported measures from the mobile device with network data. However, as pointed in [6], monitoring at the client side can pose issues of users' privacy.

Finally, one should determine when and how often to perform the data acquisition. This depends of what is been monitored and of where the measures are been taking, since computational complexity and battery life of mobile devices need to be considered.

QoE Optimization

Concerning optimization strategies, different objectives can be considered, such as, increasing battery life [13], optimizing handover decision [14], enhancing access network selection [15] and improving Radio Resource Management (RRM). Regarding the RRM, one possible approach is to consider QoE requirements when managing the limited available resources of a communication system, such as frequency spectrum and transmit power.

In this context, this work proposes an algorithm of RRA and power allocation aiming at maximizing the minimum MOS subject to a minimum number of satisfied users, wherein the MOS objectively quantifies the users' QoE.

1.2 State of the Art

According to [16], RRA problems can be classified into different categories, such as opportunistic and fair algorithms.

Opportunistic algorithms

This category of algorithms is more interested in the system overall than in the users individually. They exploit the idea of giving priority to users with the best opportunities to achieve a predefined goal, over the other users. Several algorithms use this approach with different objectives such as: rate maximization and power consumption minimization.

Rate maximization algorithms aim at maximizing the total data rate of the system. In [17], the authors develop an RRM scheme that exclusively assigns a sub-carrier to a user with the highest channel gain on that sub-carrier which maximizes the system sum rate. However, usually, the resources are allocated to the users that are close to the base station, whereas edge users generally suffer from starvation and have very low data rates [18].

In a similar way, power consumption minimization algorithms tend to keep users with bad channel conditions in starvation. In [19], a low computational algorithm is proposed to minimize power consumption with Bit Error Rate (BER) and data rate constraints for different types of services. Another power minimization problem is formulated in [20] with a minimum user data rate constraint using integer programming and continuous relaxation-based suboptimal solution methods.

Fair algorithms

The main objective of this category is to reach fairness between users, avoiding the starvation of the opportunistic algorithms. The minimum rate maximization and Round Robin are examples of this category.

In [21], a minimum rate maximization algorithm is proposed for the downlink of an Orthogonal Frequency Division Multiplexing (OFDM) broadband system. By prioritizing users with low data rate, it tends to overcome the problem of edge users' starvation.

The Round Robin technique consists of scheduling the equal amount of resources for all users in circular order. In [22], it is presented a comparison between a greedy scheduling and an opportunistic Round Robin scheme for Multiple Input Multiple Output (MIMO) systems. The results testify the fairness of this scheme.

The majority of RRA schemes in the literature considers QoS optimization criteria. However, as previously explained, 5G networks will demand the management of a wide range of QoS requirements. Therefore, new approaches based on user's experience are needed since QoS metrics would not reflect client perception of different applications anymore.

QoE-aware algorithms

In [23], the performance of three QoS-based RRA algorithms (max rate, max-min rate and proportional fair) are compared in terms of QoE metrics (average QoE and geometric mean QoE). The authors conclude that the QoE results need to be enhanced.

In fact, some authors have already addressed QoE aspects in RRA problems. A commonly studied problem in this field is the maximization of the overall QoE. In [24], the allocation problem is modeled as a bounded optimization problem to achieve the maximum overall QoE with a constraint in total transmit power. In [25], a power allocation scheme, targeting at maximizing QoE is proposed for video transmissions over MIMO systems. The problem is decomposed into sub-problems and a bisection search algorithm is used to obtain their optimal solutions.

In [26], a multicell coordination among multiple Base Stations (BSs) is investigated for interference mitigation and overall QoE maximization. The problem is formulated as a local cooperative game, where BSs are encouraged to cooperate with their peer nodes in the adjacent cells when scheduling users and allocating power.

As the other opportunistic algorithms, the disadvantage of [24–26] is that they may penalize users with poor link conditions. In [27], a similar problem is studied, but a penalty function is also considered aiming at guaranteeing the fairness among users, besides of maximizing the level of QoE in the system. Another strategy is adopted by the authors of [28] to overcome this problem. They firstly allocate sub-carriers to all the users in order to guarantee their minimal transmit rate requirement, then the remaining sub-carriers are allocated to the users who can achieve the best QoE gain. In [29], a proportional fair scheduling is proposed considering not only the users' QoE maximization but as also the fairness among users.

In [30], the authors propose a QoE-aware scheduler that maximizes the average number of satisfied users. Their scheme needs the users' participation informing their satisfaction over a one-bit feedback.

Another studied problem is the maximization of the minimal MOS in the system. In [31], a frequency spectrum assignment based on game theory together with a water-filling power allocation is proposed. The system is modeled as a market place where, after a random assignment, the users, in pairs, negotiate for the resources. The same problem is studied in [32]. The Hungarian algorithm is used to assign frequency spectrum, and the optimal solution of a Tchebycheff problem is used for the power allocation.

1.3 Open Problem and Contributions

As far as we know, the problem of maximizing the minimum MOS of the system considering a satisfaction factor, i.e., a constraint on the minimum number of users that must be satisfied, was not studied yet. This constraint is an important operator requirement and was considered in other contexts [33–35]. In a real network, this fraction is a parameter defined by the network operator.

First of all, we analyze the optimal solution of this problem, as a Mixed Integer Linear Problem (MILP). Since it requires a high computational effort, we propose a heuristic solution called Power and Resource Allocation Based on Quality of Experience (PRABE).

Figure 1.1 presents an overview of PRABE. The proposed framework is a QoE management scheme which deals with MOS values. Independently of service or device, we consider functions mapping QoS requirements into a MOS value. PRABE is divided into two parts: the resource assignment and the power allocation. Each one of them tries first to satisfy the required minimum number of satisfied users and then to maximize the minimum MOS in the system.

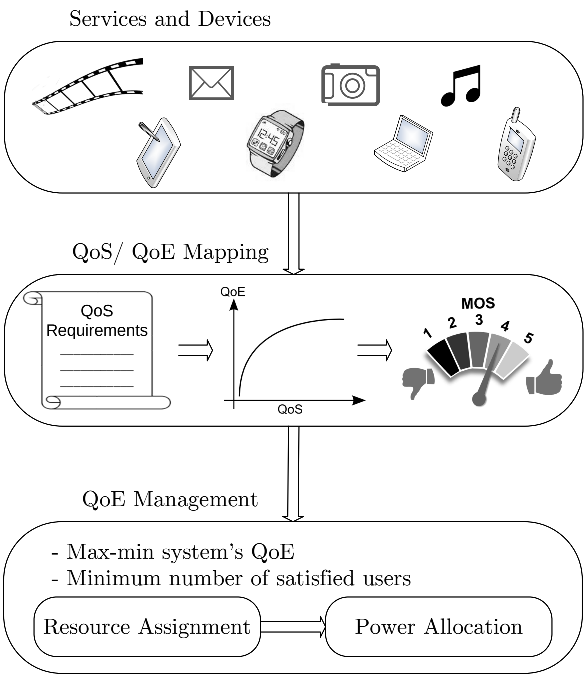


Figure 1.1: Framework context.

In summary, the main contributions of this master's thesis are:

i. Problem formulation: we formulate a max-min problem for the MOS considering a satisfaction factor, an operator requirement not yet explored by previous works in this context, as far as we know. With this constraint, we need to ensure that at least a specific fraction of the total number of users meets a minimum MOS value.

ii. Characterization of optimal solution: the original problem has non-linear constraints and may require a prohibitive computational effort. We transform it and solve it optimally as a MILP using standard algorithms, with lower complexity.

iii. Proposal of heuristic solution: we propose a suboptimal solution including radio resource assignment and power allocation requiring lower complexity than the optimal one does.

iv. Performance evaluation: we show that the proposed heuristic outperforms benchmarking solutions in the different analyzed scenarios, besides of performing close to the optimal one.

1.4 Thesis Organization

In Chapter 2, we present the main assumptions in this thesis related to the system model, which is based on 3rd Generation Partnership Project (3GPP)'s Long Term Evolution (LTE) standards. To this end, we also provide a quick insight into some relevant features of LTE and LTE-Advanced (LTE-A).

The mathematical formulation of the studied problem and its optimal solution as a MILP are presented in Chapter 3. To overcome the problem of high computational effort required by the optimal solution, we also present in this chapter a heuristic solution with lower complexity, called PRABE.

The performance evaluation is presented in Chapter 4. We consider four different scenarios to compare the performance of PRABE with two benchmarking algorithms besides of the optimal solution and a mixed one. The mixed solution is composed by two parts an optimal resource assignment considering Equal Power Allocation (EPA) and a heuristic power allocation.

The main conclusions of this master's thesis are summarized in Chapter 5. Furthermore, we also point out the main research directions that can be considered as extension of this work.

1.5 Scientific Production

The content and contributions presented in this Master's thesis were submitted with the following information:

- **Victor F. Monteiro**, Diego A. Sousa, Tarcisio F. Maciel, F. Rafael M. Lima, Emanuel B. Rodrigues and F. Rodrigo P. Cavalcanti, "Radio Resource Allocation Framework for Quality of Experience Optimization in Wireless Networks". IEEE Network special issue - QoE-Aware Design in Next-Generation Wireless Networks (submitted).

- **Victor F. Monteiro**, Diego A. Sousa, Tarcisio F. Maciel, F. Rafael M. Lima and F. Rodrigo P. Cavalcanti, "Alocação de Recursos em Redes Sem Fio Baseada na Qualidade de Experiência do Usuário". XXXIII Brazilian Telecommunications Symposium (SBrT), 2015.

- **Victor F. Monteiro**, Diego A. Sousa, Tarcisio F. Maciel, F. Rafael M. Lima and F. Rodrigo P. Cavalcanti, "Power and Resource Allocation Based on Quality of Experience". IEEE Transactions on Vehicular Technology (to be submitted).

In parallel to the work developed in the Master course that was initiated on the first semester of 2014, I have been working on other research projects related to analysis and control of trade-offs involving QoS provision. In the context of these projects, I have participated on the following papers and technical reports:

- **Victor F. Monteiro**, Diego A. Sousa, F. Hugo C. Neto, Emanuel B. Rodrigues, Tarcisio F. Maciel and F. Rodrigo P. Cavalcanti, "Throughput-based Satisfaction Maximization for a Multi Cell Downlink OFDMA System with Imperfect CSI". XXXIII Brazilian Telecommunications Symposium (SBrT), 2015.
- Diego A. Sousa, **Victor F. Monteiro**, Tarcisio F. Maciel and F. Rafael M. Lima, "Resource Management for Rate Maximization with QoE Provisioning in Wireless Networks". IEEE Transactions on Vehicular Technology (submitted).
- **Victor F. Monteiro**, Diego A. Sousa, Tarcisio F. Maciel, F. Rafael M. Lima and F. Rodrigo P. Cavalcanti, "Power and Resource Allocation Based on Quality of Experience", GTEL-UFC-Ericsson UFC.40, Tech. Rep., March 2015, First Technical Report.
- Diego A. Sousa, **Victor F. Monteiro**, Tarcisio F. Maciel and F. Rafael M. Lima, "Resource Management for Rate Maximization with QoE Provisioning in Wireless Networks", GTEL-UFC-Ericsson UFC.40, Tech. Rep., March 2015, First Technical Report.
- F. Hugo C. Neto, **Victor F. Monteiro**, Diego A. Sousa, Emanuel B. Rodrigues, Tarcisio F. Maciel and F. Rodrigo P. Cavalcanti, "A Novel Utility-Based Resource Allocation Technique for Improving User Satisfaction in OFDMA Networks", GTEL-UFC-Ericsson UFC.33, Tech. Rep., Aug. 2014, Fourth Technical Report.

Chapter 2

System Modeling

2.1 Introduction

The system architecture adopted in this thesis is based on 3rd Generation Partnership Project (3GPP)'s Long Term Evolution (LTE) standards. To this end, Section 2.2 provides a quick insight into some relevant features of LTE and LTE-Advanced (LTE-A) for the remaining of this thesis. After that, in Section 2.3, we present the main assumptions of this thesis.

2.2 LTE Overview

With the development of highly advanced mobile devices, the demands for higher data rates and better Quality of Service (QoS) increased rapidly. Therefore, in 2004 the 3GPP has specified new standards for the mobile communications: the Evolved Universal Terrestrial Radio Access Network (E-UTRAN) and the Evolved Packet Core (EPC), which define the radio access network and the core network of the LTE system, respectively. The E-UTRAN together with the EPC are known as the Evolved Packet System (EPS).

The standards for LTE are specified in the 3GPP Release 8, as high data rates of up to 300 Mbits/s in the downlink and 75 Mbits/s in the uplink. However, these specifications do not meet the 4th Generation (4G) requirements set by the International Telecommunication Union (ITU) such as data rate up to 1 Gbits/s. As a result, the LTE-A, an enhancement of LTE, was presented as a 4G system to the ITU in 2009, and was finalized by the 3GPP in Release 10 in March, 2011.

A simplified architecture of LTE is depicted in Figure 2.1. The main logical nodes of the core network, the EPC, are the Serving Gateway (S-GW), the Mobility Management Entity (MME) and the Packet Data Network Gateway (P-GW), while the radio access network, the E-UTRAN, comprises the User Equipments (UEs) and the Evolved Node Bs (eNBs). Connections between the EPC and the E-UTRAN are established through the S1 interface between the S-GW and eNBs. The X2 interface was introduced to allow interconnections among eNBs for direct signaling, eliminating the need of channeling data back and forth through the core network.

In the EPC, the S-GW serves as the local mobility anchor point for inter-eNB handover and inter-3GPP mobility, as well as the handling of Internet Protocol (IP) packet transfer between the EPC and the associated UEs. The MME is responsible for handling the user mobility, i.e., attaches and detaches to the EPC system, and for tracking area updates. It also handles the radio bearer management where a radio bearer is a data flow or logical channel established between an eNB and a UE [36]. The P-GW serves as the medium between the EPC and other IP networks such as the Internet. It also performs IP address allocation for UEs and QoS

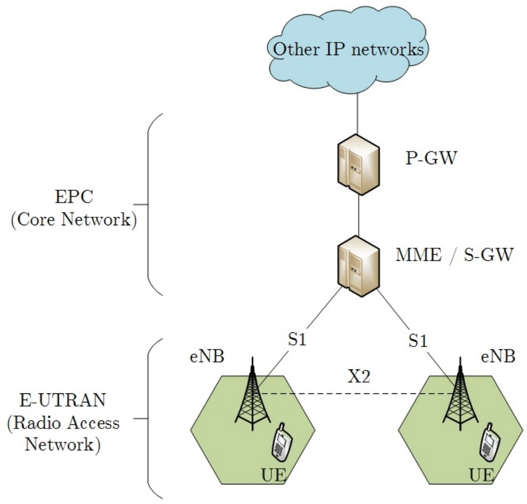


Figure 2.1: LTE architecture.

enforcement [37].

Concerning the E-UTRAN, unlike the previous 2[nd] Generation (2G) and 3[rd] Generation (3G) technologies, LTE integrates all the radio interface related functions into the eNB. The eNB manages uplink and downlink transmissions among the UEs performing Radio Resource Management (RRM) functions and control signaling.

Regarding the LTE physical layer of the downlink, some interesting concepts are relevant for the remaining of this thesis, such as the Orthogonal Frequency Division Multiple Access (OFDMA) technique and the link adaptation concept.

OFDMA

OFDMA is an extension of Orthogonal Frequency Division Multiplexing (OFDM). While OFDM splits the frequency bandwidth into orthogonal sub-carriers and use them to transmit data to a single user, OFDMA distributes sub-carriers to different users at the same time, so that multiple users can be scheduled to receive data simultaneously. For LTE systems, the sub-carrier spacing is 15 kHz.

The data symbols can be independently modulated and transmitted over these orthogonal sub-carriers. In LTE, the available downlink modulation schemes are Quadrature Phase Shift Keying (QPSK), 16-Quadrature Amplitude Modulation (QAM), and 64-QAM.

OFDMA enhances considerably the total system spectral efficiency. It performs adaptive user-to-sub-carrier assignment, based on feedback about the Channel State Information (CSI) from each user. It can also be used in combination with Time Division Multiple Access (TDMA), such that the resources are partitioned in the time-frequency plane. Figure 2.2 illustrates this partition. The minimum allocable time-frequency block is known as Resource Block (RB). An RB corresponds to a subset of sub-carries in the frequency domain and a number of OFDM symbols in the time domain [38]. A cyclic prefix is added prior to each OFDM symbol as a guard interval to avoid inter-symbol interference due to channel delay spread.

Link Adaptation

Link adaptation technique consists of dynamically adjusting the transmission parameters, such as Modulation and Coding Schemes (MCSs), to match the conditions of the users' radio link. During good propagation conditions, a high order modulation scheme with low coding redundancy is used in order to increase the transmission data rate, while during a signal fade, the system selects a more robust modulation scheme and a higher coding rate to maintain both connection quality and link stability without increasing the signal power [39].

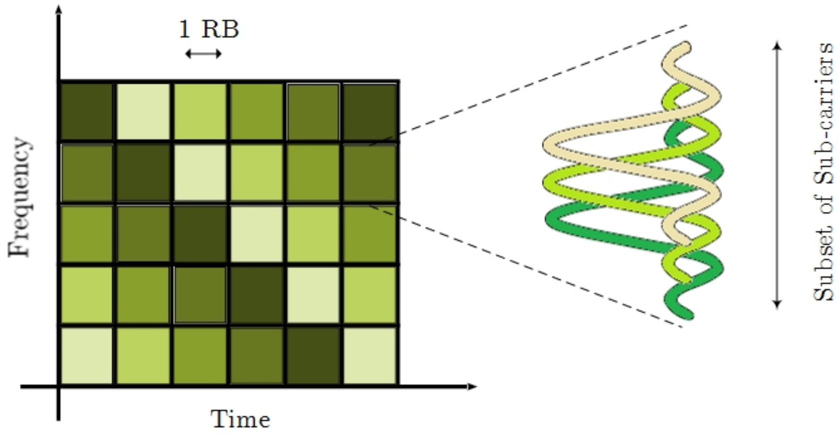


Figure 2.2: Time-frequency partition.

In LTE, the UEs transmit in the uplink the Channel Quality Indicator (CQI) to the eNB, which, in response, selects the best adapted MCS to use in the downlink. Table 2.1 presents the mapping of CQI into MCS in LTE. Note that larger CQI indexes, i.e., better channel conditions, allow to transmit more bits on each OFDM symbol and to use the channel more efficiently.

Differences in MCS bring different BLock Error Rate (BLER) performances, which can be seen in Figure 2.3. It represents the relationship between Signal to Noise Ratio (SNR), BLER and MCS. Note that for the same SNR, higher MCS index represents higher BLER, which means that a given MCS requires a certain SNR to operate with an acceptably low BLER [40].

Table 2.1: CQI and MCS mapping in LTE [41].

CQI index	Modulation	Code rate (x 1024)	Rate (Bits/symbol)	CQI index	Modulation	Code rate (x1024)	Rate (Bits/symbol)
0		Out of range		8	16QAM	490	1.9141
1	QPSK	78	0.152	9	16QAM	616	2.4063
2	QPSK	120	0.234	10	64QAM	466	2.7305
3	QPSK	193	0.377	11	64QAM	567	3.3223
4	QPSK	308	0.602	12	64QAM	666	3.9023
5	QPSK	449	0.877	13	64QAM	772	4.5234
6	QPSK	602	1.176	14	64QAM	873	5.1152
7	16QAM	378	1.477	15	64QAM	948	5.5547

2.3 System layout

In this thesis, we consider the downlink of a LTE-like system composed of a single cell in which an eNB is deployed to serve a set $\mathcal{U}$ of UEs distributed within its coverage area. Both the eNB and the UEs are equipped with single antennas, i.e., we consider a Single Input Single Output (SISO) scenario.

Due to the diversity of applications with distinct requirements, we consider that the UEs are separated into different mobile subscription plans. We define $\mathcal{S} = \{1, 2, \ldots, S\}$ as the set of subscription plans and $\mathcal{U}_s$ as the set of subscribers of service plan $s \in \mathcal{S}$, where $\bigcup_{s\in\mathcal{S}} \mathcal{U}_s = \mathcal{U}$. For example, a priority plan with higher requirements for emergency services, as fire brigade, police and ambulances, and another one for UEs in general. Moreover, we consider that each user subscribes to only a single service plan, i.e, $\bigcap_{s\in\mathcal{S}} \mathcal{U}_s = \emptyset$.

The considered LTE-like system employs OFDMA and TDMA as multiple access scheme, where, due to signaling constraints, the radio resources are assigned in blocks. The system disposes of K RBs arranged in a set $\mathcal{K}$. The time duration corresponding to the time basis at which resources are allocated to the UEs by the Radio Resource Allocation (RRA) algorithms is termed herein as Transmission Time Interval (TTI), and it is equal to the time duration of

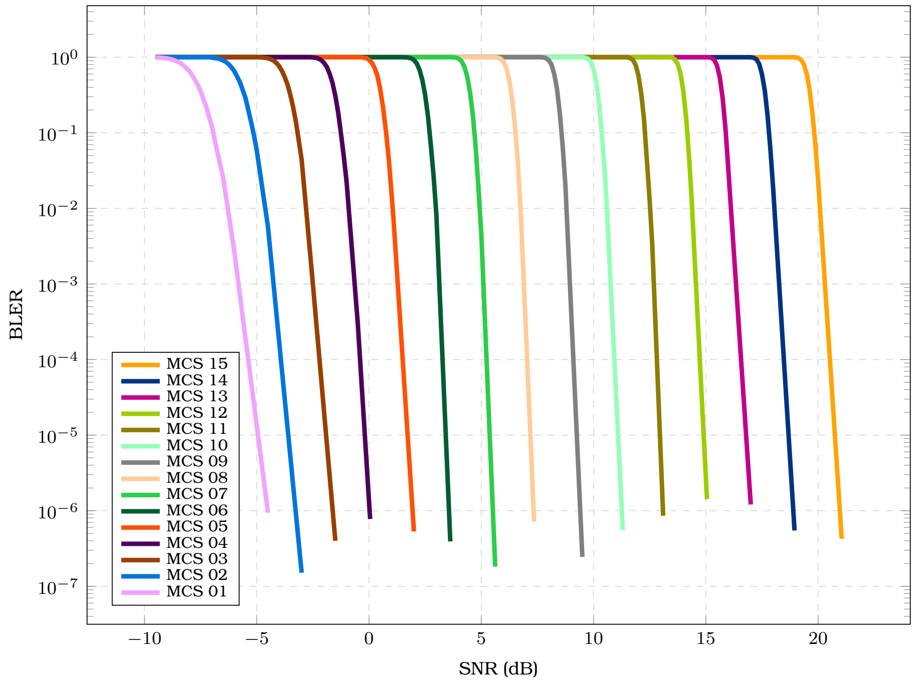


Figure 2.3: Relationship between SNR, BLER and MCS in LTE [52].

an RB. Moreover, we consider that each RB can be allocated to only one UE at each TTI.

The complex channel coefficient $h_{u,k}$ between the eNB and the UE $u \in \mathcal{U}$ over the RB $k \in \mathcal{K}$ at a specific TTI encompasses the main propagation effects on the wireless channel, namely path loss, shadowing, and small-scale fading, as well as any transmit or receive antenna gains. Furthermore, the channel coherence bandwidth is assumed to be larger than the bandwidth of an RB, resulting in a flat fading channel over each of them; and the channel response for each RB is represented by the complex channel coefficient associated with its middle subcarrier and first OFDM symbol. The UE estimates $h_{u,k}$ using pilot symbols transmitted by the eNB. The estimated channel, $\hat{h}_{u,k}$, can be modeled as described in [42]:

$$\hat{h}_{u,k} = \sqrt{(1-\xi)} h_{u,k} + \sqrt{\xi}\eta, \tag{2.1}$$

where $\xi \in (0,1)$ denotes the degradation of the channel estimation and $\eta \in \mathbb{C}$ represents a channel estimation error, which is modeled as a Zero Mean Circularly Symmetric Complex Gaussian (ZMCSCG) random variable, with $\mathbb{E}\{|\eta|^2\} = \mathbb{E}\{|h_{u,k}|^2\}$.

In this work, we are interested at studying the CSI imperfections regarding the estimation errors, i.e., we evaluate the impact of the parameter ξ. Hence, we consider that the reports are performed at every TTI and that the eNB receives the measures without delay.

The estimated instantaneous SNR $\hat{\gamma}_{u,k}$ of each UE u on each RB k at each TTI is given by

$$\hat{\gamma}_{u,k} = \frac{p_{u,k} \left|\hat{h}_{u,k}\right|^2}{\sigma^2}, \tag{2.2}$$

where $p_{u,k}$ is the power used by the eNB to transmit to UE u through the RB k and σ^2 denotes the average Additive White Gaussian Noise (AWGN) power.

As in LTE, we consider a link adaptation mechanism in which the eNB selects a MCS m from a set $\mathcal{M}$ of MCSs. The choice of the MCS depends on $\hat{\gamma}_{u,k}$ and we consider $M = |\mathcal{M}|$ different MCSs, where $|\cdot|$ applied to a set denotes its cardinality. The selected MCS $m_{u,k}$

associated to UE u in RB k is given by

$$m_{u,k} = f\left(\hat{\gamma}_{u,k}\right), \tag{2.3}$$

where $f(\hat{\gamma}_{u,k})$ is the link adaptation function. In this work, we consider that the eNB selects as the best MCS for a given UE u on an RB k the one that leads to the highest data rate for a given allocated power.

Fixing a desirable value of BLER, we can obtain from the link adaptation curves the minimum estimated SNR, $\hat{\gamma}_{u,k,m}$, that the eNB needs to transmit the information to UE u in the RB k using the m^{th} MCS and guaranteeing the desirable value of BLER. This minimum SNR is given by

$$\hat{\gamma}_{u,k,m} = f^{-1}(m_{u,k}), \tag{2.4}$$

where $f^{-1}(\cdot)$ is the inverse of link adaptation function.

From (2.4), we can obtain the values of $\hat{\gamma}_{u,k,m}$, which can be used in (2.2) to obtain the minimum transmit power, $p_{u,k,m}$, associated to MCS m. Since we consider flat fading over each RB, at each TTI, the value of $\hat{h}_{u,k}$ in (2.2) is constant for each pair $\{u, k\}$.

Defining $r_{u,k,m}$ as the throughput of UE u transmitting on RB k and using MCS m, the total throughput R_u of UE u is given by

$$R_u = \sum_{k=1}^{K=|\mathcal{K}|} \sum_{m=1}^{M=|\mathcal{M}|} r_{u,k,m} x_{u,k,m}, \tag{2.5}$$

where $x_{u,k,m}$ is the assignment index indicating whether the RB k is allocated to UE u using the MCS m.

Finally, the Quality of Experience (QoE) τ_u of a UE u can be obtained from the rate R_u using the function $\phi(\cdot)$, which maps rate into an Mean Opinion Score (MOS), as

$$\tau_u = \phi\left(R_u\right). \tag{2.6}$$

Based on all these assumptions, we are now able to introduce the studied problem, as well as its solutions, which will be done in the next chapter.

Chapter 3

Power and Resource Allocation Based on Quality of Experience

3.1 Introduction

This chapter presents the problem studied in this master thesis and its solutions. The mathematical formulation of the problem and its optimal solution as a Mixed Integer Linear Problem (MILP) are presented in Sections 3.2 and 3.3, respectively. MILPs can be solved by standard numerical optimization methods, nevertheless, they still require high computational effort. To overcome this issue, a heuristic solution is proposed in Section 3.4.

3.2 Problem Formulation

As already mentioned, the operators are changing their focus to deliver services with high Quality of Experience (QoE), independently of technical requirements, and measuring their performance based on the percentage of satisfied users in the system.

In this context, we aim to assign Resource Blocks (RBs) to the User Equipments (UEs) being served by the system and to allocate power to their corresponding channels in a way that maximizes the minimum Mean Opinion Score (MOS) perceived by these same UEs. In Figure 3.1 we have an illustration of the studied problem. Initially, the smartphone and tablet users are unsatisfied due to the low number of RBs and power allocated to them, while the notebook and smartwatch users have more RBs than they need to get satisfied. Then, the RBs are reassigned and the power is reallocated between the UEs' channels in order to maximize the minimum satisfaction in the system.

Besides the maximization of the minimum MOS t, in order to guarantee a minimum quality for the services being provided by the network operator, we require that at least φ_s UEs should be satisfied for each service plan s, i.e, have a MOS equal to or higher than a given target MOS value n_s. We call the ratio $\alpha_s = \dfrac{\varphi_s}{U_s}$ as the satisfaction factor of the service plan s.

Moreover, our problem is also constrained in transmit power, which should be equal to or lower than the total transmit power P_{t} available at the Evolved Node B (eNB). Based on these assumptions and on the models presented in Section 2.3, this problem can then be

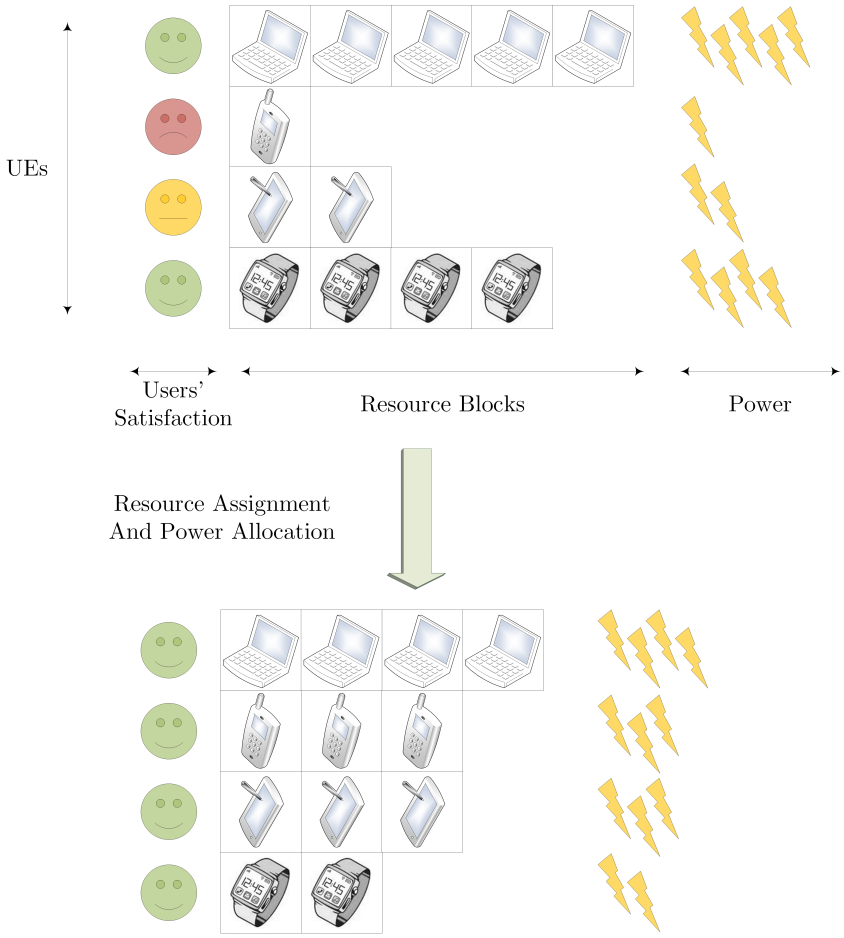


Figure 3.1: Studied problem.

formulated as

$$\begin{aligned} \text{maximize} \quad & t && \text{(3.1a)} \\ \text{subject to} \quad & \tau_u \geq t, \forall u \in \mathcal{U}, && \text{(3.1b)} \\ & \sum_{u=1}^{U_s} u\left(\tau_u, n_s\right) \geq \varphi_s, \forall s \in \mathcal{S}, && \text{(3.1c)} \\ & \sum_{u=1}^{U} \sum_{k=1}^{K} \sum_{m=1}^{M} p_{u,k,m} x_{u,k,m} \leq P_{\mathrm{t}}, && \text{(3.1d)} \\ & \sum_{u=1}^{U} \sum_{m=1}^{M} x_{u,k,m} \leq 1, \forall k \in \mathcal{K}, && \text{(3.1e)} \\ & x_{u,k,m} \in \{0,1\}, \forall u \in \mathcal{U}, \forall k \in \mathcal{K}, \forall m \in \mathcal{M}, && \text{(3.1f)} \end{aligned}$$

where $u(a, b)$ represents the step function given by

$$u(a,b) = \begin{cases} 1, & \text{if } a \geq b, \\ 0, & \text{if } a < b. \end{cases} \tag{3.2}$$

The objective function t being maximized in (3.1a) represents the system minimum MOS, which is guaranteed by constraint (3.1b). The inequality in (3.1c) imposes that, for each service s, at least φ_s out of the U_s UEs have MOS equal to or greater than n_s. In (3.1d), we have the transmit power constraint. Finally, the last two constraints, (3.1e) and (3.1f), assure that an RB will be allocated to only one UE at a time.

The problem described in (3.1) is nonlinear, due to constraint (3.1c), and mixed integer since $x_{u,k,m}$ is a binary variable and t is a continuous variable. Therefore, its optimal solution may require a prohibitive computational effort [43]. To reduce its complexity, in the next section we will convert (3.1) into a linear optimization problem.

3.3 Optimal Solution

The main objective of this section is to reformulate the problem (3.1) as an MILP, which has lower complexity than the formulation presented in Section 3.2 and can be solved by standard algorithms, such as the Branch and Bound (BB) method [44]. We take two main steps. The first one is to linearize the constraint in (3.1c). The second one is to rewrite the problem in a compact form, using tensor notation.

Considering $\phi(\cdot)$ as a strictly increasing function, then there is an inverse function $\phi^{-1}(\cdot)$ mapping the possible MOS values of the UEs into corresponding required data rate values [45]. Replacing (2.5) and (2.6) into (3.1b), we obtain

$$\begin{aligned} \tau_u = \phi\left(R_u\right) \geq t \Rightarrow \phi\left(\sum_{k=1}^{K}\sum_{m=1}^{M} r_{u,k,m}x_{u,k,m}\right) \geq t \\ \Rightarrow \sum_{k=1}^{K}\sum_{m=1}^{M} r_{u,k,m}x_{u,k,m} \geq \phi^{-1}\left(t\right) \\ \Rightarrow \phi^{-1}\left(t\right) - \sum_{k=1}^{K}\sum_{m=1}^{M} r_{u,k,m}x_{u,k,m} \leq 0, \forall u. \end{aligned} \tag{3.3}$$

Similarly, replacing (2.5) and (2.6) into the constraint (3.1c), we can rewrite it as

$$\sum_{u=1}^{U_s} u\left(\tau_u, n_s\right) \geq \varphi_s \Rightarrow \sum_{u=1}^{U_s} u\left(\sum_{k=1}^{K}\sum_{m=1}^{M} r_{u,k,m}x_{u,k,m}, \psi_u\right) \geq \varphi_s, \forall s \in \mathcal{S}, \tag{3.4}$$

where $\psi_u = \phi^{-1}(n_s), \forall u \in \mathcal{U}_s$ and $\forall s \in \mathcal{S}$, denotes the required transmit rate for UE u to be satisfied.

We introduce a binary operator ρ_u defined as

$$\rho_u = \begin{cases} 1, & \text{if } \tau_u \geq \phi(\psi_u), \\ 0, & \text{if } \tau_u < \phi(\psi_u), \end{cases} \tag{3.5}$$

to replace the step function in (3.4). This variable assumes the value 1 if the user u is satisfied and 0 otherwise.

Restating (3.4), we have:

$$\sum_{k=1}^{K}\sum_{m=1}^{M} r_{u,k,m}x_{u,k,m} \geq \psi_u \cdot \rho_u, \tag{3.6a}$$

$$\sum_{u=1}^{U} q_{u,s}\rho_u \geq \varphi_s, \forall s \in \mathcal{S}, \tag{3.6b}$$

where $q_{u,s}$ is equal to 1 if the UE u subscribes the service plan s.

In this way, (3.1) can be rewritten as:

$$\text{maximize} \quad \phi^{-1}(t), \tag{3.7a}$$

$$\text{subject to} \quad \phi^{-1}(t) - \sum_{k=1}^{K}\sum_{m=1}^{M} r_{u,k,m}x_{u,k,m} \leq 0, \forall u \in \mathcal{U}, \tag{3.7b}$$

$$\sum_{k=1}^{K}\sum_{m=1}^{M} r_{u,k,m}x_{u,k,m} \geq \psi_u \cdot \rho_u, \tag{3.7c}$$

$$\sum_{u=1}^{U} q_{u,s}\rho_u \geq \varphi_s, \forall s \in \mathcal{S}, \tag{3.7d}$$

$$\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{m=1}^{M} p_{u,k,m}x_{u,k,m} \leq P_{\mathrm{t}}, \tag{3.7e}$$

$$\sum_{u=1}^{U}\sum_{m=1}^{M} x_{u,k,m} \leq 1, \forall k \in \mathcal{K}, \tag{3.7f}$$

$$x_{u,k,m} \in \{0,1\}, \forall u \in \mathcal{U}, k \in \mathcal{K}, m \in \mathcal{M}. \tag{3.7g}$$

At this point, we will reformulate (3.7) in a matrix form. For this, we need to introduce some concepts and definitions related to tensors. The first one is the concept of unfolding, illustrated in Figure 3.2. We arrange the elements $x_{u,k,m}$ in a multi-dimensional array $\underline{\mathbf{X}} \in \mathbb{R}^{U\times K\times M}$ and we denote $\mathbf{X}^{(2)} \in \mathbb{R}^{K\times U\cdot M}$ as the mode-2 unfolding of $\underline{\mathbf{X}}$, where the elements $x^{(2)}$ of $\mathbf{X}^{(2)}$ are defined in function of the elements of $\underline{\mathbf{X}}$ as $x^{(2)}_{k,u+(m-1)U} = x_{u,k,m}$ [46]. In a similar way, the elements $r_{u,k,m}$ and $p_{u,k,m}$ form the multi-dimensional arrays $\underline{\mathbf{R}}$ and $\underline{\mathbf{P}}$, respectively, and $\mathbf{R}^{(2)}$ and $\mathbf{P}^{(2)}$ are the mode-2 unfolding of $\underline{\mathbf{R}}$ and $\underline{\mathbf{P}}$, respectively.

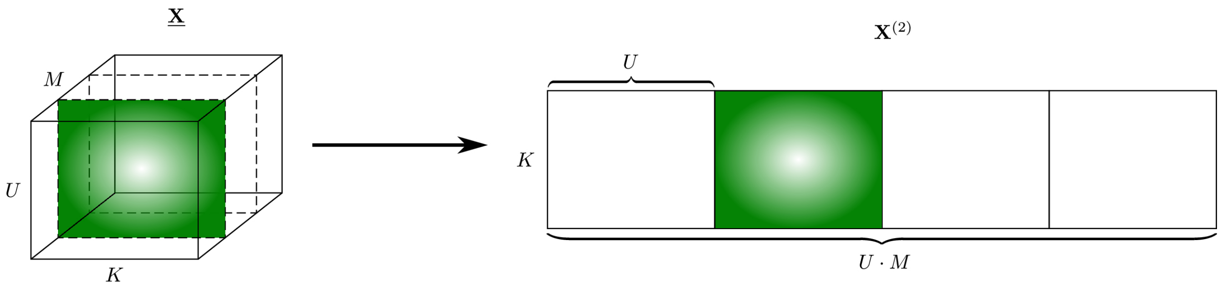


Figure 3.2: Mode-2 unfolding of a third-order matrix [46].

We consider $\mathbf{A} \odot \mathbf{B}$ as the element-wise product between two equal-size matrices, called Hadamard product, and $\mathbf{A} \otimes \mathbf{B}$ as the Kronecker product expressed as

$$\mathbf{A} \otimes \mathbf{B} = \begin{bmatrix} a_{11}\mathbf{B} & a_{12}\mathbf{B} & \cdots & a_{1J}\mathbf{B} \\ a_{21}\mathbf{B} & a_{22}\mathbf{B} & \cdots & a_{2J}\mathbf{B} \\ \vdots & \vdots & \ddots & \vdots \\ a_{I1}\mathbf{B} & a_{I2}\mathbf{B} & \cdots & a_{IJ}\mathbf{B} \end{bmatrix},$$

where $\mathbf{A} \in \mathbb{R}^{I\times J}$ and $\mathbf{B} \in \mathbb{R}^{T\times R}$. Finally, we define the $\mathrm{vec}\{\cdot\}$ operation as $\mathrm{vec}\{\mathbf{Z}\} = \left[\mathbf{z}_1^{\mathrm{T}}\ \mathbf{z}_2^{\mathrm{T}}\ \ldots\ \mathbf{z}_n^{\mathrm{T}}\right]^{\mathrm{T}}$, where $\mathbf{z}_i$ is the i-th column of matrix $\mathbf{Z}$.

To simplify the notation, we rename the following variables: $\mathbf{x} = \mathrm{vec}\left\{\mathbf{X}^{(2)\mathrm{T}}\right\}$, $\mathbf{p} = \mathrm{vec}\left\{\mathbf{P}^{(2)\mathrm{T}}\right\}$ and $\mathbf{r} = \mathrm{vec}\left\{\mathbf{R}^{(2)\mathrm{T}}\right\}$. Arranging the elements $q_{u,s}$ into the matrix $\mathbf{Q}$, we can now rewrite (3.7) in matrix form as

$$\begin{aligned}
&\text{maximize} \;\; \phi^{-1}(t), && \text{(3.8a)}\\
&\text{subject to} \;\; \phi^{-1}(t)\cdot\mathbf{1}_U - \Big[\big(\mathbf{1}_{MK}^{\mathrm{T}}\otimes\mathbf{I}_U\big)\odot\big(\mathbf{1}_U\otimes\mathbf{r}^{\mathrm{T}}\big)\Big]\cdot\mathbf{x}\le\mathbf{0}_U, && \text{(3.8b)}\\
&\big[\big(\boldsymbol{\psi}\otimes\mathbf{1}_U^{\mathrm{T}}\big)\odot\mathbf{I}_U\big]\cdot\boldsymbol{\rho} - \Big[\big(\mathbf{1}_{MK}^{\mathrm{T}}\otimes\mathbf{I}_U\big)\odot\big(\mathbf{1}_U\otimes\mathbf{r}^{\mathrm{T}}\big)\Big]\cdot\mathbf{x}\le\mathbf{0}_U, && \text{(3.8c)}\\
&-\mathbf{Q}^{\mathrm{T}}\boldsymbol{\rho}\le-\boldsymbol{\varphi}, && \text{(3.8d)}\\
&\mathbf{p}^{\mathrm{T}}\mathbf{x}\le P_{\mathrm{t}}, && \text{(3.8e)}\\
&\big[\mathbf{I}_K\otimes\mathbf{1}_{UM}{}^{\mathrm{T}}\big]\,\mathbf{x}\le\mathbf{1}_K, && \text{(3.8f)}\\
&\mathbf{x} \text{ and } \boldsymbol{\rho} \text{ are binary vectors}, && \text{(3.8g)}
\end{aligned}$$

where the elements ψ_s, ρ_u and φ_u are respectively arranged into the column vectors $\boldsymbol{\psi}$, $\boldsymbol{\rho}$ and $\boldsymbol{\varphi}$, $\mathbf{I}_U$ is a $U\times U$ identity matrix, $\mathbf{0}_U$ is a column vector with U zeros and $\mathbf{1}_U$ is a column vector with U ones.

At this point, the variables of our problem are: $\phi^{-1}(t)$, $\mathbf{x}$ and $\boldsymbol{\rho}$. To simplify even more the notation, they can be arranged into one single vector $\mathbf{w}$, where

$$\mathbf{w}=\left[\begin{array}{c}\phi^{-1}(t)\\ \hline \mathbf{x}\\ \hline \boldsymbol{\rho}\end{array}\right]. \tag{3.9}$$

Then, using $\mathbf{w}$ in the definition of $\mathbf{a}$, $\mathbf{B}$ and $\mathbf{C}$ as below

$$\begin{aligned}
\mathbf{a}&=\Big[\,1\,\Big|\,\mathbf{0}_{UMK}^{\mathrm{T}}\,\Big|\,\mathbf{0}_U^{\mathrm{T}}\,\Big]^{\mathrm{T}}\Rightarrow\mathbf{a}^{\mathrm{T}}\mathbf{w}=\phi^{-1}(t), && \text{(3.10a)}\\
\mathbf{B}&=\Big[\,\mathbf{0}_{UMK}\,\Big|\,\mathbf{I}_{UMK}\,\Big|\,\mathbf{0}_{UMK\times U}\,\Big]\Rightarrow\mathbf{B}\mathbf{w}=\mathbf{x}, && \text{(3.10b)}\\
\mathbf{C}&=\Big[\,\mathbf{0}_{U\times(1+UMK)}\,\Big|\,\mathbf{I}_U\,\Big]\Rightarrow\mathbf{C}\mathbf{w}=\boldsymbol{\rho}, && \text{(3.10c)}
\end{aligned}$$

we can finally rewrite the optimization problem as

$$\begin{aligned}
&\text{minimize} \;\; -\mathbf{a}^{\mathrm{T}}\cdot\mathbf{w}, && \text{(3.11a)}\\
&\text{subject to} \;\; \mathbf{D}\cdot\mathbf{w}\le\mathbf{e}, && \text{(3.11b)}
\end{aligned}$$

where

$$\mathbf{D}=\left[\begin{array}{c}
\mathbf{1}_U\mathbf{a}-\big[\big(\mathbf{1}_{MK}^{\mathrm{T}}\otimes\mathbf{I}_U\big)\odot\big(\mathbf{1}_U\otimes\mathbf{r}^{\mathrm{T}}\big)\big]\,\mathbf{B}\\
\big[\big(\boldsymbol{\psi}\otimes\mathbf{1}_U^{\mathrm{T}}\big)\odot\mathbf{I}_U\big]\cdot\mathbf{C}-\big[\big(\mathbf{1}_{MK}^{\mathrm{T}}\otimes\mathbf{I}_U\big)\odot\big(\mathbf{1}_U\otimes\mathbf{r}^{\mathrm{T}}\big)\big]\,\mathbf{B}\\
-\mathbf{Q}^{\mathrm{T}}\mathbf{C}\\
\mathbf{p}^{\mathrm{T}}\mathbf{B}\\
\big[\mathbf{I}_K\otimes\mathbf{1}_{UM}^{\mathrm{T}}\big]\,\mathbf{B}
\end{array}\right], \tag{3.12}$$

and,

$$\mathbf{e}=\Big[\,\mathbf{0}_U^{\mathrm{T}}\,\Big|\,\mathbf{0}_U^{\mathrm{T}}\,\Big|\,-\boldsymbol{\varphi}^{\mathrm{T}}\,\Big|\,P_{\mathrm{t}}\,\Big|\,\mathbf{1}_K^{\mathrm{T}}\,\Big]^{\mathrm{T}}. \tag{3.13}$$

We have been able to reformulate (3.1) into an equivalent MILP in standard form, (3.11), with only linear constraints and which can be solved by standard methods, such as the BB method.

3.4 Proposed Solution

For real time systems, the optimal solution presented in Section 3.3 can still be impractical, since, depending on the problem dimensions, it can still require high computational effort. Motivated by this, in this section we develop a suboptimal heuristic solution, called Power and Resource Allocation Based on Quality of Experience (PRABE), to solve (3.1) and to overcome the complexity problem.

The proposed solution divides the problem (3.7) into two parts: the resource assignment and the power allocation. In Section 3.4.1, we describe the resource assignment which is performed considering Equal Power Allocation (EPA) among the RBs. In Section 3.4.2, we describe the power allocation, which is done considering the previously performed resource assignment.

3.4.1 Resource Allocation

Considering EPA among RBs, (3.7e) is always fulfilled (at most with equality) so that we can rewrite problem (3.7) as

$$\text{maximize} \quad \phi^{-1}(t) \tag{3.14a}$$

$$\text{subject to} \quad \phi^{-1}(t) - \sum_{k=1}^{K} \widetilde{r}_{u,k}\widetilde{x}_{u,k} \leq 0, \forall u \in \mathcal{U}, \tag{3.14b}$$

$$\sum_{k=1}^{K} \widetilde{r}_{u,k}\widetilde{x}_{u,k} \geq \psi_u \cdot \rho_u, \forall u \in \mathcal{U}, \tag{3.14c}$$

$$\sum_{u=1}^{U} q_{u,s}\rho_u \geq \varphi_s, \forall s \in \mathcal{S}, \tag{3.14d}$$

$$\sum_{u=1}^{U} \widetilde{x}_{u,k} \leq 1, \forall k, \tag{3.14e}$$

$$\widetilde{x}_{u,k} \text{ and } \rho_u \in \{0,1\}, \forall u \in \mathcal{U} \text{ and } k \in \mathcal{K}, \tag{3.14f}$$

where $\widetilde{x}_{u,k}$ is the binary assignment variable indicating whether the RB k is allocated to UE u. Because the power per RB is constant, there is a single rate $\widetilde{r}_{u,k}$ achievable by UE u transmitting on an RB k, so that the total throughput R_u of UE u can be redefined as

$$R_u = \sum_{k=1}^{K} \widetilde{r}_{u,k}\widetilde{x}_{u,k}. \tag{3.15}$$

As done with (3.7), we can reformulate (3.14) into a matricial form. Arranging the elements $\widetilde{r}_{u,k}$ and $\widetilde{x}_{u,k}$ in the matrices $\widetilde{\mathbf{R}}$ and $\widetilde{\mathbf{X}}$, respectively, and denoting the Khatri-Rao product for two matrices $\mathbf{A} = \left[\mathbf{a}_1 \ \mathbf{a}_2 \ \cdots \ \mathbf{a}_J\right] \in \mathbb{R}^{I \times J}$ and $\mathbf{B} = \left[\mathbf{b}_1 \ \mathbf{b}_2 \ \cdots \ \mathbf{b}_J\right] \in \mathbb{R}^{T \times J}$ as

$\mathbf{A} * \mathbf{B} = \left[\mathbf{a}_1 \otimes \mathbf{b}_1 \ \mathbf{a}_2 \otimes \mathbf{b}_2 \ \cdots \ \mathbf{a}_J \otimes \mathbf{b}_J\right]$ we have

$$\text{maximize} \quad \phi^{-1}(t), \tag{3.16a}$$

$$\text{subject to} \quad \phi^{-1}(t) \cdot \mathbf{1}_U - \left(\widetilde{\mathbf{R}}^{\mathrm{T}} * \mathbf{I}_U\right)^{\mathrm{T}} \cdot \widetilde{\mathbf{x}} \leq \mathbf{0}_U, \tag{3.16b}$$

$$\left[\left(\boldsymbol{\psi} \otimes \mathbf{1}_U^{\mathrm{T}}\right) \odot \mathbf{I}_U\right] \cdot \boldsymbol{\rho} - \left(\widetilde{\mathbf{R}}^{\mathrm{T}} * \mathbf{I}_U\right)^{\mathrm{T}} \cdot \widetilde{\mathbf{x}} \leq \mathbf{0}_U, \tag{3.16c}$$

$$-\mathbf{Q}^{\mathrm{T}} \boldsymbol{\rho} \leq -\boldsymbol{\varphi}, \tag{3.16d}$$

$$\left[\mathbf{I}_K \otimes \mathbf{1}_U{}^{\mathrm{T}}\right] \widetilde{\mathbf{x}} \leq \mathbf{1}_K, \tag{3.16e}$$

$$\widetilde{\mathbf{x}} \text{ and } \boldsymbol{\rho} \text{ are binary vectors,} \tag{3.16f}$$

where $\widetilde{\mathbf{x}} = \mathrm{vec}\left\{\widetilde{\mathbf{X}}\right\}$.

In order to collect the optimization variables in a single vector, we define

$$\widetilde{\mathbf{w}} = \left[\begin{array}{c} \phi^{-1}(t) \\ \hline \widetilde{\mathbf{x}} \\ \hline \boldsymbol{\rho} \end{array}\right], \tag{3.17}$$

so that

$$\widetilde{\mathbf{a}}^{\mathrm{T}} \cdot \widetilde{\mathbf{w}} = \phi^{-1}(t) \ \text{ with } \widetilde{\mathbf{a}} = \left[1 \ \ \mathbf{0}_{(UK+U)}{}^{\mathrm{T}}\right]^{\mathrm{T}}, \tag{3.18a}$$

$$\widetilde{\mathbf{B}} \cdot \widetilde{\mathbf{w}} = \widetilde{\mathbf{x}} \ \text{ with } \widetilde{\mathbf{B}} = \left[\mathbf{0}_{UK} \ \ \mathbf{I}_{UK} \ \ \mathbf{0}_{UK \times U}\right], \tag{3.18b}$$

$$\text{and } \widetilde{\mathbf{C}} \cdot \widetilde{\mathbf{w}} = \boldsymbol{\rho} \ \text{ with } \widetilde{\mathbf{C}} = \left[\mathbf{0}_{U \times (1+UK)} \ \ \mathbf{I}_U\right]. \tag{3.18c}$$

Finally, using (3.18), the optimization problem can be rewritten as

$$\text{minimize} \quad -\widetilde{\mathbf{a}}^{\mathrm{T}} \cdot \widetilde{\mathbf{w}} \tag{3.19a}$$

$$\text{subject to} \quad \widetilde{\mathbf{D}} \cdot \widetilde{\mathbf{w}} \leq \widetilde{\mathbf{e}} \tag{3.19b}$$

where

$$\widetilde{\mathbf{D}} = \begin{bmatrix} \mathbf{1}_U \widetilde{\mathbf{a}}^{\mathrm{T}} - \left(\widetilde{\mathbf{R}}^{\mathrm{T}} * \mathbf{I}_U\right)^{\mathrm{T}} \widetilde{\mathbf{B}} \\ \left[\left(\boldsymbol{\psi} \otimes \mathbf{1}_U^{\mathrm{T}}\right) \odot \mathbf{I}_U\right] \cdot \widetilde{\mathbf{C}} - \left(\widetilde{\mathbf{R}}^{\mathrm{T}} * \mathbf{I}_U\right)^{\mathrm{T}} \widetilde{\mathbf{B}} \\ -\mathbf{Q}^{\mathrm{T}} \widetilde{\mathbf{C}} \\ \left[\mathbf{I}_K \otimes \mathbf{1}_U^{\mathrm{T}}\right] \widetilde{\mathbf{B}} \end{bmatrix} \tag{3.20}$$

and,

$$\widetilde{\mathbf{e}} = \left[\, \mathbf{0}_U^{\mathrm{T}} \middle| \mathbf{0}_U^{\mathrm{T}} \middle| -\boldsymbol{\varphi} \middle| \mathbf{1}_K^{\mathrm{T}} \right]^{\mathrm{T}}. \tag{3.21}$$

Problem (3.19) solves the resource assignment in an optimal way. Furthermore, compared to (3.11), it has lower complexity since it solves the resource assignment considering EPA and, thus, eliminating the power dimension of the optimization problem. However, its complexity is still high for real time systems. Therefore, in order to obtain a suboptimal but efficient and low-complexity solution to (3.19) we propose a new heuristic method presented in Figure 3.3. Algorithm 3.1 presents, in algorithm form, how it can be implemented.

The flowchart in Fig. 3.3 is divided into two parts. On the first one we try to satisfy at least φ_s UEs for each plan s, blocks (1) to (7). It is done in a loop, where in each step, an RB is allocated to the UE that can achieve the highest transmit data rate on this RB. If this user achieves the target MOS of his/her plan, he/she is removed from the set of users, block (3).

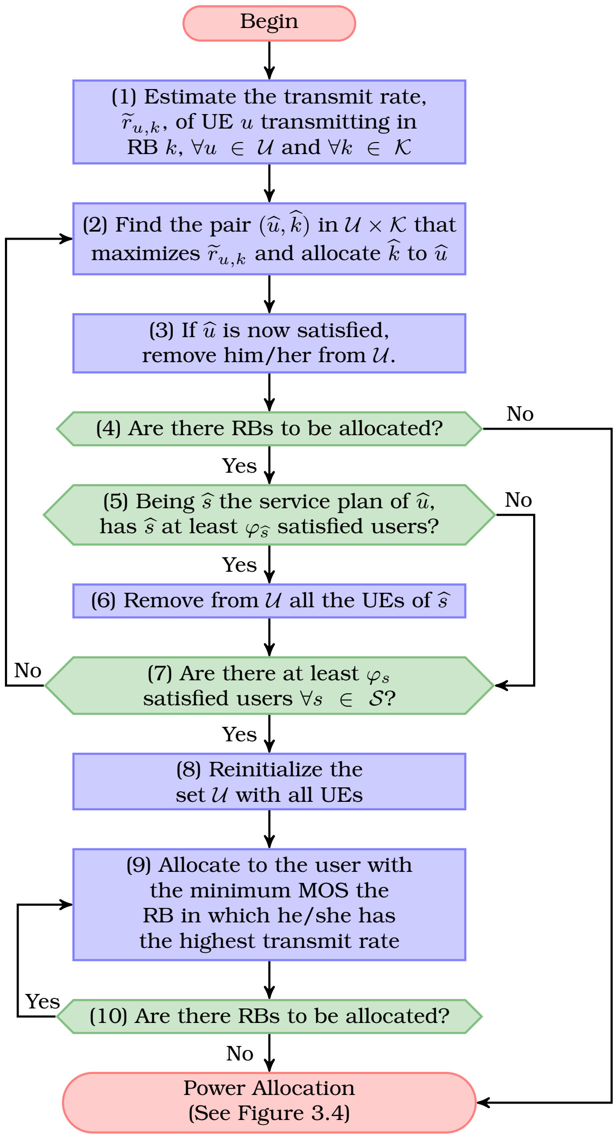


Figure 3.3: Flowchart of proposed resource assignment algorithm.

Besides, if his/her plan has already achieved the minimum number of satisfied users, the other users of this plan are also removed from $\mathcal{U}$, blocks (5) and (6). This process continues until all plans have at least φ_s satisfied users, block (7), or until all RBs have been allocated, block (4). On the second part, blocks (8) to (10), we maximize the minimum MOS, assigning the available resources to the users with the lowest MOS.

Algorithm 3.1 presents the description of Figure 3.3 in a more detailed form. In the beginning, no RB has been assigned and all users are unsatisfied. Therefore we initialize the allocation matrix $\widetilde{\mathbf{X}}$ with only zeros (line 1). For each plan, we also initialize the number of users already satisfied, $\mathbf{u}_{\text{sat}}$, as zeros (line 2), and we initialize the number of unassigned RBs, RB_{free}, as the number of available RBs, K (line 3). Next, we allocate RBs until all resources have been assigned or the minimum number of satisfied users, φ_s, has been achieved for all plans (lines 4 to 17). In line 5, we select the UE $\widehat{u}$ and the resource $\widehat{k}$ associated to the highest rate in $\widetilde{\mathbf{R}}$, then we allocate $\widehat{k}$ to $\widehat{u}$ (line 6). In the sequel, we remove $\widehat{k}$ from the set of resources, $\mathcal{K}$, and update the number of available RBs (lines 8 and 9, respectively). If the user $\widehat{u}$ is now satisfied, he/she is removed from the set of users $\mathcal{U}$ and we update the number of users already satisfied of his/her plan (lines 10 to 12). In the same way, if his/her plan has achieved the minimum number of satisfied users, the other users of this plan are also removed. In line 18, we have three possibilities: the number of satisfied users has already been achieved by all plan, all resources have been assigned or both. If there are still available resources (in lines 18 to 28), they will be allocated aiming to maximize the minimum MOS. First we identify, among all users, the one with the lowest MOS (line 21). Next, we chose for him/her the remaining RB which maximizes his/her transmit data rate (line 22). This algorithm finishes after the last available resource has been allocated.

Algorithm 3.1 Resource Allocation considering EPA.

1: $\widetilde{\mathbf{X}} \leftarrow \mathbf{0}_{U \times K}$ ▷ Initialize the allocation matrix
2: $\mathbf{u}_{\text{sat}} \leftarrow \mathbf{0}_S$ ▷ For each plan, initialize the number of users already satisfied
3: $RB_{\text{free}} \leftarrow K$ ▷ Initialize the number of unassigned RBs
4: **while** $(RB_{\text{free}} > 0 \;\&\; \mathbf{u}_{\text{sat}} < \boldsymbol{\varphi})$ **do**
5: $\quad (\widehat{u}, \widehat{k}) \leftarrow \arg\max_{u \in \mathcal{U}, k \in \mathcal{K}} \widetilde{r}_{u,k}$
6: $\quad x_{\widehat{u},\widehat{k}} \leftarrow 1$ ▷ Assign RB $\widehat{k}$ to user $\widehat{u}$
7: $\quad$ Update $\tau_{\widehat{u}}$
8: $\quad \mathcal{K} \leftarrow \mathcal{K} \setminus \{\widehat{k}\}$ ▷ Remove RB $\widehat{k}$ from $\mathcal{K}$
9: $\quad RB_{\text{free}} \leftarrow RB_{\text{free}} - 1$ ▷ Update RB_{free}
10: $\quad$ **if** $\tau_{\widehat{u}} \geq \phi(\psi_u)$ **then** ▷ Test if user $\widehat{u}$ is satisfied
11: $\quad\quad \mathcal{U} \leftarrow \mathcal{U} \setminus \{\widehat{u}\}$ ▷ Remove user $\widehat{u}$ from $\mathcal{U}$
12: $\quad\quad \mathbf{u}_{\text{sat}}(\widehat{s}) \leftarrow \mathbf{u}_{\text{sat}}(\widehat{s}) + 1$ ▷ Update $\mathbf{u}_{\text{sat}}(\widehat{s})$, where $\widehat{u} \in \mathcal{U}_{\widehat{s}}$
13: $\quad\quad$ **if** $\mathbf{u}_{\text{sat}}(\widehat{s}) \geq \varphi_{\widehat{s}}$ **then**
14: $\quad\quad\quad \mathcal{U} \leftarrow \mathcal{U} \setminus \mathcal{U}_{\widehat{s}}$ ▷ Remove of $\mathcal{U}$ the UEs of $\widehat{s}$
15: $\quad\quad$ **end if**
16: $\quad$ **end if**
17: **end while**
18: **if** $RB_{\text{free}} > 0$ **then**
19: $\quad$ Reinitialize the set $\mathcal{U}$ with all users
20: $\quad$ **while** $(RB_{\text{free}} > 0)$ **do**
21: $\quad\quad \widehat{u} \leftarrow \arg\min_{u \in \mathcal{U}} \tau_u$ ▷ Find the user with the lowest MOS
22: $\quad\quad \widehat{k} \leftarrow \arg\max_{k \in \mathcal{K}} \widetilde{r}_{\widehat{u},k}$
23: $\quad\quad x_{\widehat{u},\widehat{k}} \leftarrow 1$ ▷ Assign RB $\widehat{k}$ to user $\widehat{u}$
24: $\quad\quad$ Update $\tau_{\widehat{u}}$
25: $\quad\quad \mathcal{K} \leftarrow \mathcal{K} \setminus \{\widehat{k}\}$ ▷ Remove RB $\widehat{k}$ from $\mathcal{K}$
26: $\quad\quad RB_{\text{free}} \leftarrow RB_{\text{free}} - 1$ ▷ Update RB_{free}
27: $\quad$ **end while**
28: **end if**

3.4.2 Power Allocation

After the assignment of RBs to the UEs has been performed, it can be considered as a fixed input for the proposed power allocation algorithm whose flowchart is illustrated in Figure 3.4. Algorithm 3.2 presents, in algorithm form, how it can be implemented.

The first step is to estimate the amount of power, p_u^{need}, needed for each UE to achieve the target MOS $\phi(\psi_u)$, block (1) of Figure 3.4 and lines 1 and 2 of Algorithm 3.2, where $\mathcal{K}_u$ is the set of RBs allocated to UE u and p_u^{need} is the sum of powers $p_{u,k}^{\text{need}}$ needed in each resource $k \in \mathcal{K}_u$. The method to estimate these values is presented in Algorithm 3.3, which will be described later.

Next, the vector $\mathbf{p}^{\text{sort}}$ receives these powers divided in 2 parts, each one sorted in ascending order: the first one is composed by the φ_s lowest values of service s, $\forall\ s \in \mathcal{S}$ and the second one is composed by the other values. This step can be seen in block (2) of Figure 3.4 and lines 3 and 4 of Algorithm 3.2.

Next, we verify if the sum of all p_u^{need} is lower than the power in excess, P_{exc}, which is initialized as P_{t}. If $\sum_{u \in \mathcal{U}} p_u^{\text{need}} \leq P_{\text{t}}$, it means that we have enough power to satisfy all the users, so we set the number of users to be satisfied, U_{sat}, equal to U. Otherwise, we will try to satisfy at least the minimum number of users required by each service, $\sum_{s=1}^{|\mathcal{S}|} \varphi_s$. This is illustrated in blocks (4), (5a) and (5b) of Figure 3.4 and lines 6 to 11 of Algorithm 3.2.

Next, we start allocating the values of power in $\mathbf{p}^{\text{sort}}$, in ascending order, blocks (6) to (8) and lines 12 to 17. There are three stop conditions: 1) the number of expected users

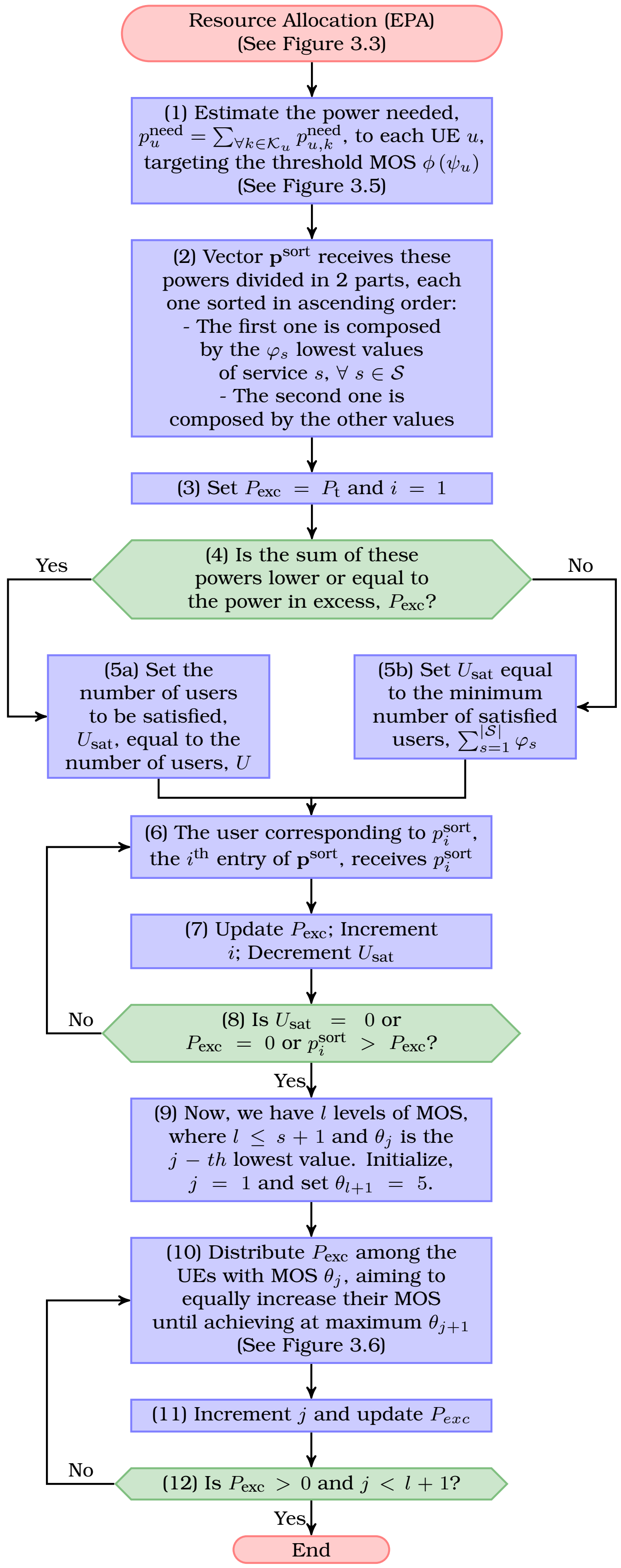


Figure 3.4: Flowchart of proposed power allocation algorithm.

to be satisfied, $U_{\text{sat}} = \sum_{s=1}^{|\mathcal{S}|} \varphi_s$, has been achieved, 2) there is a lack of in-excess power to be allocated or 3) the next value of power, p_u^{need}, to be allocated is higher than the excess of power.

At this point, we have l levels of MOS, with $1 \leq l \leq s+1$, where $l = 1$ if all UEs have MOS

Algorithm 3.2 Power allocation.

1: $\forall u \in \mathcal{U}$, call Algorithm 3.3 to estimate $p^{\text{need}}_{u,k}$, $\forall k \in \mathcal{K}_u$, aiming MOS $\phi(\psi_u)$
2: $\forall u \in \mathcal{U}$, $p^{\text{need}}_{u} \leftarrow \sum_{\forall k \in \mathcal{K}_u} p^{\text{need}}_{u,k}$
3: $\forall u \in \mathcal{U}_s$ and $\forall s \in \mathcal{S}$, $\mathbf{p}^s \leftarrow \text{sort}(p^{\text{need}}_u)$
4: $\mathbf{p}^{\text{sort}} \leftarrow \text{sort}\left(\bigcup_{\forall i\in[1,\varphi_s]}^{\forall s\in\mathcal{S}} p_i^s\right) \bigcup \text{sort}\left(\bigcup_{\forall i\in[\varphi_s+1,U_s]}^{\forall s\in\mathcal{S}} p_i^s\right)$
5: $i \leftarrow 1$
6: $P_{\text{exc}} \leftarrow P_{\text{t}}$
7: **if** $\sum_{u\in\mathcal{U}} p^{\text{need}}_u \leq P_{\text{exc}}$ **then**
8: $\quad U_{\text{sat}} \leftarrow U$ ▷ Satisfy all the users
9: **else**
10: $\quad U_{\text{sat}} \leftarrow \sum_{s=1}^{|\mathcal{S}|} \varphi_s$ ▷ Try to satisfy at least the minimum number of users required for each service
11: **end if**
12: **while** $(U_{\text{sat}} > 0 \ \& \ P_{\text{exc}} > 0 \ \& \ p^{\text{sort}}_i \leq P_{\text{exc}})$ **do**
13: $\quad p_{i,k} \leftarrow p^{\text{sort}}_{i,k}, \forall k \in \mathcal{K}_i$ ▷ Power allocation of user i
14: $\quad P_{\text{exc}} \leftarrow P_{\text{exc}} - \sum_{\forall k\in\mathcal{K}_i} p^{\text{sort}}_{i,k}$ ▷ Update P_{exc}
15: $\quad U_{\text{sat}} \leftarrow U_{\text{sat}} - 1$ ▷ User i is satisfied, so decrease U_{sat}
16: $\quad i \leftarrow i + 1$ ▷ Increment i
17: **end while**
18: $\boldsymbol{\theta} \leftarrow$ unique(sort($\boldsymbol{\tau}$)) ▷ $\boldsymbol{\theta_j}$ is the $\boldsymbol{j-th}$ lowest MOS
19: $\boldsymbol{\theta_{l+1} \leftarrow 5}$ ▷ 5 is the highest MOS that can be achieved
20: $\boldsymbol{j \leftarrow 1}$
21: **while** $\boldsymbol{P_{\text{exc}} > 0 \ \& \ j < l+1}$ **do**
22: $\quad$ Call Algorithm 3.4 to distribute $\boldsymbol{P_{\text{exc}}}$ among the UEs with MOS $\boldsymbol{\theta_j}$ aiming at maximum the MOS $\boldsymbol{\theta_{j+1}}$
23: $\quad \boldsymbol{j \leftarrow j+1}$
24: **end while**

equal to zero and $l = s + 1$ if at least one UE of each service has achieved the target MOS of its service and there are still some UE with MOS equal to zero. These l levels are arranged in ascending order in $\boldsymbol{\theta}$, where $\boldsymbol{\theta_j}$ is the $\boldsymbol{j}$-th lowest value and $\boldsymbol{\theta_{l+1} = 5}$ is the highest MOS that can be achieved, block (7) and lines 18 and 19.

Finally, in steps (9) to (12) and lines 21 to 23, for each level of MOS we will distribute $\boldsymbol{P_{\text{exc}}}$ among the UEs of this level aiming to achieve the next level of MOS. If there is still $\boldsymbol{P_{\text{exc}}}$ these UEs will joint the UEs of the next level and the power distribution will be repeated. The algorithm to distribute the in-excess power among a set of users in a way that all achieve the same MOS is presented in Algorithm 3.4.

It is also worthy to mention that Algorithms 3.3 and 3.4 are based on Hughes-Hartogs Bit-Loading Algorithm [47]. Given a specific UE $\hat{\boldsymbol{u}}$ and the set of RBs allocated to it, $\boldsymbol{\mathcal{K}_{\hat{u}}}$,

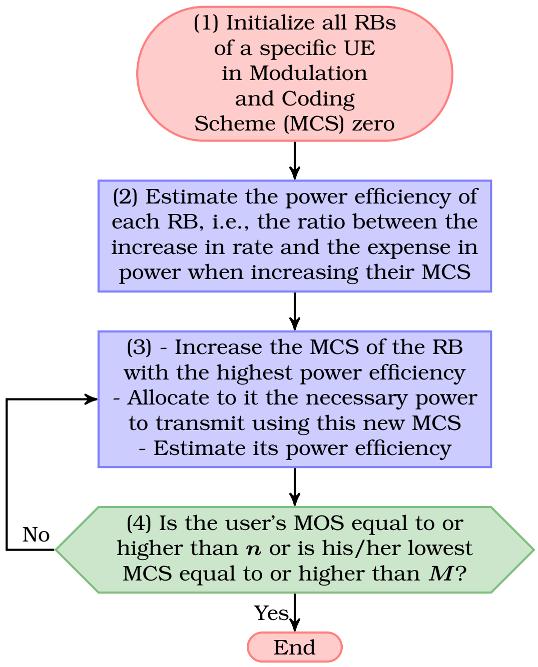


Figure 3.5: Flowchart of proposed power calculation to achieve a target MOS for a specific user.

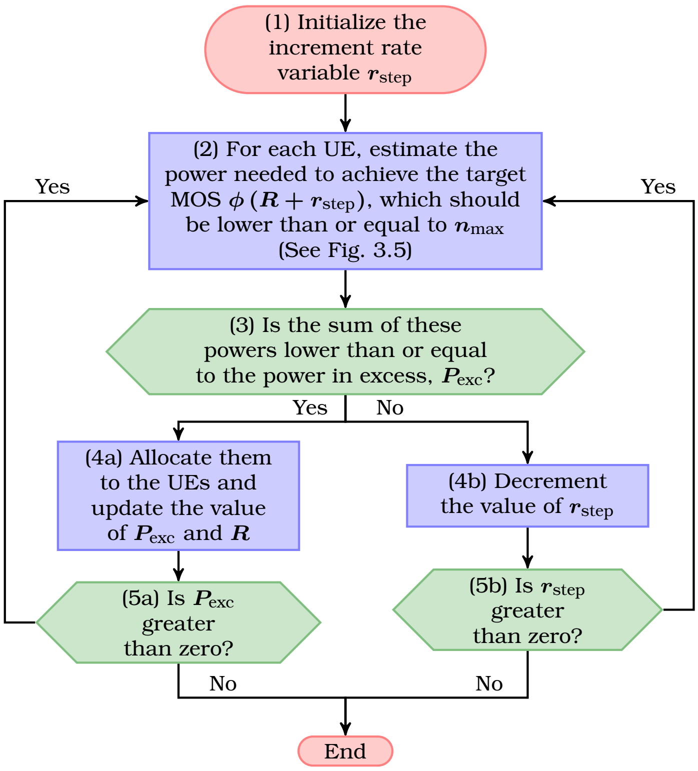


Figure 3.6: Flowchart of proposed power distribution targeting a uniform MOS.

Algorithm 3.3 calculates the power allocation among these RBs aiming to achieve a target MOS n and minimizing the total power used. Considering that RB k is using MCS m_k, in the beginning, we select MCS zero to all resources (line 1), i.e. zero power for all RBs. We define ΔP_k as the additional power needed for RB k to use MCS $m_k + 1$ and ΔR_k as the increase in transmit rate in RB k when changing from MCS m_k to $m_k + 1$. These variables are initialized in lines 2 and 3. While user $\widehat{u}$ has not achieved the target MOS n and at least one RB is not transmitting at the highest MCS, we repeat the steps between lines 4 and 14. In line 5, we identify the resource $\widehat{k}$ with the highest power efficiency $E_{\widehat{k}}$, where E_k is the ratio between the increase in rate and the power expenditure to change the MCS of RB k from m_k to $m_k + 1$. After this identification, we increase the MCS of $\widehat{k}$ (line 6) and we update ΔP_k and ΔR_k (lines 7 to 13). In line 11, we guarantee that the maximum MCS achieved by any RB k will be M by setting ΔR_k equal to -1 when it is already in MCS M. In that way, E_k will be negative and it will not be selected anymore. Finally, we calculate the values $p^{\text{need}}_{\widehat{u},k}$ in line 15.

Algorithm 3.3 Power calculation targeting a target MOS (PCTSM).

Require: A MOS target n and the set of RBs of user $\widehat{u}$, $\mathcal{K}_{\widehat{u}}$
Ensure: Estimation of $p^{\text{need}}_{\widehat{u},k}$, $\forall k \in \mathcal{K}_{\widehat{u}}$

1: $m_k \leftarrow 0$, $\forall k \in \mathcal{K}_{\widehat{u}}$ ▷ Initialize all RBs in MCS zero
2: $\Delta P_k \leftarrow p_{\widehat{u},k,(m_k+1)}$, $\forall k \in \mathcal{K}_{\widehat{u}}$ ▷ Additional power needed
3: $\Delta R_k \leftarrow r_{\widehat{u},k,(m_k+1)}$, $\forall k \in \mathcal{K}_{\widehat{u}}$ ▷ Increment in transmit rate
4: **while** $(\tau_u < n \ \& \ \min_{k \in \mathcal{K}_{\widehat{u}}} m_k < M)$ **do**
5: $\quad \widehat{k} \leftarrow \arg\max_{k \in \mathcal{K}_{\widehat{u}}} E_k = \frac{\Delta R_k}{\Delta P_k}$ ▷ Find RB with highest power eff.
6: $\quad m_{\widehat{k}} \leftarrow m_{\widehat{k}} + 1$ ▷ Update MCS of RB $\widehat{k}$
7: $\quad$ **if** $m_{\widehat{k}} < M$ **then** ▷ Update the increment in rate and power
8: $\quad\quad \Delta R_{\widehat{k}} \leftarrow r_{\widehat{u},\widehat{k},(m_{\widehat{k}}+1)} - r_{\widehat{u},\widehat{k},m_{\widehat{k}}}$
9: $\quad\quad \Delta P_{\widehat{k}} \leftarrow p_{\widehat{u},\widehat{k},(m_{\widehat{k}}+1)} - p_{\widehat{u},\widehat{k},m_{\widehat{k}}}$
10: $\quad$ **else**
11: $\quad\quad \Delta R_{\widehat{k}} \leftarrow -1$
12: $\quad\quad \Delta P_{\widehat{k}} \leftarrow 1$
13: $\quad$ **end if**
14: **end while**
15: $p^{\text{need}}_{\widehat{u},k} \leftarrow p_{\widehat{u},k,m_k}$, $\forall k \in \mathcal{K}_{\widehat{u}}$ ▷ Set needed power for all RBs

Algorithm 3.4 Power distribution targeting a uniform MOS (PDTUM).

Require: A set of UEs $\mathcal{U}'$, their RBs, an excess of power, P_{exc}, and an upper bound $n_{\max}$
1: Initialize r_{step}
2: **while** $P_{\text{exc}} > 0$ & $\phi(R + r_{\text{step}}) \leq n_{max}$ **do**
3: $\forall u \in \mathcal{U}'$, call Alg.3.3 to estimate $p^{\text{need}}_{u,k}$, $\forall k \in \mathcal{K}_u$, aiming $\phi(R + r_{\text{step}})$
4: $p^{\text{need}}_{u,k} \leftarrow PCTSM(\phi(R + r_{\text{step}}))$, $\forall u \in \mathcal{U}'$
5: **if** $p_{u,k} = p^{\text{need}}_{u,k}, \forall u \in \mathcal{U}', k \in \mathcal{K}_u$ **then**
6: Stop
7: **end if**
8: **if** $\sum_{\forall u \in \mathcal{U}'} \sum_{\forall k \in \mathcal{K}_u} (p^{\text{need}}_u - p_u) \leq P_{\text{exc}}$ **then**
9: $p_{u,k} \leftarrow p^{\text{need}}_{u,k}, \forall u \in \mathcal{U}', k \in \mathcal{K}_u$
10: $P_{\text{exc}} \leftarrow P_{\text{exc}} - \sum_{\forall u \in \mathcal{U}'} \sum_{\forall k \in \mathcal{K}_u} \left(p^{\text{need}}_{u,k} - p_{u,k}\right)$
11: $R \leftarrow R + r_{\text{step}}$
12: **else**
13: Decrement r_{step}
14: **if** $r_{\text{step}} = 0$ **then**
15: Distribute P_{exc} in ascending order of $\sum_{\forall k \in \mathcal{K}_u} p^{\text{need}}_u$
16: **end if**
17: **end if**
18: **end while**

Given an amount of power P_{exc} and a set of users, $\mathcal{U}'$, in which all users have approximatively the same transmit rate R and so approximatively the same MOS $\phi(R)$, Algorithm 3.4 allocates P_{exc} among these users and their RBs, in a way that all users increase their MOS equally. It works as follow: 1) We fix a target value of rate $R + r_{\text{step}}$, where $\phi\left(R + r_{\text{step}}\right)$ must be lower than or equal to an upper bound $n_{\max}$, and, in line 4, we use Algorithm 3.3, to estimate the needed power for all UEs to transmit using the rate $R + r_{\text{step}}$; 2) If the increase in power that we need to have to achieve this purpose is lower than or equal to P_{exc}, in lines 8 to 11, we distribute the power and update the value of R; 3) Otherwise, we decrement the value of r_{step} and try again. In case r_{step} becomes zero, we stop. The initial value of r_{step} and the way it will decrement is chosen by the operator. This choice has an important impact on the algorithm complexity.

3.5 Partial Conclusions

In this chapter, we presented a radio resource assignment problem aiming at maximizing the minimum MOS of the system subject to attaining at least a minimum number of satisfied users. It was initially formulated as a non-linear problem, but we managed to reformulate it as a MILP, solvable by standard methods, as the BB. Finally, we presented our proposal, consisting of two parts. The first one assigns the resources considering EPA, while the second one allocates power considering the previous resource allocation. In the next chapter, we evaluate our proposal, by means of simulations, comparing it with the optimal solution, as well as with two benchmarking algorithms and with a mixed solution, which uses as resource assignment the optimal solution of (3.19) and as power allocation the heuristic proposed in Algorithm 3.2, Section 3.4.2.

Chapter 4

Performance Evaluation

4.1 Introduction

In this chapter, we evaluate the proposed Power and Resource Allocation Based on Quality of Experience (PRABE) algorithm and compare its performance with that of the optimal solution, of a mixed-solution, as well as with that of two benchmarking algorithms. In Section 4.2, we present the simulation parameters, the benchmarking algorithms, the evaluated scenarios and the evaluation metrics. In Section 4.3, we present the results and the discussions.

4.2 Simulation Assumptions

The system model configuration presented in Chapter 2 was adopted for all simulations. The system parameters were aligned with the 3rd Generation Partnership Project (3GPP) Long Term Evolution (LTE) architecture.

A hexagonal cell with 1 km radius was considered, within which there was one Evolved Node B (eNB) with a three-sectored antenna. We adopted a system bandwidth of 5 MHz and carrier frequency of 2 GHz. The system disposed of 25 Resource Blocks (RBs), each one consisting of 12 adjacent subcarriers. The propagation effects on the wireless channel included a lognormal shadowing component and a distance-dependent path-loss, as well as small-scale fading. We also adopted a 3D antenna model, as in [48], considering a downtilt angle in order to increase cell isolation and to mitigate the effects of inter-cell interference.

Table 4.1 presents the main adopted parameters. In subsections 4.3.1, 4.3.2 and 4.3.4 we consider path loss model 1 and in subsection 4.3.3 we consider path loss model 2.

The Mean Opinion Score (MOS) function, $\phi(\cdot)$, adopted for the simulations is proposed in [53]. It is an utility function for web connections in LTE, in accordance with the scenario adopted in this master's thesis. It is presented in (4.1) and illustrated in Figure 4.1.

$$\phi(R_u) = 5 - \frac{578}{1 + \left(\frac{R_u + 541.1}{45.98}\right)^2}, \tag{4.1}$$

where R_u is the total throughput of UE u.

Four different scenarios were adopted to evaluate the performance of the proposed algorithm:

- The first one considered only one service plan. We analyzed the impact of the target MOS for different numbers of UEs in the system, as well as the impact of the satisfaction

Table 4.1: Simulation parameters.

Parameter	Value
Maximum eNB transmit power (P_t)	43 dBm [49]
eNB antenna radiation pattern	Three-sectored [49]
Cell radius	1 km
UE speed	3 km/h [50]
Carrier frequency	2 GHz [50]
System bandwidth	5 MHz [49]
Subcarrier bandwidth	15 kHz
Number of RBs (K)	25
Number of subcarriers per RB	12
Path loss model 1[a]	$15.3 + 37.6 \log_{10}(d)$ [50]
Path loss model 2[a]	$34.5 + 35 \log_{10}(d)$ [51]
Antenna gain[b]	$G_h(\theta_h) + G_v(\theta_v)$ [48]
Downtilt angle	8 degrees
Log-normal shadowing standard deviation	8 dB [50]
Small-scale fading	IID
AWGN power per sub-carrier	-123.24 dBm
Noise figure	9 dB
Link adaptation	Link level curves from [52]
Traffic model	Full buffer
Transmission Time Interval	1 ms
Number of snapshots	3000

[a] d is the distance from the eNB to the UE in m.
[b] θ_h and θ_v represents the horizontal and vertical angles related to the eNB, respectively.

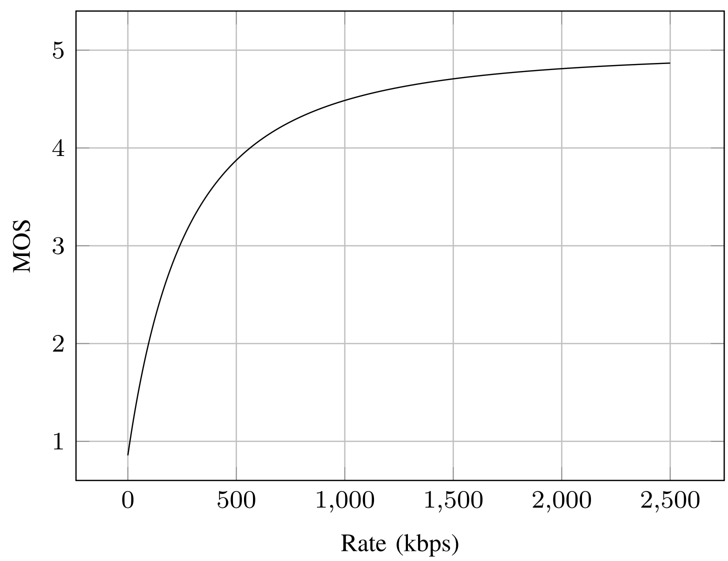


Figure 4.1: MOS function [53].

factor for a specific number of UEs.

- On the second one, we divided 20 UEs into two service plans. First, we fixed the satisfaction factor of both services ($\alpha_1 = \alpha_2 = 1$) and the target MOS of service one ($n_1 = 4.4$), then we analyzed the impact of changing the target MOS of service two (n_2) and the percentage of UEs in each service. After that, we analyzed the impact of n_2 for different values of α_2.
- The third one was similar to the first one, but we considered a stronger path loss.
- The last one, analyzed the impact of different values of degradation in the Channel State Information (CSI) and different values of target MOS in a system with 5 UEs, all in the

same service plan. We did this analysis twice, one considering $\alpha = 1$ and the other one considering $\alpha = 0.8$, i.e, satisfy 4 among 5 UEs.

The proposed algorithm, PRABE, was compared to four other methods:

- The optimal solution, obtained solving (3.11) using the ILOG CPLEX solver [54].
- A mixed solution using as resource assignment the optimal solution of (3.19), also solved using the ILOG CPLEX solver [54], and as power allocation the heuristic proposed in Algorithm 3.2, Section 3.4.2.
- A benchmarking algorithm proposed in [31]. First, it partitions the subcarrier set into groups which are randomly assigned to the UEs, then the UEs are grouped in pairs to negotiate the RBs. At the same time, a water-filling power allocation is done.
- A second benchmarking algorithm proposed in [32]. It uses the Hungarian algorithm [55] to assign frequency spectrum and the optimal solution of a Tchebycheff problem for the power allocation.

The benchmarking algorithms were not used when evaluating the variation of the satisfaction factor, since they do not consider this concept.

We adopted two metrics to evaluate the different algorithms. The first one was the minimum MOS perceived among the UEs in the system, since our main objective is to maximize this metric. The second one was the outage, which is defined as the percentage of cases in which the minimum number of satisfied users φ_s is not achieved in at least one of the services.

4.3 Results

4.3.1 Single Service Plan

This first scenario considers only one service plan. In Figure 4.2, we present the outage rate as a function of the number of UEs considering three different values of target MOS and a satisfaction factor equal to 1, i.e., satisfy all the UEs.

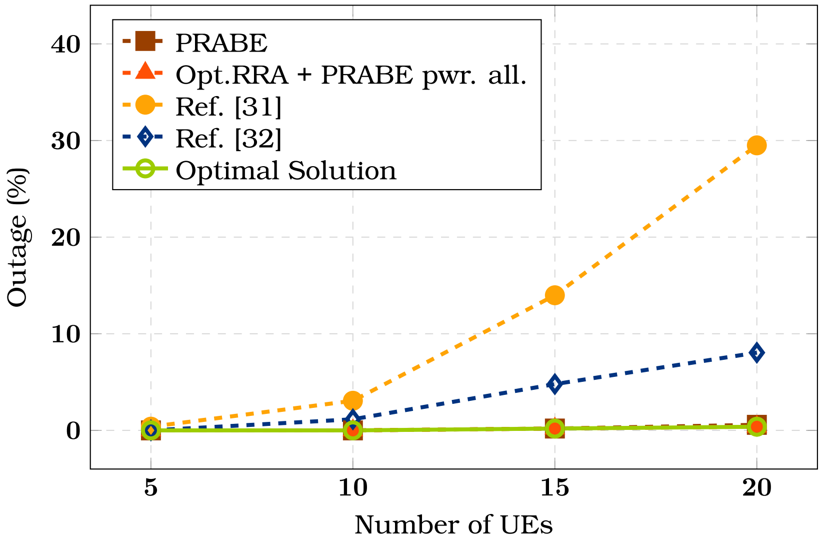
In Figure 4.2(a), target MOS equal to 3.6, different of the two benchmarking algortihms, the outage of PRABE and of the mixed solution are optimal and equal to zero, for all the evaluated numbers of UEs.

Sugiro que você se refira aos algoritmos 31 e 32 no mesmo formato usado nas figuras: Ref. [31]. – *tfm*

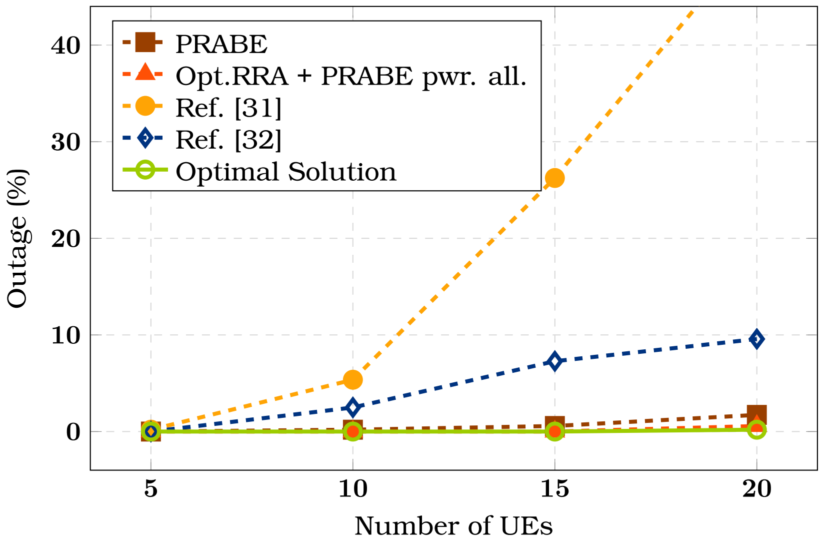
In Figure 4.2(b), target MOS equal to 4, the outage of PRABE and of the mixed solution still present near optimal values. On the other hand, the outage of [31] increases fast with the increase of the number of UEs. Comparing Figures 4.2(a) and 4.2(b), we see that even if the outage of [32] slightly varies with the increase of the target MOS, the outage of PRABE varies even less.

In Figure 4.2(c), we compare the performance of the evaluated algorithms for target MOS of 4.4, which is already a very high value. In this case, [31] reaches an unacceptable value for outage higher than 10% for 10 UEs, while PRABE reaches a similar value only for 20 UEs. At the same time, for 20 UEs, [32] has almost the double of the outage of PRABE.

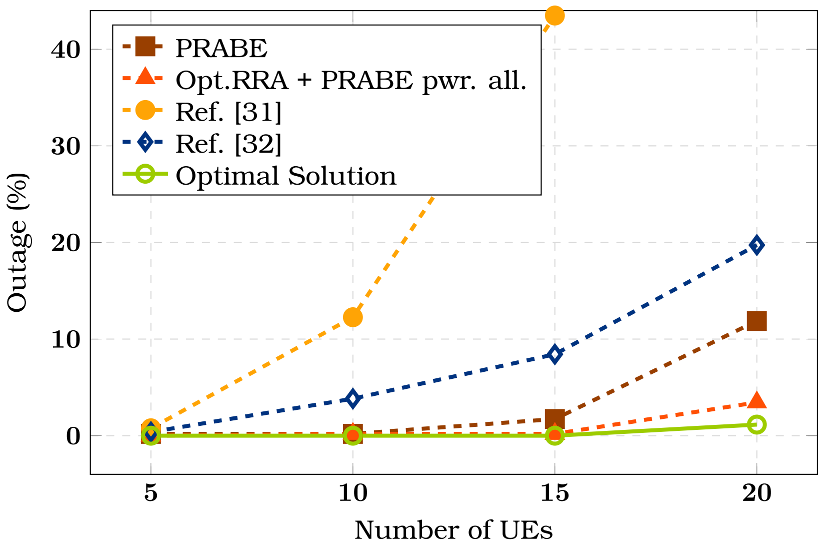
Comparing Figures 4.2(a), 4.2(b) and 4.2(c), we conclude that [31] has the worst performance. It decreases faster then the others with the increase of the target MOS and of the number of UEs. This occurs due to the fact that the assignment is not centralized, but done in pairs and, therefore, when the number of UEs increases it becomes difficult for it to finish with the RBs that benefit the users the most.



(a) Target MOS = 3.6.



(b) Target MOS = 4.



(c) Target MOS = 4.4.

Figure 4.2: Impact of the number of UEs on the outage for satisfaction factor, α, equal to 1.

The analyses of the minimum MOS versus the number of UEs are presented in Figure 4.3, considering the same setup of the outage analyses, Figure 4.2. In order to perform a fair comparison, we consider only the cases where the optimal solution is feasible.

In Figure 4.3(a), target MOS equal to 3.6, we notice that the performance of PRABE and of the mixed solution is almost indistinguishable of the optimal one. We also identify a considerable gap between PRABE and [31]. For 20 UEs, the minimum MOS of [31] does not even reach the target MOS, 3.6.

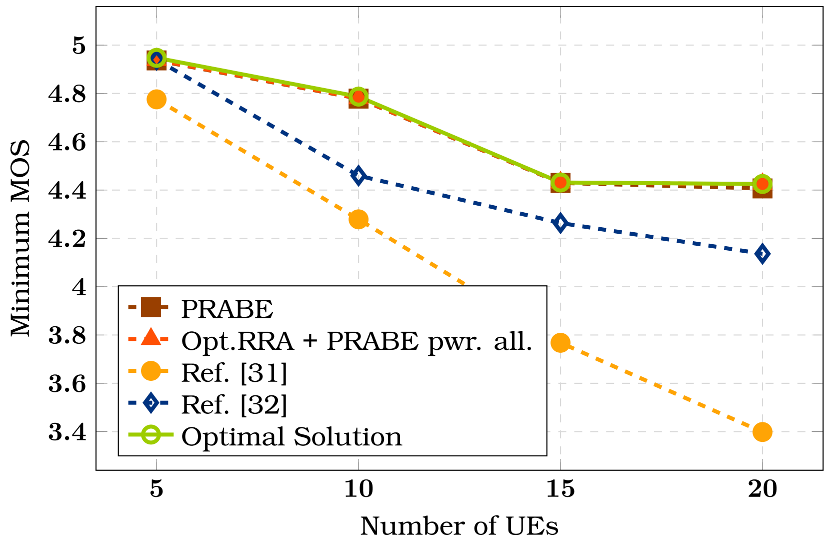
In Figure 4.3(b), target MOS equal to 4, we notice that PRABE still has a near optimal performance. Its minimum MOS still reaches values higher than the target MOS for all the number of UEs, while [31] does not achieve this value when we have more than 15 UEs. In this case, the algorithm of [32] is better than [31] but still worse than PRABE.

Comparing Figures 4.3(a) and 4.3(b), we notice that, for the same number of UEs, when the target MOS changes from 3.6 to 4, the gap between the minimum MOS of [31] and [32] decreases due to the enhancement of [31]. However, the difference between PRABE and the benchmarking algorithms is still considerable.

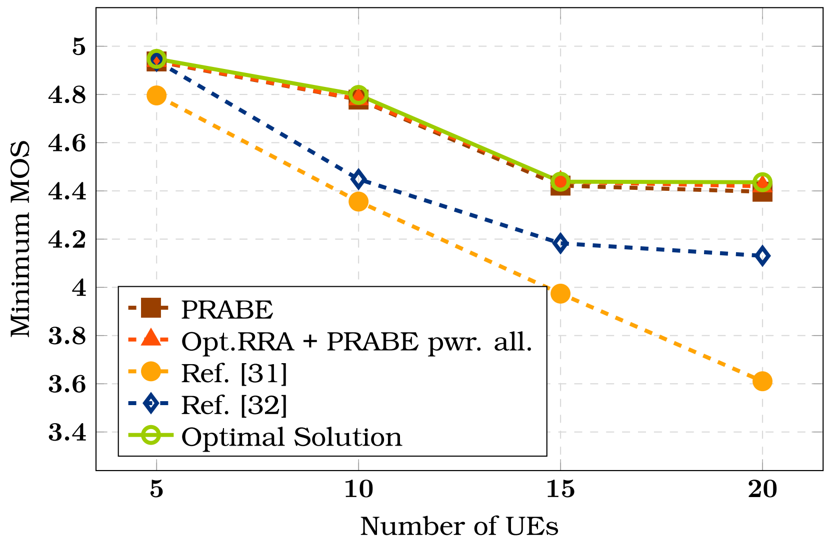
In Figure 4.3(c), target MOS 4.4, PRABE still has a near optimal behavior, differing from the optimal solution only when we have 20 UEs in the system. Different of the benchmarking algorithms, only in this case, the minimum MOS is lower than the target MOS, indicating cases of outage.

It is important to note in Figures 4.2 and 4.3 that the proposed algorithm, PRABE, performs very close to the optimal solution, deviating from it only when the target MOS becomes high and the number of UEs becomes close to the number of RBs. Nevertheless, the performance of the proposed algorithm is still considerably better than those of the benchmarking algorithms.

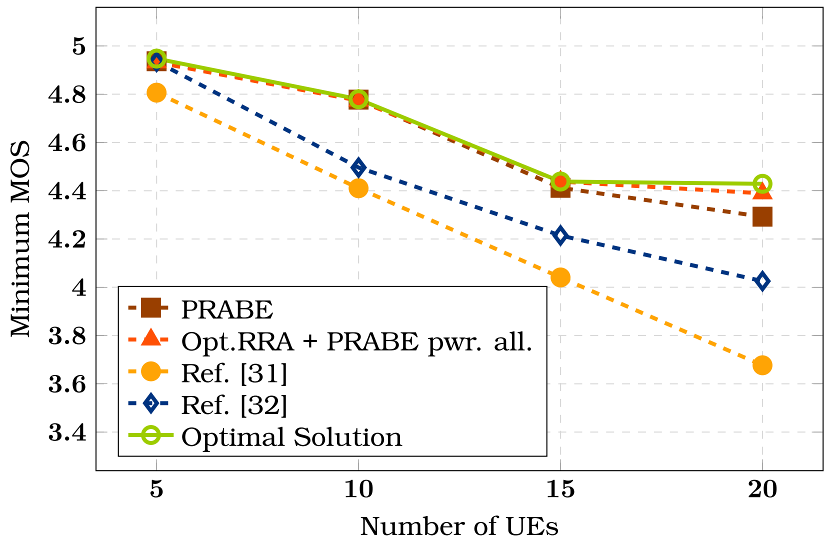
One way of increasing the performace of PRABE, for high values of target MOS and UEs in the system, is reducing the satisfaction factor. Figure 4.4 presents the outage versus the satisfaction factor, in percentage, in a system with 20 UEs and target MOS equal to 4.4. This analysis does not consider the benchmarking algorithms, [31] and [32], since they were not designed to support a satisfaction factor lower than 1. However, this parameter plays an important role, especially for network operators, since it is not always possible to satisfy all UEs at the same time in real-life networks. As we can observe in Figure 4.4, just by changing this parameter from 100% (satisfy 20 users out of 20) to 95% (satisfy 19 users out of 20) is enough to obtain an acceptable value of outage.



(a) Target MOS = 3.6.



(b) Target MOS = 4.



(c) Target MOS = 4.4.

Figure 4.3: Impact of the number of UEs on the minimum MOS for satisfaction factor, α, equal to 1.

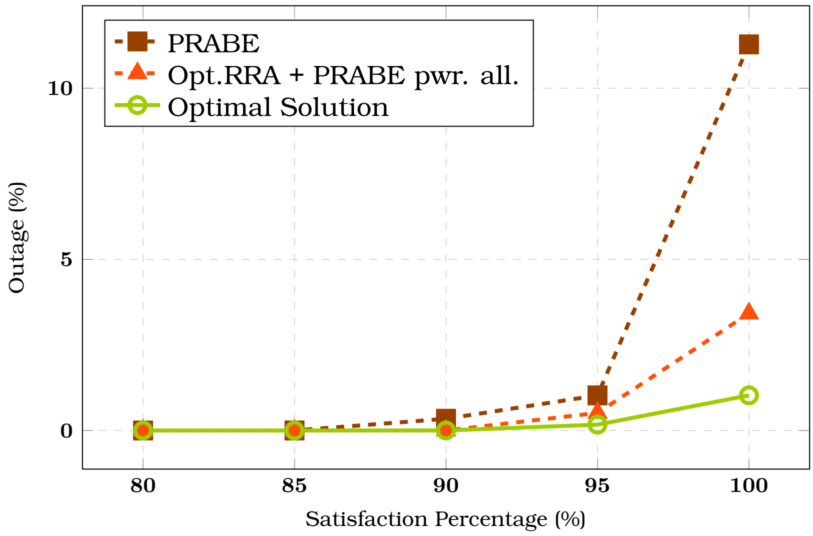


Figure 4.4: Impact of the satisfaction factor on the outage for number of UEs, U, equal to 20 and target MOS equal to 4.4.

4.3.2 Multiple Service Plans

In Section 4.3.1, it was noticed that, in the adopted scenario, for high values of target MOS and UEs in the system, the outage of PRABE can achieve values higher than 10%. The presented solution to overcome this issue was to reduce the satisfaction factor. In this case, all the UEs are treated equally and any one can be chosen not to be satisfied. Other option to overcome this issue is to divide the UEs into service plans with different requirements of target MOS and satisfaction factor. For example, a priority plan with higher requirements for emergency services, as fire brigade, police and ambulances, and another one for users in general. Figures 4.5 and 4.6 analyze this option. In both cases, 20 UEs are divided into two service plans.

In Figure 4.5, we present the outage rate as function of the target MOS of service plan two, n_2, considering three different partitions of the UEs among the service plans. For all of them, we considered the satisfaction factor of both service plans equal to 1, $\alpha_1 = \alpha_2 = 1$, and the target MOS of service plan one equal to 4.4, $n_1 = 4.4$.

In Figure 4.5(a), we considered 15 UEs in service plan one, $U_1 = 15$, and the others in service plan two, $U_2 = 5$. As we can see, for $n_2 = 4.2$, we already have an outage lower than 10%. However, it is important to mention that the gap between PRABE and the mixed solution is higher than the one between the mixed solution and the optimal one. In this case we need to choose between a better result or a lower computational effort. These gaps can still be reduced if we change the number of UEs in each service plan, which is done in Figure 4.5(b), for $U_1 = U_2 = 10$.

Comparing Figures 4.5(a) and 4.5(b), we note that, while the first case only achieves gaps between PRABE and the optimal solution lower than 5% for $n_2 \leq 3.6$, the second case achieves this values for $n_2 \leq 4.2$.

In Figures 4.5(c), we reduce even more the number of UEs in service plan one, $U_1 = 5$ and $U_2 = 15$. In this case PRABE has very low outage rates and performs close to the mixed solution.

An interesting comparison can be done between Figure 4.2(b) and 4.5(c). In Figure 4.2(b), for 20 UEs, PRABE achieves an outage rate of 1.7%, while in Figures 4.5(c), for $n_2 = 4$, the outage rate is of 2.6%. This means that trying to satisfy 5 UEs with MOS 4.4 and 15 UEs with MOS 4, has almost the same outage rate than assuring 20 UEs with MOS 4, which validates the multi service plans as an option for increasing the system satisfaction.

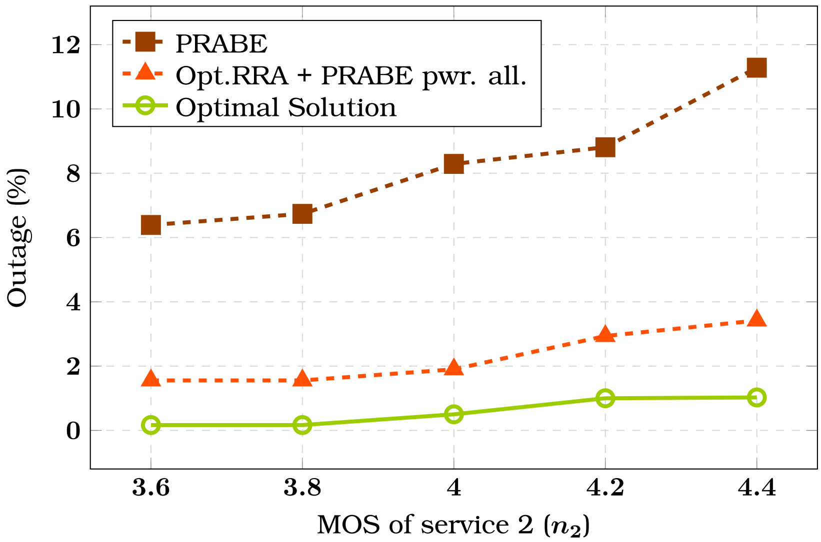
Comparing Figures 4.5(a), 4.5(b) and 4.5(c), we note that the increase of U_2 changes the behavior of PRABE from linear to exponential. This occurs due to the fact that, for higher values of U_2, changing n_2 impacts more users of the system. So, in Figure 4.5(c), to decrease n_2 means to reduce the target MOS of more users, which can clearly decrease the outage.

Focusing on the case $U_1 = U_2 = 10$, Figure 4.6 presents the relationship between the outage rate and the target MOS of service plan two, n_2, considering three different values for the satisfaction factor of service two, α_2. For all of them, we considered the satisfaction factor of service plan one equal to 1, $\alpha_1 = 1$, and the target MOS of service plan one equal to 4.4, $n_1 = 4.4$.

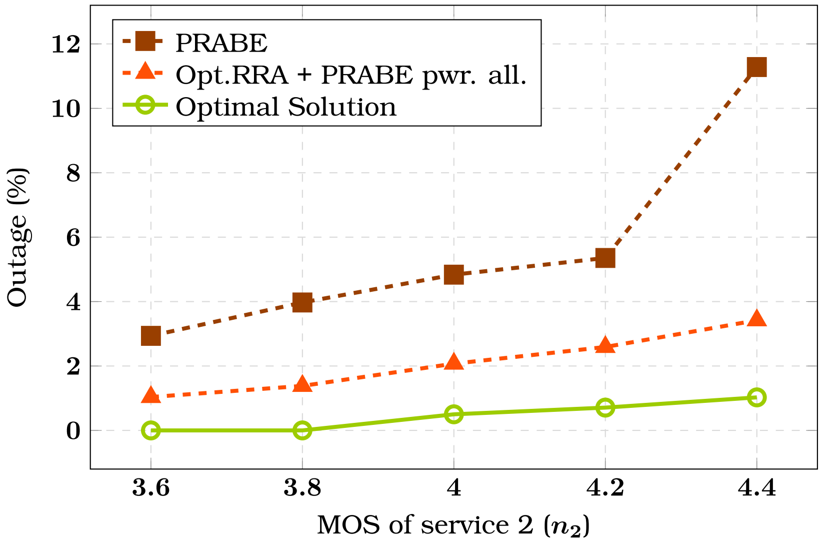
Figure 4.6(a), presents the case of $\alpha_2 = 0.9$, i.e., satisfy 9 out of 10 UEs. We note that reducing n_2 from 4.4 to 4.2 the outage reduces almost 2%, however reducing even more does not give higher gains. Similar conclusions can be obtained in Figure 4.6(b), where we have $\alpha_2 = 0.8$.

At this point, a brief summary can be done. In Figure 4.2(c), we have seen that, in the considered scenario, for 20 UEs in the system, target MOS equal to 4.4 and satisfaction factor equal to 1, PRABE achieves an outage rate of 12%, while the optimal solution achieves 1%. Aiming to reduce the outage of PRABE, we have studied two options: reduce the satisfaction factor and divide the users into service plans.

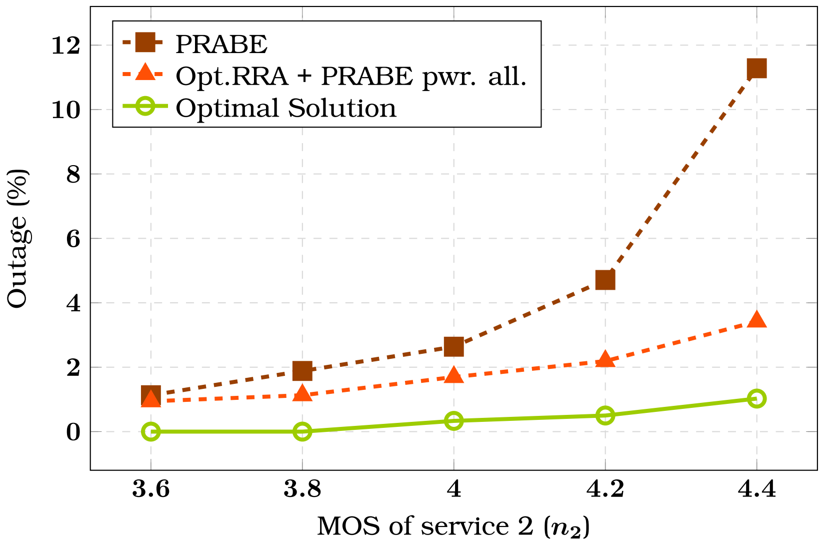
In Figure 4.4, we have analyzed the impact of the satisfaction factor, based on the same scenario. In this case, reducing the satisfaction factor from 1 to 0.95, i.e, satisfy 19 out of 20 UEs, the outage rate of PRABE has been reduced to 1%. The problem with this option is that any user can be chosen not to be satisfied. To overcome this issue, we have divided the UEs into two service plans, both with satisfaction factor 1. The target MOS of one service was kept in a high value, 4.4, and the other one was reduced. Considering this option, in Figure 4.5(c), PRABE has presented an acceptable value of outage rate, 2.6%, for $U_1 = 5$, $U_2 = 15$ and $n_2 = 4$. We also evaluated the reduction of α_2, Figure 4.6, however the gains were marginal, if we consider that we need to keep some users unsatisfied.



(a) Number of UEs per service: $U_1 = 15$ and $U_2 = 5$.

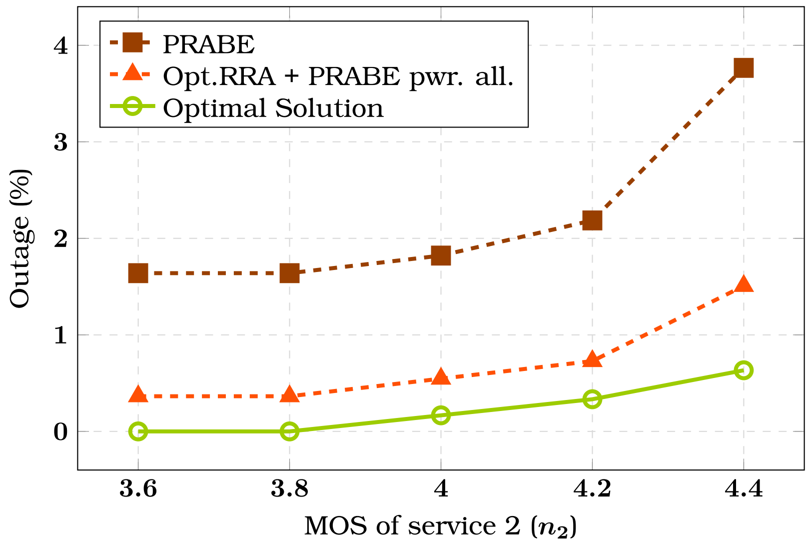


(b) Number of UEs per service: $U_1 = 10$ and $U_2 = 10$.

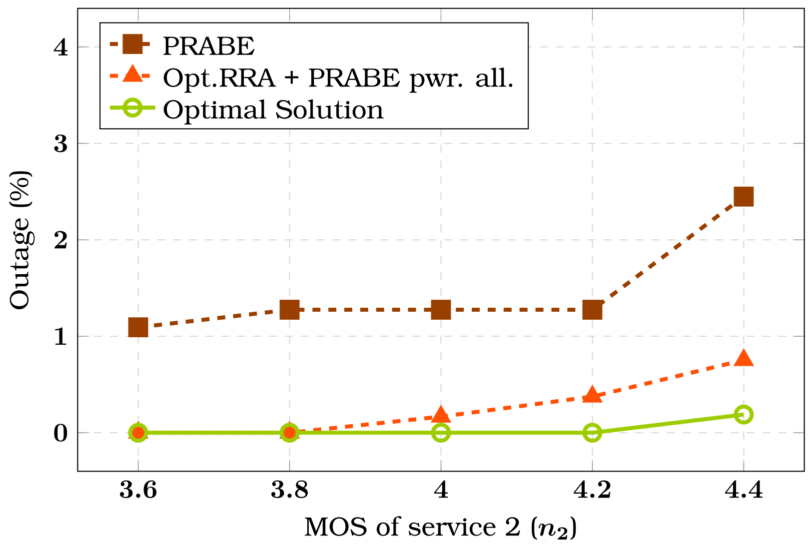


(c) Number of UEs per service: $U_1 = 5$ and $U_2 = 15$.

Figure 4.5: Impact of the target MOS of service 2, n_2, on the outage for satisfaction factor $\alpha_1 = \alpha_2 = 1$ and target MOS of service 1 $n_1 = 4.4$.



(a) Satisfaction factor of service plan 2: $\alpha_2 = 0.9$.



(b) Satisfaction factor of service plan 2: $\alpha_2 = 0.8$.

Figure 4.6: Impact of the target MOS of service 2, n_2, on the outage for 10 UEs in each service, $U_1 = U_2 = 10$, satisfaction factor $\alpha_1 = 1$ and target MOS of service 1 $n_1 = 4.4$.

4.3.3 Low Coverage Scenario

Until now, we have seen that PRABE has a near optimal performance in a scenario with good coverage, path loss model 1 of Table 4.1. Aiming to evaluate its performance in a scenario with worse coverage, in this section we consider path loss model 2 of Table 4.1.

In Figure 4.7, we present the outage rate as a function of the number of UEs considering three different values of target MOS and satisfaction factor equal to 1.

In Figure 4.7(a), target MOS equal to 3.6, we see that all the studied algorithms are negatively affected by the increase of the path loss, as expected. This is due to the fact that we need more RBs and power to overcome the increase of path loss and to achieve similar rates as those in Section 4.3.1. However, as we know, RBs and power are limited resources.

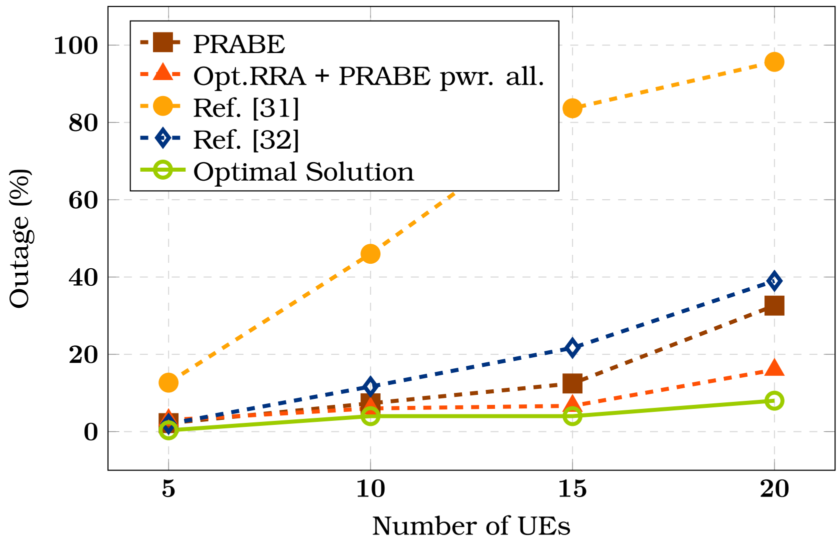
In Figure 4.7(b) we increase the target MOS to 4. In this case, even the optimal solution reaches unacceptable values of outage rate. Comparing Figures 4.7(a) and 4.7(b), we see that the performance of [31] is less degraded than the other algorithms by the increase of the target MOS, but this occurs because it already has the worst performance.

In Figure 4.7(c), we observe that the increase of the number of UEs negatively impacts all the studied algorithms. This occurs because this increase leads to more UEs competing for the same amount of resources. Thus, in average, the resources-per-UE will decrease and, consequently, the users' satisfaction too.

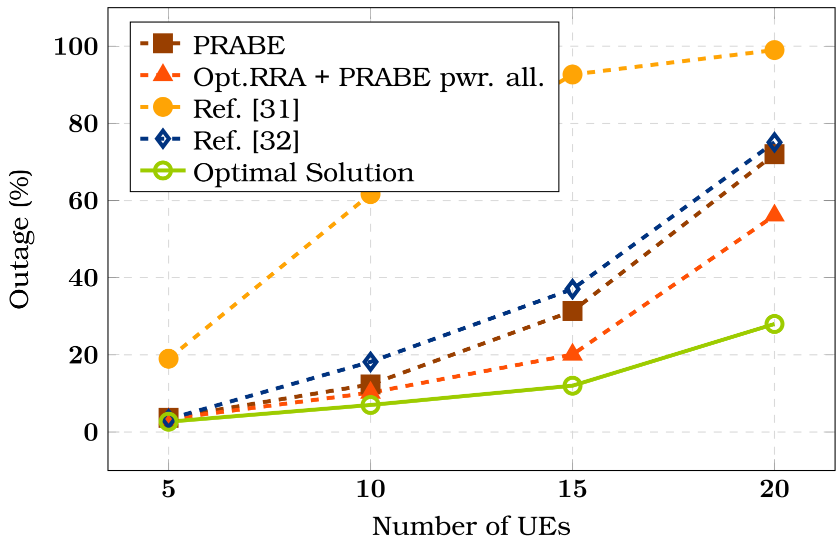
Comparing Figures 4.7(a), 4.7(b) and 4.7(c), we clearly see the gap between PRABE and [32] decreasing. [32] uses the optimal solution of a Tchebycheff problem to allocate power, whereas PRABE has a less complex power allocation, but not optimal. In a scenario with low coverage, this difference may be evidenced. However, it is important to remark that PRABE still has a better performance.

Also note that the outage for 20 UEs for the three cases of Figure 4.7 are very high. As in Section 4.3.1, we can reduce the satisfaction factor in order to decrease the outage. Figure 4.8 presents the outage versus the satisfaction factor, in percentage, in a system with 20 UEs.

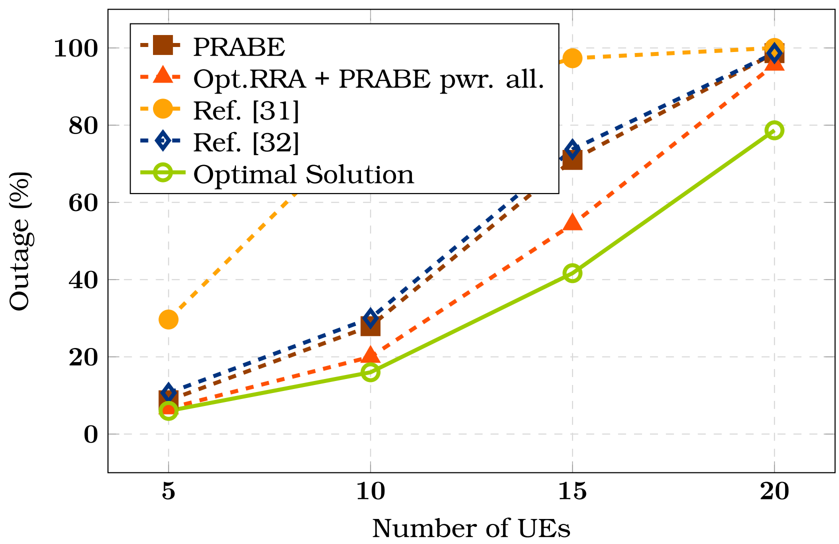
As we can observe in Figure 4.8(a), for target MOS equal to 3.6, just by changing this parameter from 100% (satisfy 20 users out of 20) to 95% (satisfy 19 users out of 20) is enough to obtain an acceptable value of outage, which is near optimal. For a target MOS equal to 4, Figure 4.8(b), we need to reduce even more, for example, to 90%, i.e., 18 out of 20. The most impressive result is illustrated in Figure 4.8(c), target MOS equal to 4.4. When decreasing the satisfaction factor from 100% to 80%, i.e., 16 UEs out of 20, the outage rate of PRABE and of the optimal solution decrease from 98% and 78% to 10% and 1%, respectively. This validates the importance of the satisfaction factor.



(a) Target MOS = 3.6.

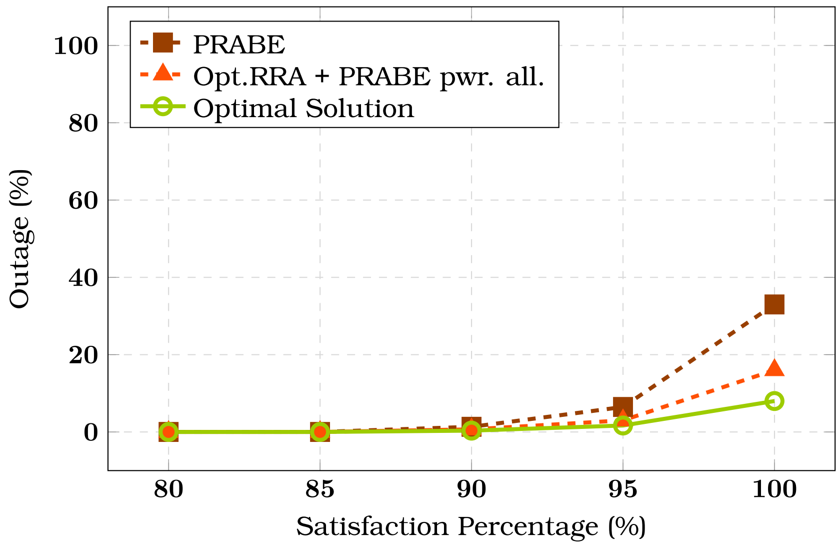


(b) Target MOS = 4.

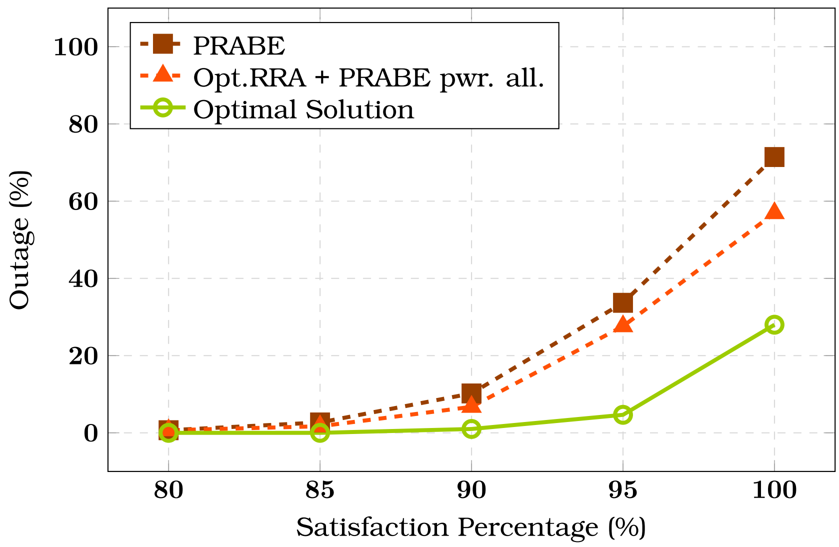


(c) Target MOS = 4.4.

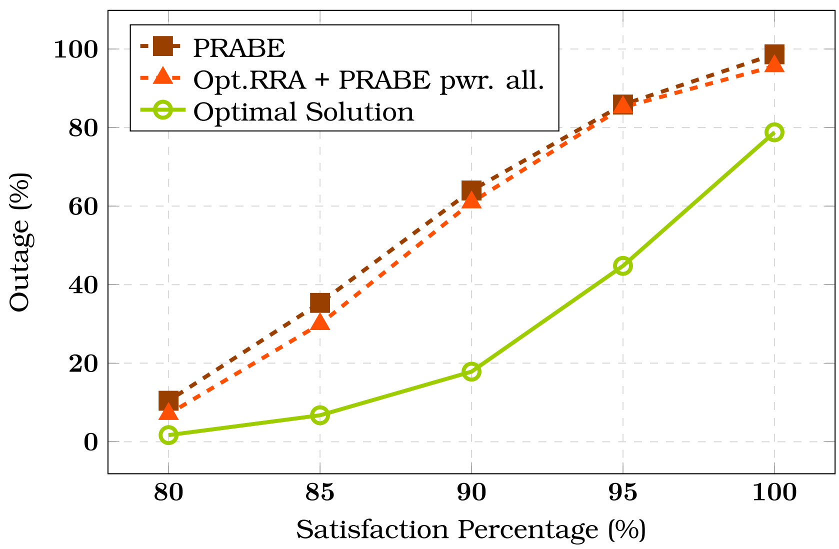
Figure 4.7: Impact of the number of UEs on the outage for satisfaction factor, α, equal to 1.



(a) Target MOS = 3.6.



(b) Target MOS = 4.



(c) Target MOS = 4.4.

Figure 4.8: Impact of the satisfaction factor on the outage for number of UEs, U, equal to 20.

4.3.4 Imperfect CSI

The previous analyses considered perfect CSI, which is a simplified assumption. In this section, we analyze the impact of considering imperfect CSI. Aiming to see only the effects of the imperfect CSI, we consider a system with 5 UEs, since this is the only case where all the algorithms present approximately zero outage for perfect CSI, as shown in Figure 4.2 of Section 4.3.1.

Figure 4.9 presents the impact of the degradation, ξ, presented in (2.1), on the outage for satisfaction factor, α, equal to 1. For target MOS equal to 3.6, in Figure 4.9(a), we note that in the considered degradation interval, from 0% to 10%, the gap between the studied algorithms is small and lower than 5%.

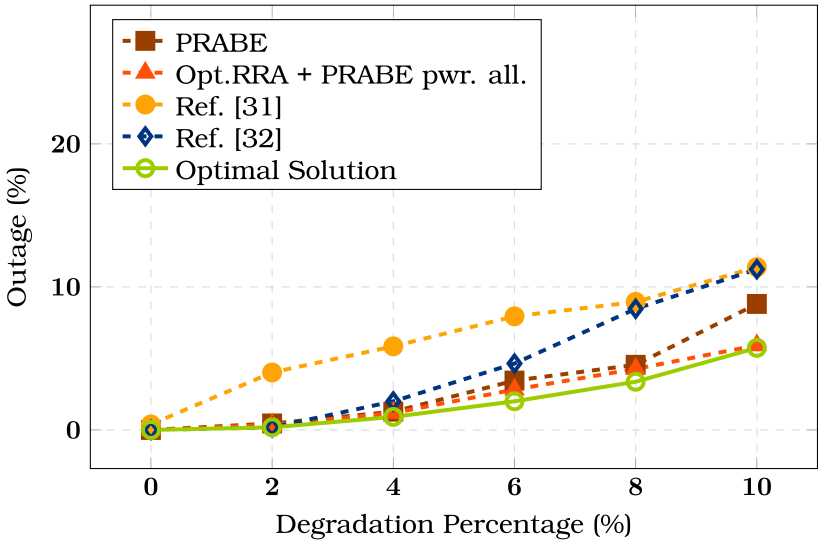
Changing the target MOS to 4, in Figure 4.9(b), the gap between [31] and the optimal solution increases to 12%, while the gap between PRABE and the optimal solution is of 4%. Comparing Figures 4.9(a) and 4.9(b), it appears that [31] is more sensitive to the CSI imperfections than the other algorithms.

Rising the target MOS to 4.4, in Figure 4.9(c), we can see that the imperfect CSI negatively impacts all the algorithms, since their performance is very deteriorated even in a system with only 5 UEs. However, it is important to note that the relative performance between the algorithms do not change significantly from the ones obtained in the previous sections.

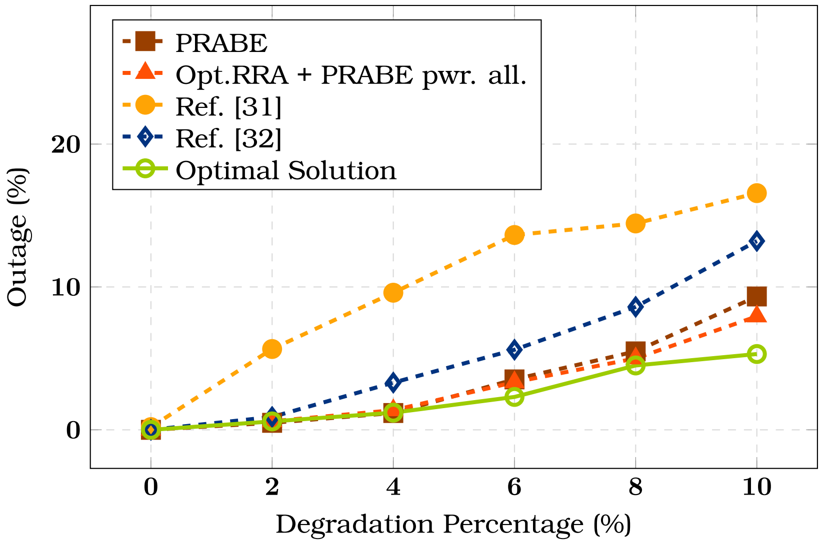
In this scenario, we also analyzed the impact of the satisfaction factor, since it has brought gains in the other scenarios. Figure 4.10 presents similar evaluations but considering α equal to 0.8 instead of 1, which means satisfy 4 users out of 5.

In Figure 4.10(a) we consider target MOS equal to 3.6. Comparing it to its equivalent with $\alpha = 1$, Figure 4.9(a), we can see an improvement in the performance of PRABE. Its outage has decreased to values close to zero, which means that PRABE was able to satisfy 4 of 5 users in almost all the simulations.

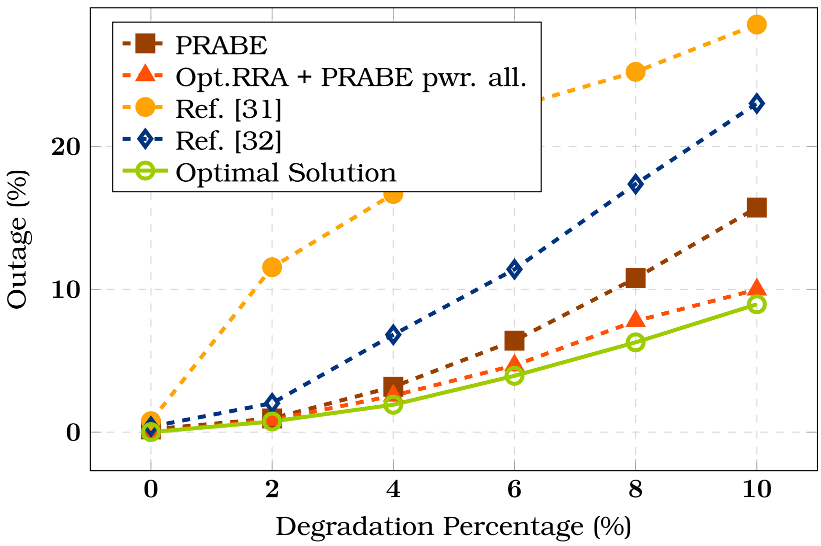
Figures 4.10(b) and 4.10(c) consider target MOS equal to 4 and 4.4, respectively. As in Figure 4.10(a), the outage has been reduced if compared to their respective graphs in Figure 4.9.



(a) Target MOS = 3.6.

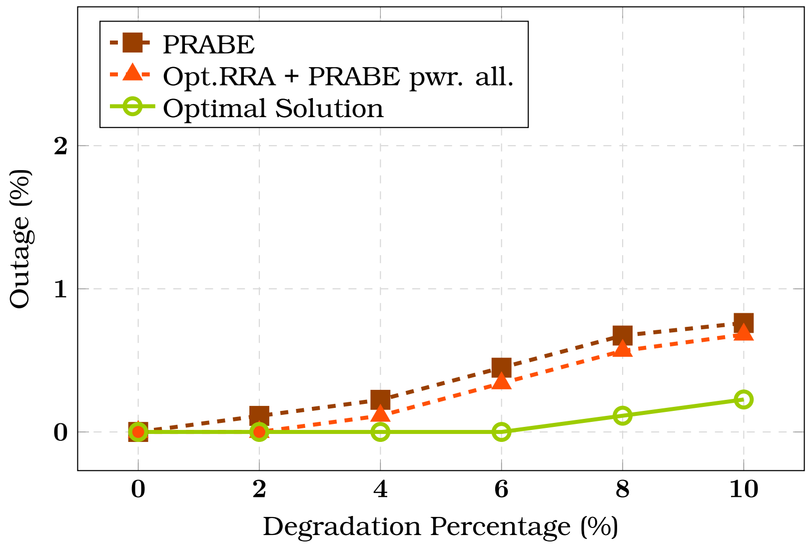


(b) Target MOS = 4.

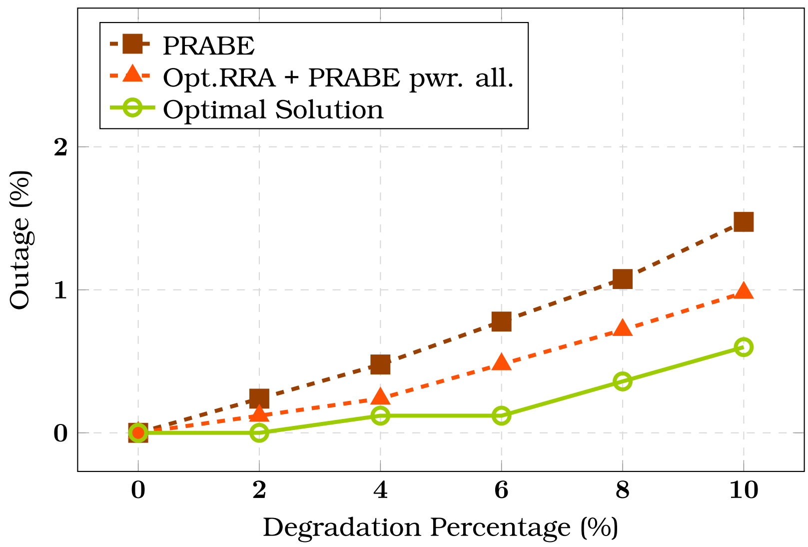


(c) Target MOS = 4.4.

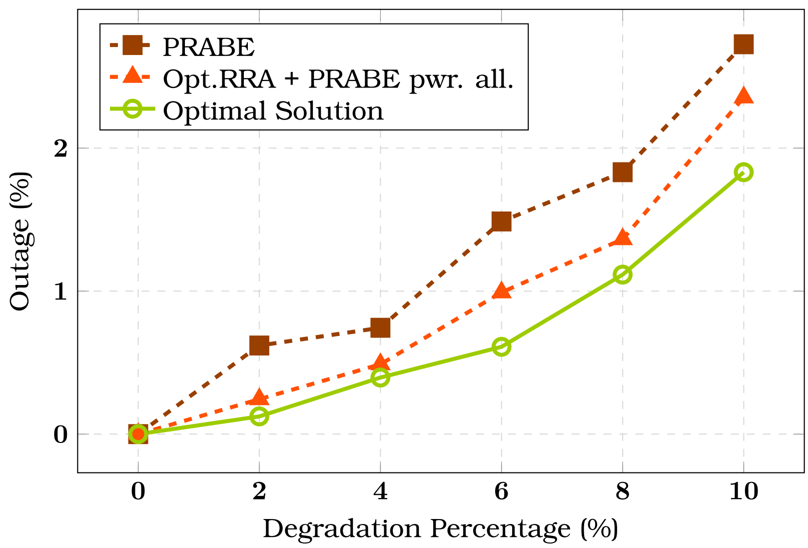
Figure 4.9: Impact of the degradation, ξ, on the outage for satisfaction factor, α, equal to 1 and number of UEs equal to 5.



(a) Target MOS = 3.6.



(b) Target MOS = 4.



(c) Target MOS = 4.4.

Figure 4.10: Impact of the degradation, ξ, on the outage for satisfaction factor, α, equal to 0.8.

Chapter 5

Conclusions and Future Work

In this master's thesis, we have studied a new optimization problem in the fields of Quality of Experience (QoE) and Radio Resource Allocation (RRA), taking into account constraints on the total transmit power and on the fraction of users that must be satisfied.

More specifically, in Chapter 1, we have introduced some of the motivations that are guiding operators to change their focus to delivering high-quality service experience, independently of technical requirements. We have also presented an overview of what is being doing in the three fields of QoE: modeling, measuring and optimization. Concerning the optimization category, we have listed the main works that have already considered QoE aspects when doing RRA.

In Chapter 3, a QoE-based RRA technique was studied from an optimization point of view. We have mathematically formulated the problem of maximizing the minimum Mean Opinion Score (MOS) of the users in a system constrained in transmit power and subject to satisfy a minimum number of users called satisfaction factor. We were able to reformulate it as a Mixed Integer Linear Problem (MILP), which solution can be obtained by standard solvers. Motivated by the high computational effort required by the optimal solution, we have proposed a framework called Power and Resource Allocation Based on Quality of Experience (PRABE).

In Chapter 4, we presented the performance evaluation. PRABE was evaluated in 4 different scenarios. The first one considered only one service plan. In this scenario, differently from the benchmarking algorithms, PRABE performed very close to the optimal solution, differing from it only for high values of target MOS and User Equipments (UEs) in the system. In this case, the satisfaction factor reduction has enhanced PRABE's performance. However, as all UEs are treated as equal, any one can be chosen to not be satisfied.

To overcome this issue, in the second scenario, we divided the UEs into two service plans: one with higher target MOS than the other. The obtained results validated the multi service plans scenario as a good option to improve the system performance. We also evaluated the reduction of the satisfaction factor of one of the plans, however the gains were marginals, if we consider that we need to keep some users unsatisfied.

While the first two scenarios had a good coverage, the third one evaluated the performance of PRABE in a scenario with worse coverage. The gap between PRABE and one of the benchmarking algorithms has reduced in this analysis. However, it is important to remark that PRABE still has a better performance and a less complex solution, since this benchmarking algorithm uses the optimal solution of an optimization problem to allocate power.

The last analyzed scenario studied the impact of considering imperfect Channel State Information (CSI). As expected, the imperfect CSI negatively impacted all the algorithms. However, the relative results between the algorithms did not change significantly from the ones obtained in the other scenarios, where PRABE outperformed the benchmarking algorithms.

Some perspectives for the continuation of this master's thesis work are listed below:

- **Time extension:** in this work, we considered that the users need to be satisfied at each Transmission Time Interval (TTI). If we consider a satisfaction factor equal to one, this assumption limits the number of UEs in the system to be at maximum the number of Resource Blocks (RBs), since for higher quantities of UEs we are sure that someone will not be allocated RBs leading to an unsatisfied state. Another approach could consider that the users need to be satisfied in the average over a number of TTIs, this way we can increase the number of UEs in the system. In this case, the target throughput rate of each UE in each TTI will change according to the previous resource allocations.
- **Multiple mapping functions:** in this work, all the service plans have the same function mapping throughput rate into MOS. However, it would be interesting to consider that each service plan has its own mapping function.
- **Mapping functions with other Quality of Service (QoS) parameters:** another possible extension to this work is to consider functions mapping other QoS parameters into MOS, e.g. the delay, rather than just the throughput.

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