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AI-DRIVEN FAILURE MANAGEMENT FOR MOBILE COMMUNICATION NETWORKS.

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En dicho trabajo, se han propuesto aportaciones originales para el análisis y diseño de metodologías para la gestión de fallos automática en redes móviles basadas en AI/ML. Los resultados de dicha tesis han dado lugar a las diversas publicaciones en revista, así como a aportaciones a congresos, superando el requisito de 1 punto ANECA del programa de doctorado regulado por el Real Decreto 99/2011.

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To those who have loved, supported, and walked beside me
— in every chapter, then, now, and always

“Success is the sum of small efforts,
repeated day in and day out.”

Robert Collier

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Summary of contributions

The various publications resulting from this research are listed below, starting with those that support the thesis.

Journal articles

[1] **José A. Trujillo**, I. de-la-Bandera, D. Palacios, R. Barco, "Framework for Behavioral Analysis of Mobile Networks", in *Sensors* 2021, 21, 3347. https://doi.org/10.3390/s21103347

[2] **José A. Trujillo**, I. de-la-Bandera, J. Burgueño, D. Palacios, E. Baena, R. Barco, "Active Learning Methodology for Expert-Assisted Anomaly Detection in Mobile Communications", in *Sensors* 2023, 23, 126. https://doi.org/10.3390/s23010126

[3] **José A. Trujillo**, R. Lykke, I. de-la-Bandera, S. Søndergaard, Troels B. Sønrensen, R. Barco, P. Mogensen,"Real-Time Overshoot and Undershoot Detection in Cellular Networks," in *IEEE Access*, vol. 13, pp. 22325-22341, 2025, doi: 10.1109/ACCESS.2025.3537327.

Additional contributions:

[4] **José A. Trujillo**, M. Martínez, I. de-la-Bandera, R. Barco, "Reinforcement learning methodology for coverage failures in 5G mmWave beamforming scenarios", under review in *IEEE Open Journal of the Communications Society.*

[5] Ana Gonzalez Bermudez, Miquel Farreras, Milan Groshev, **José A. Trujillo**, Isabel de la Bandera, Raquel Barco, "Graph Neural Networks for O-RAN Mobility Management: A Link Prediction Approach", under review in *IEEE Vehicular Technology Magazine.*

International conferences/workshops

[6] **José A. Trujillo**, I. de-la-Bandera, J. Burgueño, D. Palacios, and R. Barco, "Methodology for autonomous monitoring of mobile networks", in *IEEE Workshop on Complexity in Engineering (COMPENG)*, Florence, Italy, 2022, pp. 1-5, doi: 10.1109/COMPENG50184.2022.9905449. .

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[7] O. S. Peñaherrera-Pulla, C. Baena, H. Luo-Chen, **José A. Trujillo**, S. Fortes, R. Barco, "KQI-driven network slice resource configuration", in *European Conference on Networks and Communications (EuCNC)*, Poznan, Poland, 2025. .

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[8] **José A. Trujillo**, Isabel de-la-Bandera, David Palacios, Raquel Barco, "Sistema para la clasificación y detección de patrones de celdas en redes móviles", in *XXXV Simposium nacional de la Unión Científica Internacional de Radio*, Málaga, 2020.

[9] **José A. Trujillo**, Isabel de-la-Bandera, Jesús Burgueño, David Palacios, Raquel Barco, "Metodología de monitorización autónoma de redes móviles", in *XXXVI Simposium nacional de la Unión Científica Internacional de Radio*, Vigo, 2021.

[10] **José A. Trujillo**, Isabel de-la-Bandera, Raquel Barco, "Diagnosis automática con 5G para entornos de emergencia", in *XXXVIII Simposium nacional de la Unión Científica Internacional de Radio*, Cáceres, 2023.

Additional contributions:

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Contents

Abstract

The field of mobile communications has undergone significant advancements in recent decades, with continuous evolution being a permanent feature. The advent of 5G technology represents a milestone in mobile communications, as it will make it possible to cover a wide range of scenarios and functionalities not previously envisaged in this domain. This advance is characterised by substantial enhancements in transmission speed and latency, as well as a radical transformation in network architecture to support services with stringent latency and reliability requirements, Ultra Reliable Low Latency Communications (URLLC), and in environments with a substantial number of connected devices, massive Machine-Type Communications (mMTC). Consequently, the implementation of 5G will establish the foundations for the deployment of a wide variety of applications, including the connected vehicle, the Internet of Things (IoT) and telemedicine.

Concurrent with the implementation of these advancements, the network is undergoing a concomitant increase in complexity, thereby establishing an unparalleled management framework. Consequently, 5G technology not only expands technological possibilities, but also poses new challenges that require more advanced solutions. In this regard, the concept of Self-Organising Networks (SON) becomes fundamental to achieving efficient network management. The SON, defined as the automation of network management tasks, is subdivided into three categories: self-configuration, self-optimization, and self-healing. The concept has evolved to more advanced paradigms, such as Next Generation SON (NG-SON), which aims to automate the management of 5G networks, or Zero Touch Network (ZTN) which seeks to achieve a fully automated network.

The concept of self-healing encompasses a range of tasks related to the management of network failures, including the identification, diagnosis, compensation, and recovery of such issues. The automation of these tasks could be a significant challenge, which may be further

complicated by the implementation of 5G networks. The central objective of this thesis is to address the automation of fault management tasks, from detection to compensation of emerging problems that may arise in the network. To this end, this thesis establishes different lines of research that focus on the analysis, detection, and compensation of faults in 5G and beyond networks using Machine Learning (ML) and Artificial Intelligence (AI) techniques.

Firstly, it is important to extract useful information from all the available data concerning the network and its performance. In particular, different Key Performance Indicator (KPI) are studied to identify network behavior patterns, considering different aspects of the network (traffic, radio link, quality, among others). In this thesis, a methodology founded on ML techniques is presented, aiming to characterize the network through its behavioral patterns. This provides a the foundation for preliminary identification of anomalies and the acquisition of contextual understanding relevant to the behavior of the network.

Secondly, methodologies aimed at automating the performance monitoring of a mobile network are investigated, with particular attention to capturing and analyzing the valuable information that reflects the actual performance of the network. In this regard, two distinct approaches are presented. The first aims to detect changes in cell behavior patterns, while the second aims to detect deviations in network performance relative to its recent operation. These contributions enhance the ability to perform proactive and adaptive network monitoring.

Thirdly, the challenging task of detecting anomalies in a mobile network is addressed. To this end, a preliminary scenario is examined in which the expertise of engineering specialists in network management is integrated into automatic anomaly detection algorithms. In this sense, an approach based on active learning is promoted, which allows the combination of these algorithms with the knowledge of experts, with minimal human intervention. Additionally, the investigation encompasses anomalies associated with coverage issues, a persistent challenge in mobile networks. To this end, a framework is proposed that enables real-time detection of overshoot and undershoot problems in scenarios where the density of base stations and connected devices is increasing, as 5G dense urban.

In the final phase of a self-healing system, anomalies that have been identified are addressed and subsequently repaired. In this regard, the present study undertakes a comprehensive study of some of the functionalities introduced by the 5G technology, not only to detect possible failures associated with them, but also to take advantage of them to solve these problems. In this regard, a reinforcement learning-based method is proposed as a solution for beamforming scenarios, where certain beams are affected. This approach utilizes effective compensation by reconfiguring the parameters of the unaffected beams.

Therefore, this thesis presents a complete automation of the tasks considered in self-healing by means of the contributions through different methodologies and approaches. It is noteworthy that the implementation and evaluation of the proposed methodologies have been carried out using a 5G network system level simulator, as well as with commercial mobile network data.

Resumen

El campo de las comunicaciones móviles experimenta una evolución constante, con avances significativos en las últimas décadas. La aparición de la tecnología 5G supone un hito en las comunicaciones móviles, ya que permite abarcar una gran diversidad de escenarios y funcionalidades que no se contemplaban hasta ahora en este ámbito. Este avance no solo se manifiesta en mejoras significativas en términos de velocidad de transmisión y latencia, sino que propone una transformación radical en la arquitectura de las redes para soportar servicios con exigentes requisitos en cuanto a latencia y fiabilidad (URLLC), así como en entornos con una gran cantidad de dispositivos conectados (mMTC). En consecuencia, el despliegue de 5G sentará las bases para el despliegue de una amplia variedad de aplicaciones, tales como el vehículo conectado, el IoT o la telemedicina.

De manera paralela a la introducción de estos avances, la red también se vuelve más compleja, lo que establece unos requisitos de gestión sin precedentes. En consecuencia, la tecnología 5G no solo amplía las posibilidades tecnológicas, sino que también plantea nuevos desafíos que requieren soluciones más avanzadas. En este contexto, el concepto de red auto-organizada (SON) adquiere una relevancia fundamental para lograr una gestión eficiente de la red. La SON, definida como la automatización de las tareas de gestión de la red, se subdivide en tres categorías: self-configuration, self-optimization y self-healing. Este concepto ha evolucionado hacia paradigmas más avanzados, como el NG-SON, que busca automatizar la gestión de redes 5G, o el ZTN, cuyo objetivo es lograr una red completamente automatizada.

Self-healing engloba las tareas relacionadas con la gestión de fallos en la red, que incluyen la detección, la diagnosis, la compensación y la recuperación. La automatización de estas tareas constituye un desafío considerable que puede complicarse aún más con la implementación de las redes 5G. La presente tesis tiene como objetivo principal abordar la automatización de las tareas de gestión de fallos, abarcando desde la

detección hasta la compensación de los nuevos problemas que puedan surgir en la red. En consecuencia, esta tesis establece diferentes líneas de investigación que se centran en el análisis, detección y solución de problemas en las redes de nueva generación mediante el uso de técnicas de aprendizaje automático (ML) y la inteligencia artificial (AI).

En primer lugar, se plantea la necesidad de extraer la información útil de toda la cantidad de datos disponibles sobre la red y su rendimiento. Específicamente, se examinan diversos indicadores de rendimiento (KPI) con el propósito de identificar patrones de comportamiento en las redes, considerando diversos aspectos de estas (tráfico, enlace radio, calidad, entre otros). También se presenta una metodología basada en técnicas de ML capaz de caracterizar la red a través de sus patrones de comportamiento. Esto provee una base para la identificación preliminar de anomalías y la adquisición de un conocimiento contextual relevante para el comportamiento de la red.

En segundo lugar, se investigan metodologías destinadas a la automatización de la monitorización del rendimiento de una red móvil, prestando especial atención a la recopilación y el análisis de la información que realmente refleja el rendimiento de la red. En este sentido, se presentan dos enfoques diferentes: el primero busca detectar cambios en el patrón de comportamiento de las celdas y el segundo, detectar desviaciones en el rendimiento de la red con respecto a su funcionamiento reciente. Estas contribuciones mejoran la capacidad de realizar una monitorización proactiva y adaptativa de la red.

En tercer lugar, se aborda la ardua tarea de detectar anomalías en una red móvil. Para ello se contempla un primer escenario en el que se pretende integrar el conocimiento de ingenieros expertos en gestión de redes en algoritmos automáticos de detección de anomalías. En este sentido, se promueve un enfoque basado en active learning que permita la combinación de dichos algoritmos con el conocimiento de los expertos. Por otro lado, se exploran las anomalías relacionadas con problemas de cobertura, un aspecto siempre crítico en las redes móviles. Para ello, se propone un marco de trabajo que posibilita la detección en tiempo real de problemas de overshoot y undershoot en escenarios donde la densidad de estaciones base y dispositivos conectados cada vez es mayor, como es el caso de las redes urbanas densas 5G.

En la última fase de un sistema de self-healing se compensan y reparan las anomalías detectadas. En este contexto, se examinan algunas de las funcionalidades que introduce la tecnología 5G con el fin no solo de detectar posibles fallos relacionados con ellas, sino también de aprovecharlas para solucionar estos problemas. En consecuencia, se propone un método basado en el aprendizaje por refuerzo como solución para escenarios de beamforming, donde ciertos beams se ven afectados. Este enfoque logra una compensación eficaz mediante la reconfiguración de los parámetros de los beams que no se ven afectados.

De esta forma, esta tesis presenta una automatización completa de las tareas contempladas en el self-healing mediante las contribuciones a través de las diferentes metodologías y enfoques. Es relevante mencionar que la implementación y evaluación de las metodologías propuestas se ha llevado a cabo utilizando un simulador a nivel de sistema de red 5G, así como con datos de redes móviles comerciales.

Acronyms

1G First Generation.

3G Third Generation.

3GPP 3rd Generation Partnership Project.

4G Fourth Generation.

5G Fifth Generation.

5GC 5G Core Network.

5GS 5G System.

6G Sixth Generation.

AAU Aalborg University.

AF Application Function.

AI Artificial Intelligence.

AMC Adaptive Modulation and Coding.

AMF Access and Mobility Management Function.

API Application Programming Interface.

ASP Application Service Provider.

AUSF Authentication Server Function.

BBU Baseband Unit.

BLER Block Error Rate.

BS Base Station.

CA Carrier Aggregation.

CAPEX Capital Expenditure.

CDMA Code Division Multiple Access.

CM Configuration management parameters.

CN Core Network.

CNF Cloud-Native Network Function.

CP Control Plane.

CQI Channel Quality Indicator.

CU Centralized Unit.

D2D Device-to-Device.

DL Downlink.

DU Distributed Unit.

E-UTRAN Evolved Universal Terrestrial Radio Access Network.

eMBB enhanced Mobile BroadBand.

eNB Evolved Node B.

EPC Evolved Packet Core.

EPS Evolved Packet System.

FRs Frequency Ranges.

gNB Next Generation Node B.

GSM Global System for Mobile Communications.

HARQ Hybrid Automatic Repeat reQuest.

HO Handover.

HSS Home Subscriber Server.

IMS IP Multimedia Subsystem.

IoT Internet of Things.

IP Internet Protocol.

ITU International Telecommunication Union.

JCR Journal Citation Reports.

kNN k-Nearest Neighbors.

KPI Key Performance Indicator.

LLS Low Layer Split.

LOS Line of Sight.

LR Logistic Regression.

LTE Long Term Evolution.

LTE-A LTE Advanced.

MAC Medium Access Control.

MCS Modulation and Coding Scheme.

MDT Minimization of Drive Tests.

MIMO Multiple Input Multiple Output.

MISO Multiple Input Single Output.

ML Machine Learning.

MME Mobility Management Entity.

mMTC massive Machine-Type Communications.

mmWave millimeter Wave.

MNOs Mobile Network Operators.

MTC Machine-Type Communications.

MU-MIMO Multi-User MIMO.

NAS Non Access Stratum.

NB Naive Bayes.

Near-RT Near-Real Time.

NEF Network Exposure Function.

NF Network Function.

NG-RAN Next Generation Radio Access Network.

NG-SON Next Generation SON.

NGMN Next Generation Mobile Networks Alliance.

NLOS Non-Line of Sight.

Non-RT Non-Real Time.

NR New Radio.

NRF Network Repository Function.

NSA Non-Standalone.

NWDAF Network Data Analytics Function.

O-CU Open Centralized Unit.

O-DU Open Distributed Unit.

O-RAN Open Radio Access Network.

O-RU Open Radio Unit.

OFDM Orthogonal Frequency Division Multiplexing.

OFDMA Orthogonal Frequency Division Multiple Access.

OPEX Operational Expenditure.

P-GW Packet Data Network Gateway.

PCF Policy Control Function.

PCRF Policy and Charging Rules Function.

PDCP Packet Data Convergence Protocol.

PHY Physical layer.

PM Performance management parameters.

PPO Proximal Policy Optimization.

QoS Quality of Service.

RAN Radio Access Network.

rApp RAN Application.

RAT Radio Access Technology.

RF Random Forest.

RIC Radio Intelligent Controller.

RL Reinforcement Learning.

RLC Radio Link Control.

RNC Radio Network Controller.

RRC Radio Resource Control.

RRM Radio Resource Management.

RRU Remote Radio Unit.

RTT Round Trip Time.

RU Radio Unit.

S-GW Serving Gateway.

SA Standalone.

SAE System Architecture Evolution.

SBA Service-Based Architecture.

SIMO Single Input Multiple Output.

SINR Signal to Interference plus Noise Ratio.

SME Service Management Element.

SMF Session Management Function.

SMO Service Management Orchestration.

SMS Short Messaging Service.

SOM Self-Organizing Map.

SON Self-Organising Networks.

SU-MIMO Single-User MIMO.

SVM Support Vector Machine.

UDM Unified Data Management.

UE User Equipment.

UMa Urban Macro.

UMi Urban Micro.

UMTS Universal Mobile Telecommunications System.

UP User Plane.

UPF User Plane Function.

URLLC Ultra Reliable Low Latency Communications.

VNF Virtual Network Function.

WCN Wireless Communications Section.

xApp eXtended Application.

ZTN Zero Touch Network.

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Part I

Background

Chapter 1

Introduction

Content

The aim of this first chapter is to expose the motivation and the purpose of this thesis, to present the objectives and to describe the organization of this document.

1.1 Motivation

In recent decades, mobile networks have evolved at an astounding rate, leading to a communications revolution. At the inception of mobile networks, voice calls and text messaging were the basic functionalities. Present-day mobile phones provide access to the Internet, thereby enabling a multitude of applications and functionalities, including video streaming, e-commerce, banking, and web browsing. The ongoing evolution has resulted in a paradigm where all things and all people are connected to the network. Given this context, mobile communications have emerged as a key agent of societal and economic transformation.

The arrival of the 5G of mobile networks represents a significant milestone in the evolution of telecommunications, leading to a remarkable expansion in the range of services and functionalities provided by these networks [15]. Under this new paradigm, the aim is not only to provide enhanced Mobile BroadBand (eMBB) services, but also to provide new services and scenarios standardized by 3rd Generation Partnership Project (3GPP) [16]. Beyond the aforementioned eMBB, a pair of other principal services must be considered: Ultra Reliable Low Latency Communications (URLLC) and massive Machine-Type Communications (mMTC). URLLC services include use cases requiring critical communications that are highly reliable and have minimal latency, such as autonomous driving, emergency scenarios and healthcare applications such as robotic surgery. Meanwhile, mMTC services cover use cases related to the Internet of Things (IoT), with a large number of connected devices that consume low power and require reduced bandwidth, such as industrial automation, environmental monitoring and others.

Notwithstanding, technological demands continue to evolve, driving research into Sixth Generation (6G) networks. This new generation will not only enhance the capabilities of 5G networks but also introduce novel use cases that are likely to disrupt existing paradigms. These include real-time holographic communication, native artificial intelligence within the network, and the integration of non-terrestrial systems [17]. These advancements are poised to unlock a new dimension of advanced scenarios in the domains of connectivity and automation. In this context, the Open Radio Access Network (O-RAN) architecture emerges as a fundamental technology to facilitate these advancements by enabling more flexible, interoperable, and programmable networks [18]. The O-RAN approach, based on virtualization and open interfaces, enables the efficient implementation of URLLC and mMTC services, allowing network resources to be optimized in real time and dynamically adapted to the requirements of future 6G use cases.

The continuous evolution of mobile networks, alongside the proliferation of connected devices and services, contributes to the complexity of network management and operation tasks. Consequently, Mobile Network Operators (MNOs) are exploring avenues for automation to address these challenges. This approach enables the optimization of network and its resource management, while avoiding the increase in Capital Expenditure (CAPEX) and Operational Expenditure (OPEX).

The need for automation of these tasks led to the introduction of the Self-Organising Networks (SON) concept by Next Generation Mobile Networks Alliance (NGMN) in 2008 [19, 20]. Subsequently, 3GPP established the requirements for SONs [21], categorizing their functionalities into three domains: self-configuration [22], self-optimization [22], and self-healing [23]. Self-configuration functionalities enable the automatic incorporation of new elements into the network [24, 25, 26]. Self-optimization encompasses tasks related to the reconfiguration of the network to adapt to changes in the environment while maintaining its proper functioning [27, 28, 29, 30]. Finally, self-healing involves tasks related to the detection of anomalies [31, 32, 33], the diagnosis of the cause of anomalies [34, 35, 36, 37], and the suggestion of potential actions to compensate or recover the network [38, 39, 40].

In parallel, advancements in SON functionalities have generated significant interest in the scientific community, leading to a proliferation of proposals for network management algorithms [41]. Hence, Machine Learning (ML) [42] is emerging as a pivotal approach to address the complexity inherent in the diversity of services and the magnitude of users in mobile networks [43]. Evidence of this is the integration of ML and Artificial Intelligence (AI) in the evolution of SON for 5G, known as Next Generation SON (NG-SON), as a basis for the automation of network management and orchestration tasks [44]. Additionally, Zero Touch Network (ZTN) is a concept that has gained traction in the context of SON and 5G and beyond networks, aiming to achieve fully autonomous network management [45]. These approaches exploit the proliferation of data generated by mobile networks, endowing them with scalability, flexibility, and resilience [46, 47]. The accumulation of substantial information from mobile networks introduces challenges related to noise, redundancy, and potential biases, which have the capacity to substantially impact the performance of ML models. Consequently, meticulous data selection, preprocessing, and feature engineering are indispensable steps to ensure the accuracy, impartiality, and generalizability of ML models, thereby enhancing network self-management capabilities, particularly in critical functions such as real-time resource optimization and self-healing.

In consideration of the aforementioned context, self-healing emerges as a pivotal component within SON networks, ensuring reliability and service continuity. Traditionally, a common procedure involves the monitoring and analysis of network data to identify anomalies or failures [48]. However, advancements in mobile networks not only bring benefits but also introduce novel faults and problems in the network [49, 50]. Consequently, these methodologies have evolved to more complex methodologies and proactive approaches that aim to anticipate failures before they occur [51, 52]. This continuous evolution of self-healing remains a highly relevant research topic, especially as emerging network paradigms such as O-RAN and the transition to 6G. The adoption of open, software-driven architectures in O-RAN enables greater flexibility and programmability. However, it also demands more advanced self-healing mechanisms capable of dynamically adapting to heterogeneous and highly distributed network environments [53]. A similar necessity for advanced fault management solutions is anticipated in 6G networks, which will rely on artificial intelligence-driven automation and ultra-dense connectivity. These networks will require even more sophisticated fault management solutions to maintain optimal performance and reliability [54, 55].

1.2 Preliminaries

This thesis has been carried out at the Mobile and Aerospace Networks Lab research group (*MobileNet*), which belongs to Instituto Universitario de Investigación en Telecomunicación de la Universidad de Málaga (*TELMA*).

The *MobileNet* group was created as a result of the collaboration between the TIC-102 group and Nokia Networks in the creation of the Mobile Communications Research Centre in the Andalusia Technology Park (PTA) in Málaga in 2000.

One of the main research lines of *MobileNet* is the application of AI/ML techniques to mobile communications networks. In collaboration with Nokia Networks - Spain, one of the group's initial projects was to develop an automated Radio Access Network (RAN) troubleshooting tool. This project established the foundation for integrating real-world mobile network data with engineering expertise. As a result, automated problem solving solutions were developed.

Since then, the development of SON applications has remained a constant thematic focus in the research conducted by the group, leading to partnerships and collaborations with prestigious national and international companies. Among other initiatives, the NEREA project aimed to develop an autonomous network management tool. Fundamentally, it is a data-driven tool that relies on network counters and Key Performance Indicator (KPI) to support its various functionalities, with ML playing a pivotal role in its operation. Its functionalities encompass anomaly detection and prediction, a simulator of the impact generated by configuration changes, and decision support for network engineers.

Furthermore, *MobileNet* contributed to DAMA-5G (Detección de Anomalías Multivariable Asistida) project, where automatic methods were designed to identify degradations in network performance. This initiative incorporated the expertise of an engineer to enhance the efficacy of the detection process. Conversely, *MobileNet* participated in the PENTA (Provisión de servicios PPDR a través de Nuevas Tecnologías de Acceso Radio) project, which focused on leveraging SON functionalities in emergency scenarios. This included the implementation of self-healing mechanisms to mitigate network disruptions caused by emergency situations and the optimization of URLLC performance in disaster-stricken environments.

In accordance with this trajectory, *MobileNet* has been involved in the MAORI (Massive AI for the OpenRadIo b5G/6G network) project, which intends to implement ML methodologies and algorithms for intelligent network administration. A central objective of the project is the implementation of self-optimization and self-healing mechanisms within the RAN, focusing in the new O-RAN paradigm. The project has investigated functionalities such as the identification of radio link failures and the optimization of network performance through the use of context-aware information. Collectively, these projects establish the basis for this thesis, in addition to the development of select aspects within this thesis.

The infrastructure of *MobileNet* plays a pivotal role in the development of these projects, with a Long Term Evolution (LTE) network simulator at system level, developed within the group [56]. This tool has been a fundamental component of this thesis, being updated to New Radio (NR) and utilised as a method to evaluate algorithms and functionalities of the same. Additionally, the group has an LTE network [57] comprising 12 picocells, as well as a 5G Standalone (SA) network [58] consisting of 3 macro-cells and 6 indoor picocells. These projects have benefited from the use these networks and other emulation equipment, such as the RICTest, which has played a significant role in the development of O-RAN architectures.

1.3 Challenges and objectives

The principal objective of this thesis is to explore the potential of ML and AI techniques for the incorporation of self-healing functionalities within 5G and beyond networks. The advent of these advanced networks is expected to bring numerous benefits, but also introduce new challenges and problems that must be addressed. In particular, this thesis covers the whole cycle including the selection of relevant information, network monitoring, anomaly detection and the formulation of suitable solutions. To address these functionalities within the entire cycle, certain targets have been established, representing milestones on the road to achieving the final aim of this thesis. Figure 1.1 illustrates these specific objectives.

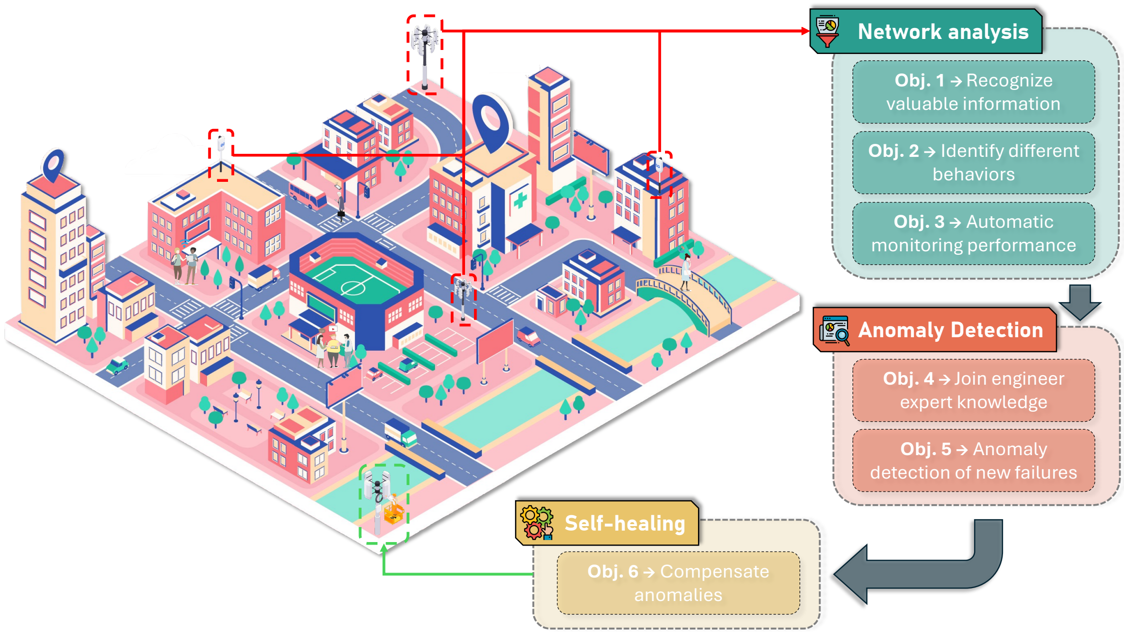


Figure 1.1: Objectives of the thesis

Recent advancements in mobile networks have precipitated a proliferation of services, use cases and functionalities, engendering novel scenarios that must be considered in network management. This plethora of novel developments inevitably generates a substantial volume of data, which can be advantageous in assessing the status of the network. However, this abundance of data presents challenges, as not all of it provides valuable information to manage the network and its resources. This challenge forms the foundation of the first specific objective of this thesis (Objective 1), which aims to identify the useful information from the irrelevant information. More specifically, the goal is to examine which aspects of the network are conducive to the automation of different network functionalities.

In the contemporary context of mobile networks, there is a pronounced trend towards heterogeneity, stemming from the coexistence of diverse access technologies and a multitude of devices with varied capabilities and requirements. This heterogeneity engenders a multitude of network behaviors that are both dynamic and complex in nature, thereby complicating the identification of anomalies and the efficient management of resources. Consequently, the comprehension of the behavioral patterns exhibited by these networks has become indispensable for the anticipation of potential failures and the optimization of self-healing mechanisms. In this regard, the subsequent objective of this thesis (Objective 2) endeavors to methodically analyze and categorize these patterns, thereby enhancing the knowledge of the network to enable enhanced anomaly detection and to develop adaptive solutions that empower network management to operate with greater efficiency and autonomy. Nonetheless, to ensure the efficacy of behavioral pattern knowledge in heterogeneous networks, its integration into a real-time monitoring system is mandatory. Considering the dynamic characteristics of mobile networks, the constant monitoring of network conditions is indispensable for the timely detection of anomalies and, ideally, the proactive anticipation of potential failures, thereby ensuring optimal service quality. The integration of this knowledge into a continuous monitoring system facilitates not only more precise detection but also enhances the implementation of self-healing mechanisms capable of autonomous and adaptive responses.In this regard, another key objective of this thesis (Objective 3) is the development of real-time monitoring capable of identifying changes in network behavior, thereby providing operators with suitable information to detect anomalies or make proactive adjustments to the network configuration. This approach will not only facilitate the early detection of problems but also enable continuous optimization of network performance, allowing for adaptation to changing conditions and enhancement of the quality of service for users.

Despite the advancements in automation and the emergence of artificial intelligence in the management of mobile networks, network operators continue to show caution regarding the implementation of fully autonomous algorithms that could potentially affect the quality of service experienced by users. Traditionally, tasks such as network configuration, optimization, and troubleshooting were performed by expert engineers, whose knowledge and experience are crucial for making critical decisions. However, the trend towards greater automation is undeniable, as evidenced by advances in 3GPP standardization and the incorporation of AI in new O-RAN elements, with the Radio Intelligent Controller (RIC) constituting a key component introduced by the O-RAN Alliance to integrate these automatic algorithms into the network architecture. Consequently, another objective of this thesis (Objective 4) is to integrate expert knowledge into ML/AI algorithms, ensuring that they not only learn from data but also incorporate the strategies and reasoning of engineers. This approach aims to generate systems that are more reliable and transparent, while maintaining the stability and performance of the network.

Due to the increased complexity of next-generation mobile networks, as previously mentioned, new challenges have emerged from the new capabilities and functionalities these networks introduce. A primary benefit of 5G is the enhancement of coverage and the availability of various services, including functionalities such as beamforming, network slicing, and the use of millimeter frequencies. Alongside these advantages, novel challenges emerge due to the implementation of these advanced features. Together with scenarios characterized by increasing variability, a multitude of traffic patterns, and an ever-expanding variety of devices, the conventional approach to anomaly detection may prove to be ineffective. In addressing this need, the present thesis aims to explore advanced ML techniques for anomaly detection (Objective 5). These techniques will capitalize on the valuable information contained within vast networks of data to identify latent issues. In contrast to conventional approaches, these techniques will facilitate more accurate and adaptive detection, thereby enabling automated decision-making without compromising network stability. Complementing advances in anomaly detection, it is equally critical to address the challenge of automatically compensating for detected network failures. The increasing complexity of next-generation mobile networks makes it challenging not only to identify anomalies, but also to effectively mitigate them in real time. Traditional recovery mechanisms often rely on predefined rules or manual intervention, which may not be sufficient in highly dynamic environments. Nevertheless, the continued evolution of ML techniques and the growing trend toward network automation, particularly through the O-RAN paradigm, provide an opportunity to improve fault recovery strategies. The introduction of RIC enables intelligent decision making at different levels of the network, enabling proactive and adaptive responses to failures. In this regard, investigating advanced machine learning techniques for fault compensation to ensure that networks can autonomously adapt and recover from faults while maintaining optimal performance and quality of service is one of the objectives of this thesis (Objective 6).

In summary, the thesis' objectives are as follows:

- **Objective 1.** To analyze and extract valuable information from vast amounts of data collected in next-generation mobile networks. In this regard, different automatic techniques are explored to determine relevant information for each functionality.
- **Objective 2.** To characterize the different behavioral patterns existing in a mobile network through automated techniques. The aim is to achieve a methodology that is able to determine from network metrics such as counters, statistics or KPIs whether the behavior patterns of two cells are similar or different. In this way it is possible to know what kind of cells exist in the network.
- **Objective 3.** To provide an autonomous monitoring methodology capable of detecting behavioral changes in network elements. The purpose is to provide real-time network status to support self-healing or self-optimization tasks and to generate valuable information about whether there are behavioral changes in the monitored network.
- **Objective 4.** To enable ML/AI algorithms to not only learn from the data generated by mobile networks, but also to integrate the knowledge of expert network management engineers. This ensures more reliable algorithms for efficient and resilient network performance.

- **Objective 5.** To explore new techniques for anomaly detection to address novel failures that may emerge in the scenarios and use cases of the new generations of mobile networks. Specifically, coverage issues due to network heterogeneity and dense networks will be investigated.
- **Objective 6.** To investigate novel ML/AI techniques to provide a framework for suggesting possible actions to be taken in the network to solve the detected problems. More precisely, scenarios that integrate novel functionalities and features, such as beamforming or the use of millimeter frequencies, will be addressed.

1.4 Document structure

This thesis is subdivided into eigth chapters, which are organized in three parts: I) Background, II) Publications and III) Conclusions. This structure is shown in Figure 1.2.

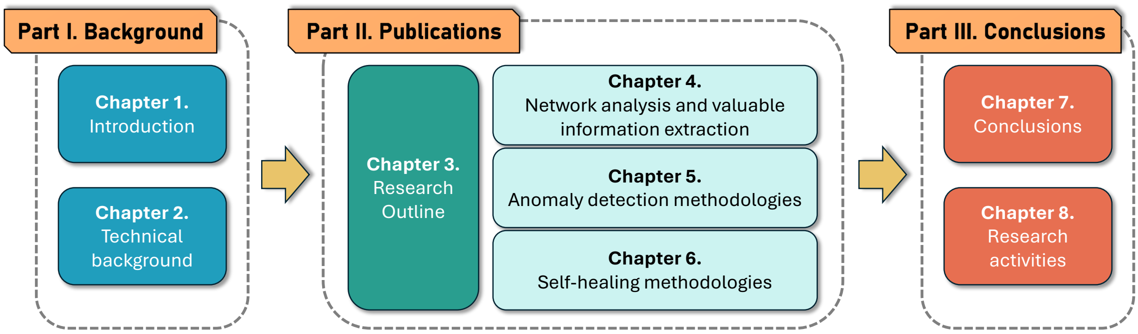


Figure 1.2: Document structure

Part I - Background

The first part of this document contains the motivation for this thesis and the technical background. It begins with Chapter 1, which introduces the context and objectives of this thesis. Following this, Chapter 2 outlines the theoretical concepts used in this thesis, introducing the fundamental aspects related to cellular networks and highlighting the emerging features and approaches adopted in the RAN. Furthermore, this introduction discusses several concepts related to the management and operation of such networks, focusing on the detection and management of the various anomalies that could potentially affect network performance.

Part II - Publications

The second part contains the set of research papers that support this PhD dissertation. Chapter 3 provides a comprehensive overview of the research conducted in this thesis. This involves a detailed identification of the challenges, objectives and results achieved. Furthermore, the methodology used in the research is explained.

Chapter 4 collects two papers related to Objectives 1, 2 and 3. The first article focuses on analyzing and extracting valuable information from the vast amounts of data collected in next-generation mobile networks. In this regard, the paper explores different automatic techniques to determine relevant information for each functionality. Furthermore, a framework for behavioral pattern characterization and classification in mobile networks is presented. The second paper presents an autonomous monitoring methodology capable of detecting behavioral changes in network elements. The purpose is to provide real-time network status to support self-healing or self-optimization tasks and to generate valuable information about whether there are behavioral changes in the monitored network.

Chapter 5 consists of two papers that are in line with Objective 4 and 5 of the thesis. These papers address the analysis and evaluation of novel ML techniques for anomaly detection in the context of cellular networks. More specifically, the first paper outlines a methodology for integrating expert knowledge into ML/AI algorithms. This methodology ensures that the algorithms not only learn from data but also incorporate the strategies and reasoning of engineers. The second paper explores techniques for anomaly detection to address coverage failures that may emerge in scenarios characterized by density and heterogeneity. In particular, a methodology is proposed to detect overshoot and undershoot problems in real time. This methodology enables operators to resolve issues in a timely manner, improving coverage optimization and overall network performance.

Chapter 6 contains a paper related to Objective 6. This paper presents a methodology for compensating coverage failures in 5G millimeter Wave (mmWave) beamforming scenarios. The methodology is based on reinforcement learning techniques and aims to provide a framework for suggesting possible actions to be taken in the network to solve the detected problems.

Part III - Conclusions

The third part of this manuscript consists of two chapters related to the outcomes of this research. Chapter 7 contains the conclusions and outlook arising from this thesis. Finally, Chapter 8 presents the research activities in which the author was involved.

Appendices

This document also includes a brief summary in Spanish, which can be found in Appendix A. Additionally, Appendix B provides a detailed description of the simulation tool used in this research. This appendix outlines the enhancements and modifications made to the simulation tool, which were necessary to adapt it to the new scenarios and functionalities addressed in this thesis.

Chapter 2

Technical background

Content

This chapter outlines the fundamental technical concepts essential for understanding the contents of this thesis. In this regard, Section 2.1 presents the basic concepts of cellular networks, describing the characteristics and architectures of different technologies such as 5G or O-RAN. Subsequently, Section 2.2 introduces an overview of the SON concept and its functionalities. Finally, Section 2.3 describes the main ML techniques that can be used to automate the SON task.

2.1 Cellular networks

Cellular networks are telecommunications systems that use radio waves to enable wireless communication between devices. Their infrastructure consists of interconnected base stations that provide coverage across different geographical areas, ensuring that users remain connected even when on the move. These networks have evolved significantly from the First Generation (1G), which supported analog voice calls exclusively, to the current 5G and future 6G networks, which incorporate ultra-high speeds, low latency, and the ability to connect millions of devices simultaneously.

In this regard, each successive generation of mobile networks has introduced different developments and features, which are reflected in the different 3GPP releases. Advancements in spectral efficiency, data transmission capacity, and service reliability are driving innovations such as IoT, augmented reality, and vehicular communications.

The architecture of mobile networks is composed of three principal components: User Equipment (UE) of the costumers, Radio Access Network (RAN), and Core Network (CN). Figure 2.1 illustrates a common mobile network architecture, which varies depending on the generation of mobile communications.

CN occupies a pivotal role within a mobile network, serving as the central node for managing data, voice, and signaling traffic between users and external networks such as the Internet or other telecom operators. It provides essential functions such as routing communications or user authentication. In contemporary architectures, CN has evolved from traditional circuit-switched and packet-switched domains to fully packet-based designs, which enable cloud-native deployments and network slicing. These advancements provide greater scalability, flexibility, and efficiency, ensuring that mobile networks can support a wide variety of applications.

RAN is a critical component of cellular networks, responsible for facilitating wireless communication to users through the radio interface. It consists of Base Station (BS) which cover different geographical areas and provide service across them. These BSs are orchestrated to manage resources, facilitate user mobility (e.g., Handover (HO), the process of switching from one base station to another), and ensure efficient coordination to utilize the same frequency spectrum and serve multiple devices at the same time. Traditional RAN architectures rely on proprietary hardware and closely integrated components, but emerging paradigms such as O-RAN promote disaggregated, software-defined architectures that enable greater flexibility, interoperability and integration of artificial intelligence-driven optimizations.

UEs are regarded as devices that enable end users to establish a connection with the network, enabling a wide range of services from anywhere. The term ”UE” has evolved in line with the evolution of cellular networks. In the Global System for Mobile Communications (GSM) era, UEs were considered as devices with the ability to realize voice calls and send Short Messaging Service (SMS). However, in the context of 5G deployments, the term ”UE” has evolved to encompass any device capable of connecting and interacting with the network to provide various services to consumers (e.g., voice, internet, cloud and so forth). This involves different types of devices: smartphones, tablets, cameras, vehicles or smartwatches.

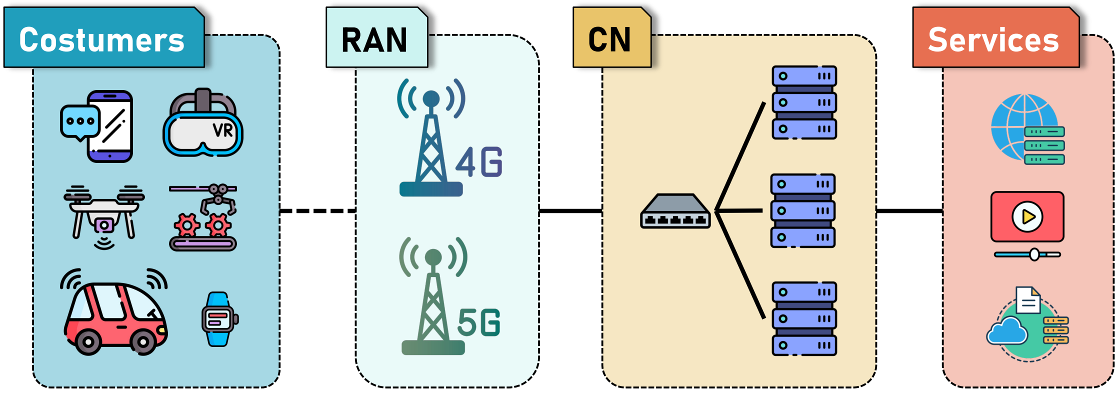


Figure 2.1: Cellular network architecture

In order to ensure a coordinated communication between these three elements (UE, RAN, and CN), 3GPP has standardized a protocol stack. This protocol stack is a structured set of communication protocols that determine how data is transmitted, managed, and processed between the different entities. Typically, a protocol stack is divided into different layers, each responsible for a specific functionality (e.g., signaling or data transport). The protocol stack is further organized into two primary operational planes: Control Plane (CP) and User Plane (UP). CP is responsible for the establishment of the connection between the user and the network, including authentication, mobility handling, and resource allocation. Conversely, UP is responsible for the transmission of user data (messages, images, or videos).

Figure 2.2 illustrates a generic protocol stack used by the three elements mentioned above. Furthermore, a distinction is made between which protocols belong to the CP and which belong to the UP. The functionality of each protocol is described below.

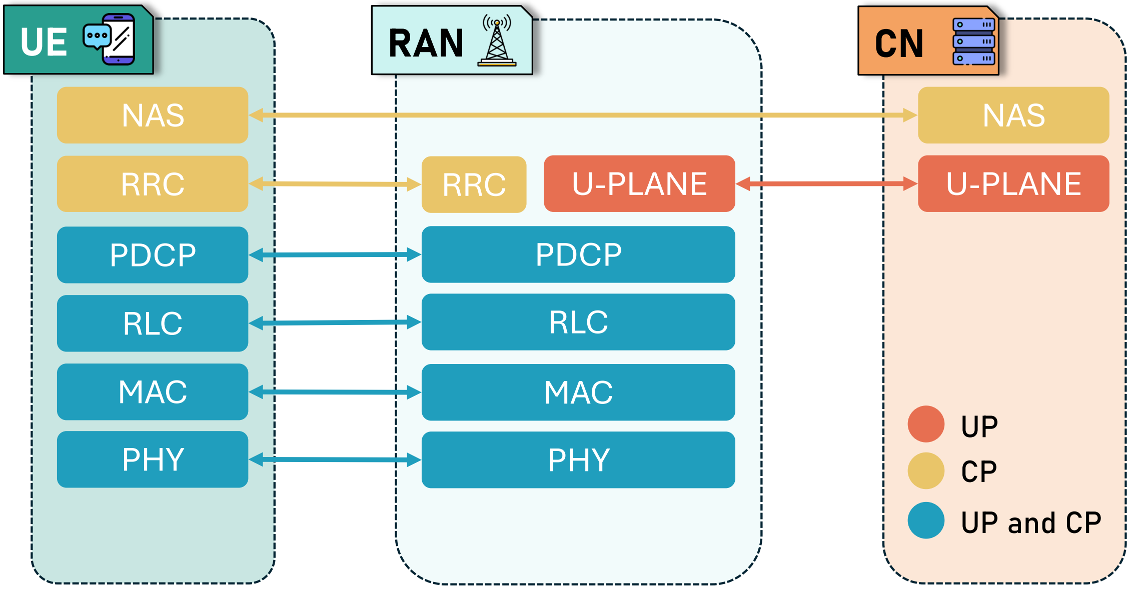


Figure 2.2: 3GPP protocol stack

- Non Access Stratum (NAS). It handles the signaling between UE and CN related to the session management, establishing and maintaining the communication session. It is also responsible for user authentication or mobility of UEs.

- Radio Resource Control (RRC). It assumes a significant role in managing the connection between the UE and the RAN with procedures such as paging, RRC connection management, handovers and some security functionalities.

- Packet Data Convergence Protocol (PDCP). It ensures the efficient transmission of data packets among RAN and UE, enabling orderly data delivery, encryption and decryption, and compression.

- Radio Link Control (RLC). This protocol performs a primarily function of assuring a reliable data transmission between UE and RAN, including error correction, segmentation and reassembly of data packets.

- Medium Access Control (MAC). It is responsible for the management of tasks related to the scheduling, multiplexing logical channels into/from transport blocks, and access control of radio resources, ensuring their efficient utilization.

Furthermore, it facilitates error connection using Hybrid Automatic Repeat reQuest (HARQ), thereby ensuring reliable communication

- Physical layer (PHY). It is the lowest layer of the protocol stack, responsible for transmission and reception of data over the radio interface. This protocol is of paramount importance for ensuring the efficient wireless communication, since it handles the link adaptation by Adaptive Modulation and Coding (AMC), radio resource mapping and antenna mapping.

Nevertheless, the protocol stack shown in Figure 2.2 and the network architecture illustrated in Figure 2.1 are both generic. Both are defined for each generation, so the nomenclature of the different protocols and RAN and CN elements varies from generation to generation. In the following subsections, the latest generations of mobile networks (LTE and 5G) are described in more detail, focusing on both RAN and CN components.

2.1.1 LTE

Evolved Packet System (EPS), commonly known as LTE, is the Fourth Generation (4G) of mobile networks which appears for the first time in the 3GPP standards in Release 8 by 2008. It emerged as an evolution of Universal Mobile Telecommunications System (UMTS) with the aim of reducing the complexity of the mobile network and addressing the growing demand for mobile data services. This evolution encompassed both the radio and core components of the network. LTE program was involved in designing a new radio network and air interface architecture called Evolved Universal Terrestrial Radio Access Network (E-UTRAN) [59], which integrates some functionalities previously performed by Radio Network Controller (RNC) (e.g., mobility procedures) in Third Generation (3G) into the Evolved Node B (eNB) that perform traffic management and ensure Quality of Service (QoS) autonomously. Conversely, the System Architecture Evolution (SAE) program focused on a new core infrastructure known as Evolved Packet Core (EPC) [60], a fully packet-based network that reduces the complexity of 3G core networks. In consequence, LTE standards include innovative features and technologies, as summarized in Figure 2.3.

The advent of LTE has brought an improvement in throughput compared to previous generations, reaching up to 100 Mbps in the Downlink (DL). A pivotal

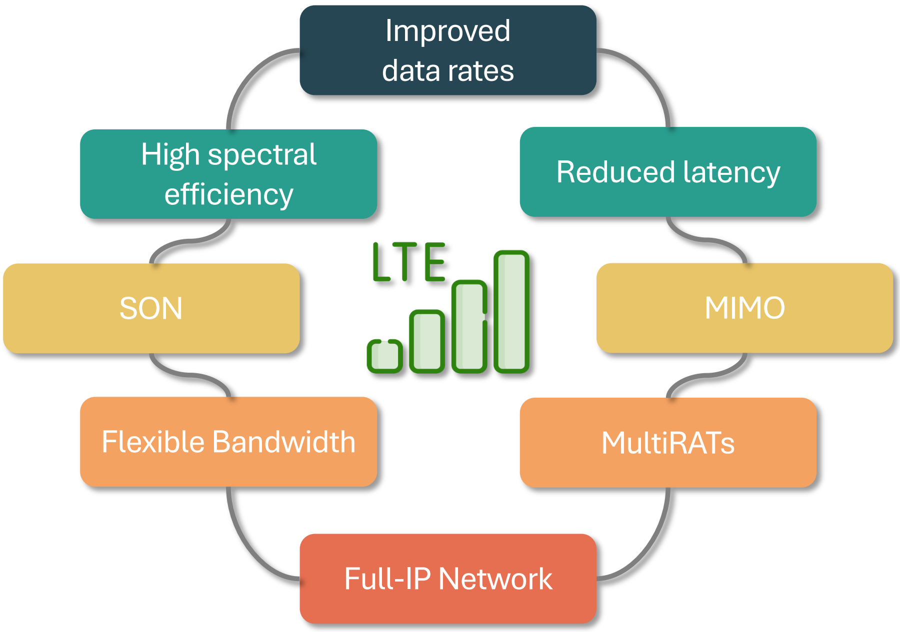


Figure 2.3: LTE features

factor in achieving these values is the deployment of flexible bandwidths, including from 1.4 to 20 MHz. In a similar way, the reduction of latency represents another relevant feature of this generation, enabling Round Trip Time (RTT) below 10 ms [61].

Moreover, the standards encompass the concept of Multiple Input Multiple Output (MIMO), which consists of transmitting multiple independent signals over the same frequency band. It is considered a key enabler to achieve better spectral efficiency. In addition, LTE is the first mobile generation to introduce Orthogonal Frequency Division Multiple Access (OFDMA) as a new transmission scheme, which is completely different from the Code Division Multiple Access (CDMA) approach of UMTS. Due to this innovation, the effects of multipath fading are reduced at the same time that spectral efficiency and data rates are enhanced. In addition, LTE was conceived as an evolution of the previous generations of mobile communications, so novel mechanisms for coexistence with other Radio Access Technology (RAT) are included in the standards. These technologies can be included in 3GPP as GSM or UMTS, but also non-3GPP networks such as WiMAX or WLAN. Finally, the standards also address the automation of tasks in LTE networks, including the SON approach.

LTE standards has undergone continuous evolution, encompassing novel advancements and enhancements in each subsequent release. In 2011, 3GPP introduced a new evolution known as LTE Advanced (LTE-A) in the standards (Release 10), which considered new bandwidths (50 and 100 MHz), improved data rates, and reduced latency. This evolution includes new MIMO schemes (up to 8 antennas in receivers and transmitters) and Carrier Aggregation (CA), which allows to reach data rates up to 1 Gbps. In subsequent releases, particularly Release 13, LTE-A Pro was introduced by incorporating features such as Wi-Fi interoperability, Machine-Type Communications (MTC), and Device-to-Device (D2D).

LTE architecture

The LTE network is composed of two primary components: the E-UTRAN, which operates as RAN, and the EPC, which acts as the core network. The E-UTRAN is comprised exclusively of the eNB, while the EPC incorporates many network elements, as illustrated in Figure 2.4.

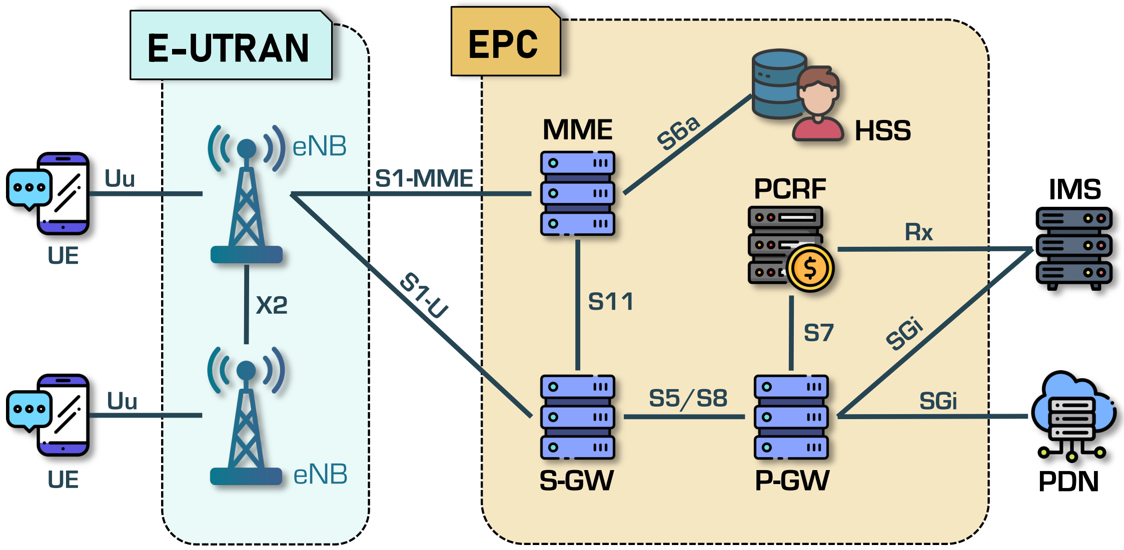


Figure 2.4: LTE architecture

EPC consists of five Network Function (NF), which are responsible for the following functionalities:

- Home Subscriber Server (HSS). It is defined as the database that contains information related with the users. In particular, its main functions are:
  - Management of user profiles and policies.
  - Support in the authentication and authorization of the users.

  - Mobility management support.
  - Serving MME location tracking.

- Mobility Management Entity (MME). It manages the control plane communication between the UE and the EPC, which responsibilities are:
  - Session (i.e., EPS bearers) management procedures including establishment, maintanence and release of the connection.
  - Mobiliy management procedures (Idle state and paging).
  - Authentication and security procedures, interacting with HSS.
- Serving Gateway (S-GW). It is responsible for the connection of the user plane between the EPC and the E-UTRAN. It performs functions such as:
  - Anchor for mobility between LTE and other 3GPP technologies.
  - Packet forwarding, routing and buffering of downlink data for UEs (idle state).
- Packet Data Network Gateway (P-GW). It performs as user plane gateway for traffic between EPS and external Internet Protocol (IP) networks, such as the Internet. The following functionalities are associated with this network function:
  - UE's IP address allocation.
  - Anchor for mobility between 3GPP and non-3GPP access networks.
  - Policy enforcement and charging support.
- Policy and Charging Rules Function (PCRF). It involves the policy and charging control of the users. Its functions are:
  - Handle services in terms of QoS.
  - Provide QoS and pricing rules to the P-GW.

Figure 2.4 illustrates the IP Multimedia Subsystem (IMS) [62], an optional element that provides the control mechanisms needed to provide multimedia services over IP-based networks (e.g. video calls, IP voice calls and others).

A single element, called eNB, comprises the E-UTRAN, which manages the connection of the UEs to the EPC. This element consists of two modules: Remote

Radio Unit (RRU) and Baseband Unit (BBU). The RRU is responsible for transmitting and receiving the radio frequency signals. Meanwhile, the BBU is responsible for processing the signals in the baseband and handling the traffic in the radio part. In summary, the main functions of the eNBs are as follows:

- Radio Resource Management (RRM), including the allocation of resources and the management of the radio interface.
- Scheduling and transmission of broadcast and paging messages.
- Mesaurement configuration for mobility and scheduling functions.
- Session management.
- Control and user plane data transmission from and towards the UE by wireless interface.
- IP header compression and encryption.

2.1.2 5G

The Fifth Generation (5G) of mobile networks, also known as 5G System (5GS), is conceptualized as an evolution of 4G in response to the increasing volume of data generated over wireless connections. Additionally, the proliferation of devices connected to the network, characterized by their increased diversity, is interacting with the network in a manner that is distinctly different from that of humans. Consequently, 5G represents a substantial advancement by introducing a novel architecture that facilitates the emergence of new use cases that address the latency, bandwidth, device density, and other requirements defined by International Telecommunication Union (ITU) in IMT-2020 and beyond [15] for next-generation networks.

The initial definition of 5G technology was established in Release 15 of the 3GPP standards [63], encompassing the novel radio aspects of the RAN and the innovative network core architecture that adopts the Service-Based Architecture (SBA) as a fundamental concept. With these innovations, it aims to address emerging use cases [64, 65], also defined by 3GPP [16], such as enhanced Mobile BroadBand (eMBB), which follows the historic trend of providing ever-greater bandwidth to users, Ultra

Reliable Low Latency Communications (URLLC) requires resilience along with sub-millisecond service latency, and massive Machine-Type Communications (mMTC) demands low overheads to enable large battery life.

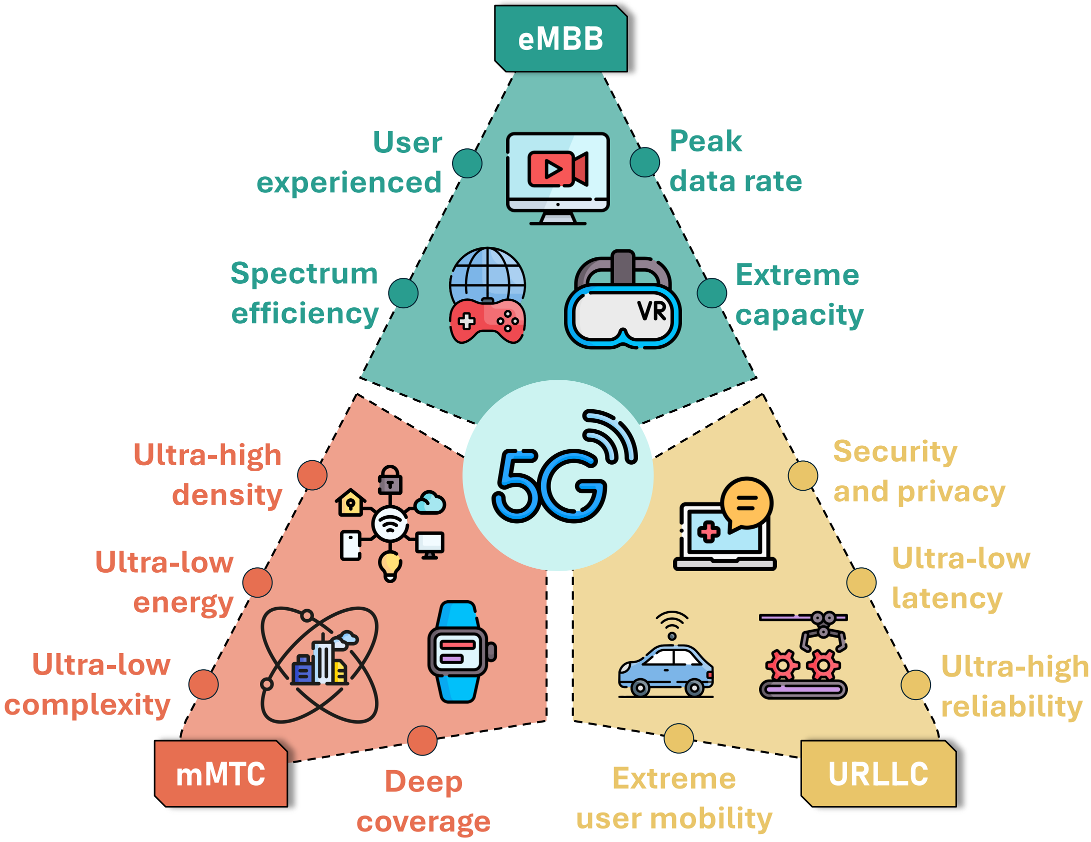


Figure 2.5: 5G features

In order to provide these emerging use cases, 5G technology extends the frequency spectrum used, exploiting both sub-6 GHz and mmWave frequencies bands to achieve speeds and capabilities that were not previously feasible. Furthermore, the combination of these frequencies with technologies such as MIMO and beamforming leads to improved spectral efficiency, ensuring reliable connections even in densely populated scenarios. Another enabling concept introduced in this generation is network slicing, which is the ability to divide the network into logical partitions over the same physical infrastructure. Each partition can be configured with the necessary capabilities and requirements of the individual services to be provided, resulting in a flexible network that can accommodate multiple use cases.

Nevertheless, network slicing capabilities are not the only flexibility introduced by the 5G standard. The virtualization of functions in the CN, known as Virtual

Network Function (VNF), in conjunction with other capabilities, such as the independence of the RAN and the CN, or the separation of the control and user plane in the RAN, enables operators to provide a fully versatile network that adapts to emerging use cases.

5G architecture

5GS comprises the Next Generation Radio Access Network (NG-RAN) [66], which is the new wireless network architecture, and 5G Core Network (5GC) [67], which is based on an SBA architecture, as previously indicated. Since the inception of its standardization, the focus of 5G has been on its compatibility with existing legacy technologies. Consequently, 3GPP has delineated two variants of network architecture: Non-Standalone (NSA) and SA, as illustrated in Figure 2.6. The first enables the NG-RAN to seamlessly interoperate with existing LTE deployments, both E-UTRAN and EPC. In this scenario, the NG-RAN is utilized exclusively for the user plane, whereas the control plane is always transmitted over LTE. Conversely, the SA mode employs an entirely new architecture, leveraging a 5GC and replacing the E-UTRAN network with the emerging NG-RAN.

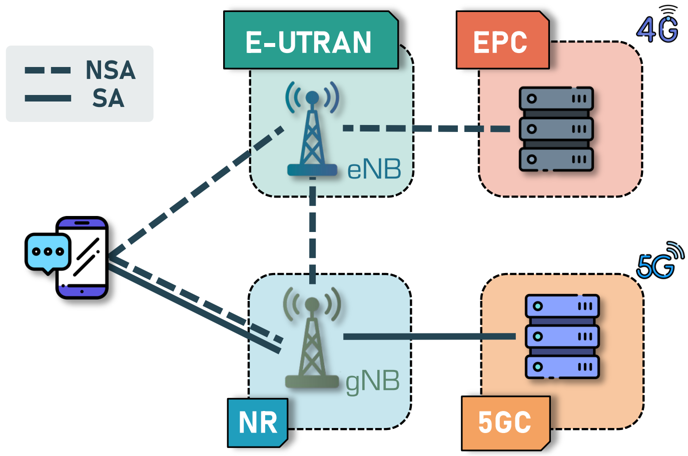


Figure 2.6: 5G Standalone and Non-Standalone modes

5GS conceptualizes an architecture that considers NF as services, enabling flexible and modular deployments. In this regard, the various NF that comprise the 5GC are mapped to some EPC functions. As illustrated in Figure 2.7, the complete set of NF that constitute the 5GC is presented. The functionality of each NF is delineated below:

- User Plane Function (UPF). It replaces S-GW and P-GW in user plane of the

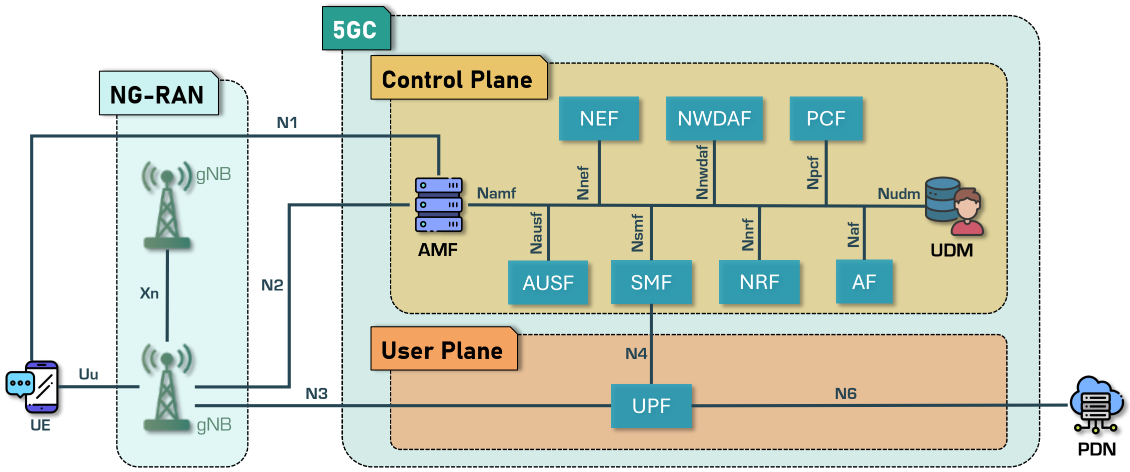


Figure 2.7: 5G architecture

EPC, serving as the user plane gateway for the 5GC. It is responsible for the following functions:

- Packet routing and forwarding.
- Traffic management, including shaping and prioritization.
- QoS enforcement.
- Anchor for intra-RAT and inter-RAT mobility.

- Access and Mobility Management Function (AMF). It is responsible for part of the functionality of the MME in 4G, managing the control plane communication between the UE and the 5GC in terms of access and mobility. Its main functions are:
  - Authentication, authorization and registration of the UE management.
  - Mobility management.
  - NAS signaling and ciphering.
- Session Management Function (SMF). It performs the other part of the MME functionality, managing the session management between the UE and the 5GC. Its main functions are:
  - Session management, including establishment, maintenance and release of the data sessions.
  - UE IP address allocation.
  - Support UPF for data and traffic management.

- Unified Data Management (UDM). It develops similar functionalities to the HSS in 4G, managing the user data and profiles. Its main functions are:
  - Handle users profiles.
  - Manage users authentication credentials.
- Authentication Server Function (AUSF). It is responsible for the authentication of the UE in the 5GC. Its main functions are:
  - Authentication of the users/devices.
  - Use UDM to validate user credentials and access.
- Policy Control Function (PCF). It replaces the PCRF in the EPC, managing the policy and charging control of the UEs. Its main functions are:
  - Provide policies concerning QoS, resource allocation and profiles.
  - Manage dynamic policies based on network analytics and conditions, and user profiles.
- Network Repository Function (NRF). It supports functionalities related to the network services:
  - Register the services that any NF provides to other NFs.
  - Provide information about the services available in the network.
- Network Exposure Function (NEF). It exposes the network services to external Application Service Provider (ASP):
  - Discovery networks capabilities.
  - Secure interaction between external applications and 3GPP network.
- Network Data Analytics Function (NWDAF). It exploits network data to provide insights for service-based network management.
  - Collect and analyze network data to the 5GC.
  - Analyze network and user performance to optimize resources and quality management.
  - Proactive assistence to identify anomalies and predict network failures.

- Application Function (AF). It communicates external services and applications with the network:
  - Communication with the 5GS for service-specific requirements.
  - Interacts with the PCF to enforce QoS.
  - Charging and billing support.

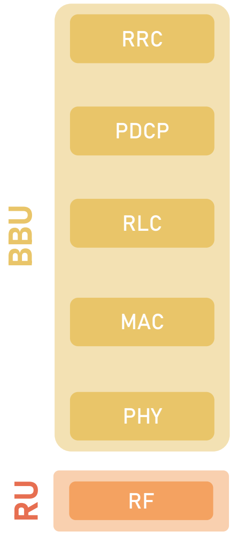
NG-RAN, such as the E-UTRAN in LTE, comprises just the nodes that provide wireless connectivity over the air interface. Such nodes are known as Next Generation Node B (gNB) and assume the following tasks:

- Mobility management.
- QoS management.
- User and control planes data routing and forwarding.
- IP header compression and data encryption.
- Tasks related to RRM, such as radio resource allocation and scheduling.
- Selection of AMF at UE attachment.

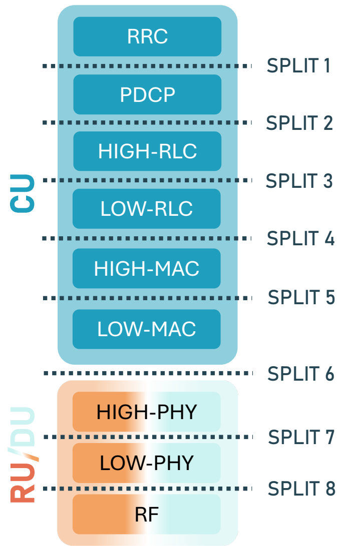
It is worth noting that 5GC has been designed considering the flexibility of the network, the NG-RAN has also applied this design mindset. In this regard, BBU is divided into two units: Distributed Unit (DU) and Centralized Unit (CU), which can be distributed throughout the network. 3GPP has introduced the concept of functional splits [68], which delineate eight distinct distributions of functionalities among different RAN units (i.e., Radio Unit (RU), CU, and DU) [69]. Figure 2.8 illustrates the most prevalent split points within the RAN. Figure 2.8(a) illustrates the legacy distribution of the previous generations of mobile networks. Figure 2.8(b) depicts the functional split 6, also named Low Layer Split (LLS), that has been standardized by 3GPP [70]. It places the separation of RU/DU and CU between the MAC and PHY layers.

5G New Radio

Similar to 5GC, the evolution of the RAT of this generation represents a significant advancement compared to the RATs adopted from previous generations. 3GPP



(a) Legacy division



(b) LLS

Figure 2.8: Functional splits of 5GS

introduces a new technology known as New Radio (NR) [71], which includes improvements in throughput, capacity, latency, or retainability, among other aspects of the network. Consequently, NR is positioned to be one of the key enablers for emerging use cases. Its capabilities involve the use of new frequency bands, numerologies, modulation schemes, massive MIMO or beamforming.

In this regard, NR introduces a new radio spectrum, defining new Frequency Ranges (FRs): FR1 and FR2, as illustrated in Figure 2.9. The first encompasses low and mid-band frequencies, spanning the spectrum from 450 MHz to 6 GHz, with bandwidths up to 100 MHz. The low band is well-suited for mMTC applications due to its capacity to provide a wider coverage area and a not so high throughput. Conversely, the mid-band is regarded as the optimal choice for 5G deployment, owing to its capacity and coverage features that meet the stringent requirements of eMBB and URLLC use cases. Conversely, FR2 contemplates the use of frequencies from 24.25 GHz to 52.6 GHz, also known as mmWave, which provides bandwidths up to 400 MHz. Despite their potential for enhancement in terms of throughput, latency, or capacity, these frequencies are challenged by the difficulties of radio wave propagation. This constrains their use to scenarios with direct line of sight, short distances and high data rates.

The advent of a novel waveform based on Orthogonal Frequency Division Multiplexing (OFDM) represents another feature of NR technology. OFDM

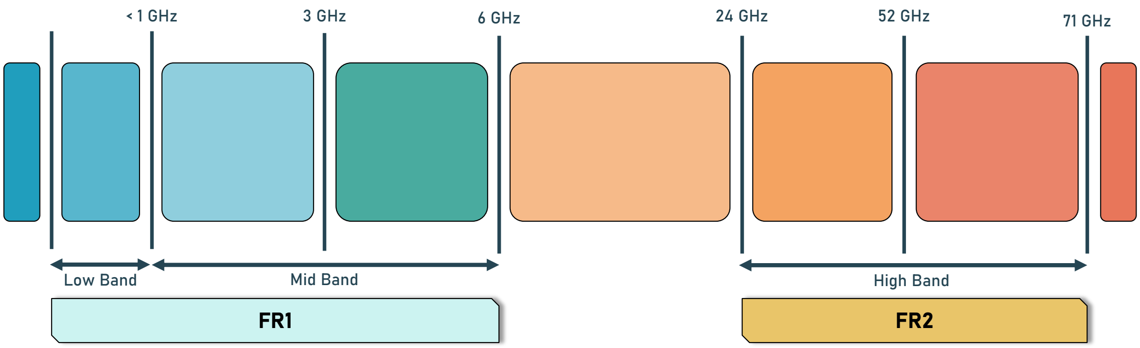
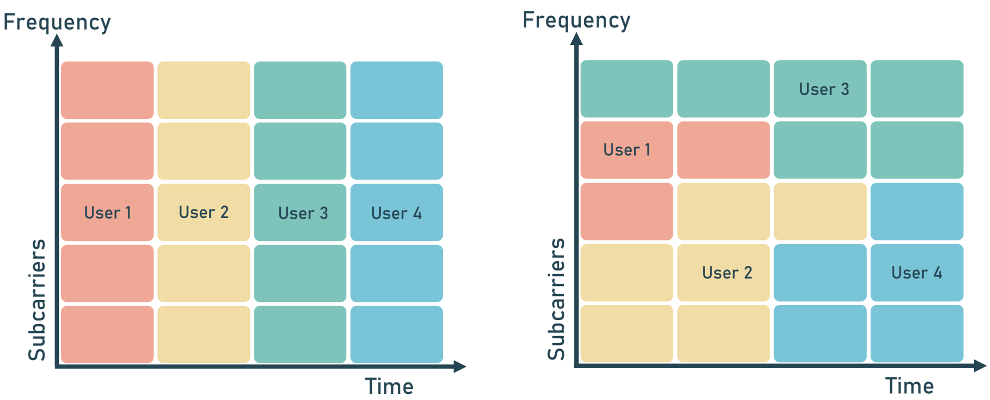


Figure 2.9: 5G frequency bands

waveforms facilitate the sharing of the same spectrum among a number of users by dividing the available frequencies into several orthogonal subcarriers. This orthogonality is pivotal in avoiding problems during demodulation. Additionally, OFDM incorporates guard intervals, or CP, which consists of replicating the end of the previous OFDM symbol at the beginning of an OFDM symbol. In addressing the high demand for devices 5G NR uses OFDMA, which enables multiple users sharing the same bandwidth at the same time. Furthermore, OFDMA facilitates resource allocation in both the time and frequency domains, a capability that OFDM lacks, as illustrated in Figure 2.10. Consequently, OFDM has emerged as a pivotal advancement in enhancing spectral efficiency in 5G networks.



(a) OFDM (b) OFDMA

Figure 2.10: Resource allocation for multiple users

In the context of transmission, the physical resources are distributed into symbols in the time domain and subcarriers in the frequency domain. In the time domain, NR adopts a scheme analogous to LTE, with 10 ms frames divided into 1 ms subframes. A significant innovation introduced by NR is the flexible numerologies that provide the ability to adapt to different requirements. Table 2.1 provides a comprehensive overview of the various numerologies incorporated within the 3GPP standard for NR. Each configuration is distinguished by the μ parameter, which determines the number of slots constituting a 5G NR subframe. These slots are formed by 14 OFDM symbols (12 in the case of a extended CP is used). Consequently, the number of symbols in each subframe is contingent on the specific numerology employed.

Table 2.1: Numerologies of 5G [13]

Numerology (μ)	**Slots per subframe**	**Subcarrier spacing (kHz)**	**Cyclic prefix**
0	1	15	Normal
1	2	30	Normal
2	4	60	Normal/Extended
3	8	120	Normal
4	16	240	Normal
5	32	480	Normal
6	64	960	Normal

Massive MIMO and Beamforming

The pinnacle of communication systems is the ability to ensure that all users enjoy the full benefits of bandwidth. 5G represents a substantial advancement in this regard, overcoming the limitations of earlier generations. Massive MIMO and beamforming represent major cornerstones of this advancement, owing to their capacity to multiplex multiple communication streams with fine spatial granularity.

MIMO concept involves the deployment of multiple antennas at the transmitter and receiver to increase the capacity and reliability of communications. In this regard, communication is performed over the radio interface ”channel” where transmitted signals are subject to effects such as shadowing, noise or destructive interference. Consequently, the received signals may be a direct strong signal, a reflected signal, a scattered signal, or a combination of these. MIMO employs the concept of diversity, leveraging the varied characteristics of these signals to enhance the transmission quality. This enhancement is achieved through the implementation of diverse schemes for antennas at both the transmitter and receiver:

- Single Input Multiple Output (SIMO). It involves using multiple antennas at the receiver to achieve diversity gain by receiving multiple versions of the transmitted signal. This approach enhances the reliability of communication by leveraging the combination of multiple received signals to generate a more robust received signal. Furthermore, in the event that a signal version is degraded, another version might be adequate to recover the transmitted signal.

- Multiple Input Single Output (MISO). This approach involves transmitting the same signal from multiple antennas to the same user, using the same spectral resources. It is hypothesized that the channel affects the transmitted signals due to multi-path propagation or different combinations of non-line-of-sight. Similar to SIMO, this scheme provides more reliability and enables the combination of received signals to improve the signal quality, e.g., avoiding destructive interferences that affect one received signal.

- Multiple Input Multiple Output (MIMO). It considers the use of antennas at both the transmitter and receiver, sending different signals to the same user over the same spectral resources simultaneously. This approach requires at least the same number of antennas at the receiver as the number of unique transmissions (also known as layers or streams). Assuming again that the channel is sufficiently diverse, the signals can be separated by the receiver. The transmission of multiple independent signals to a single receiver is referred to as spatial multiplexing, also known as Single-User MIMO (SU-MIMO), which increases the data rates.

- Multi-User MIMO (MU-MIMO). It is the generalization of SU-MIMO to multiple users, transmitting signals between multiple transmitters and multiple receivers.

LTE standards include support for high-order MIMO (16 and 32 antennas in Releases 13 and 14, respectively), meanwhile 5G standards incorporate Massive MIMO. This enables the number of antennas to be increased to hundreds, thereby increasing the gain by orders of magnitude. The 5G innovations incorporated within Release 15 facilitate the integration of MIMO with beamforming, a development that is poised to transform wireless communication systems.

The utilization of multiple antennas to enhance the capacity and reliability of the channel, thereby facilitating the transmission of additional data between the transmitter and receiver, has been previously delineated. Beamforming, on the other hand, is a technique that utilizes multiple antennas to focus signals in specific directions (also called beam). This approach enhances the reuse capacity of the spectrum and facilitates the utilization of the same spectrum for users who are spatially separated from each other. Additionally, the signal quality is enhanced due to the ability to concentrate energy in a specific direction, enabling transmissions to be more robust to obstacles and channel effects (interference or noise are reduced). To this end, the phase and amplitude of the transmissions at each element are modified to generate a constructive interference artificially in the desired direction. Conversely, destructive interference is generated in undesired directions.

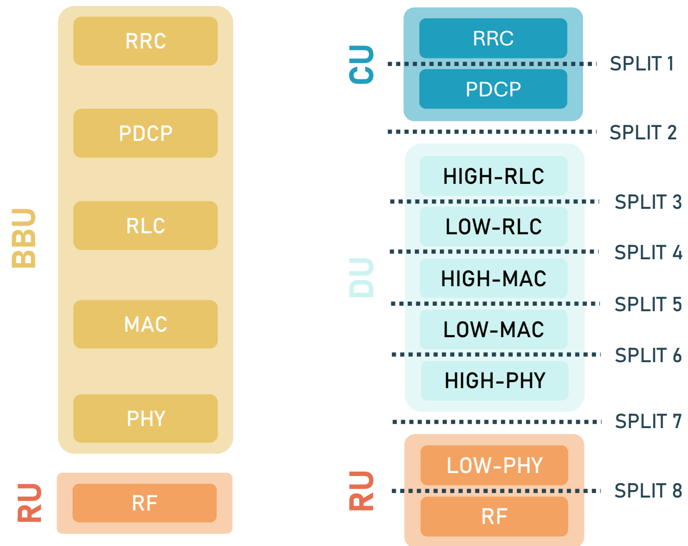
The number of beams that can be generated is constrained by the number of antenna elements available; the more antenna elements, the narrower the beams that can be generated. This is a pivotal aspect to understand how beamforming can be utilized at FR1 and FR2. At 1 GHz (FR1), the spacing between antenna elements is approximately 15 cm, whereas at 30 GHz (FR2), this separation is around 5 mm. This implies that antenna elements can be closer at FR2, therefore beamforming antennas at mmWave can be smaller and cheaper [72]. Consequently, the beams utilized at FR2 can be more constrained in width compared to those employed at FR1, thereby facilitating the implementation of beamforming as a suitable feature for coverage-limited scenarios, a benefit that is particularly advantageous given the higher propagation losses experienced at FR2.

Beamforming is characterized by two distinct operational modes: active and passive. In the active mode, the direction of the beams is reconfigured over time to track the users. Conversely, passive mode, also known as switched beamforming, involves maintaining the beams static without changing them over time. In this scenario, a user in motion moves between beams, resulting in the user being served by different beams over time.

5G NR standards exhibit great flexibility in how beams and spatial channel multiplexing can be configured. In this regard, the benefits of MIMO and beamforming are combined to place both technologies as enablers for emerging 5G use cases. MIMO contributes to the eMBB use case by enhancing spectral efficiency and capacity. Furthermore, MIMO provides support for URLLC, enabling the creation of more reliable channels against fading, shadowing, and interferences. In contrast, beamforming technology is more focused on providing eMBB services due to its ability to steer signals and its applicability at higher frequencies.

2.1.3 O-RAN

The advent of 5G has brought an evolution to traditional RANs, moving from a centralized element to a disaggregated architecture. The emergence of b5G/6G has precipitated the introduction of O-RAN, signifying a paradigm shift in the operational framework of the RAN. This transition entails a revolution from a centralized architecture, in which all elements are provided by a single vendor, to a disaggregated structure. The O-RAN architecture, as depicted in Figure 2.11 and defined by 3GPP [68], is predicated on the 7.2 split, which facilitates the provision of distinct network elements (DU, CU, and RU) from multiple vendors.



(a) Legacy division (b) O-RAN split

Figure 2.11: Functional splits O-RAN

The O-RAN Alliance [73] is an consortium of operators that oversees the definition of this novel paradigm and their use cases [74]. The requirements encompass the following:

- The definition of open and standardized interfaces that enable interoperability between components.
- The reduction of proprietary hardware and the maximization of generic hardware.
- The standardization of Application Programming Interface (API) to add intelligence to RAN.

In this regard, the O-RAN Alliance has defined a novel architecture that leverages the concept of disaggregation by introducing a Cloud-Native Network Function (CNF) [75] approach comprising Open Radio Unit (O-RU), Open Distributed Unit (O-DU) and Open Centralized Unit (O-CU). Furthermore, the innovative entities Service Management Orchestration (SMO) and RIC address the integration of intelligence in the system. Figure 2.12 illustrates the O-RAN architecture.

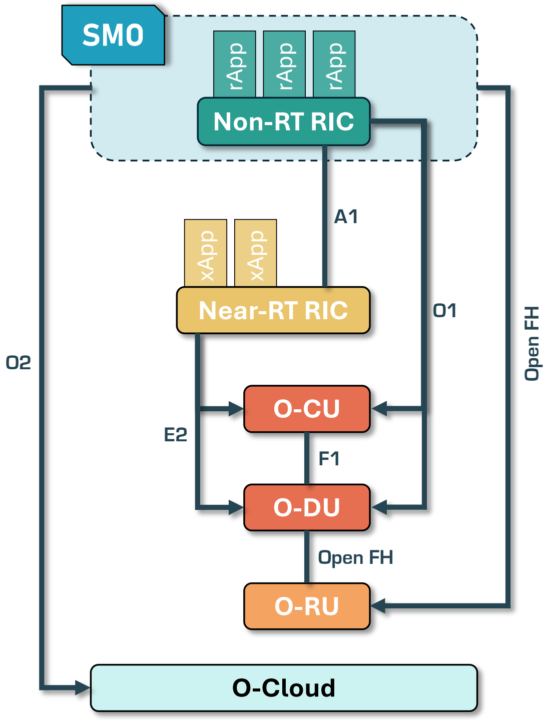


Figure 2.12: O-RAN architecture [12]

SMO is an entity that provides a centralized platform for managing and orchestrating the entire RAN. To this end, some interfaces establish the connection between the SMO and various RAN elements: O1 interface facilitates management, A1 interface enables policy-based control, and O2 interface provides communication with the O-Cloud [76]. This involves hardware and software components that provide cloud computing capabilities for the provisioning of RAN network functions. In this regard, SMO enables the efficient deployment of networks over generic hardware, achieving non-proprietary and open solutions.

Conversely, RIC is a software-defined entity that facilitates intelligence within the RAN. It is a critical enabler for the disaggregation strategy adopted by the O-RAN Alliance. The RIC is composed of two distinct components: Non-Real Time

(Non-RT) RIC and Near-Real Time (Near-RT) RIC elements. The former, the Non-RT RIC, performs management tasks that do not require a real-time response (i.e., more than 1 second). It is allocated in the SMO and primarily communicates with other entities via interfaces A1 and O1. The communication between the Non-RT RIC and the radio resource controller is facilitated via the A1 interface. In turn, the O1 interfaces between the Non-RT RIC and the Service Management Element (SME). The incorporation of intelligence is achieved through the utilization of RAN Application (rApp), which are modular, case-specific solutions for decision making, automation, or optimization. The O-RAN specifications delineate APIs that facilitate interaction between the RIC and these applications.

The Near-RT RIC, in contrast, is responsible for handling actions that take between 10 ms and 1 s to be completed. Consequently, this entity is expected to be situated at the edge of a telecommunications network. Its interaction with the rest of the components occurs through the E2 interface, mainly connecting with the O-CU and O-DU. The eXtended Application (xApp) are the solutions deployed in the Near-RT RIC to provide functionalities that perform real-time resource optimization (i.e., load balancing or traffic steering) and other RAN-related tasks that must be tailored to meet time constraints (10 ms to 1 second). As a result, Open RAN promises to revolutionize the design, deployment and operation of the next generation of cellular networks, providing the foundation for an open and flexible RAN approach [77].

2.2 Self-Organizing Networks

The continuous growth in traffic demands has led to a continuous evolution of mobile networks. To address these demands, new technologies and functionalities are implemented, resulting in networks becoming more heterogeneous and difficult to manage. Consequently, MNOs are compelled to direct their efforts toward reducing CAPEX and OPEX, a pursuit that entails the automation of management tasks. In this regard, the concept of Self-Organising Networks (SON) has emerged as a solution to reduce deployment time and cost, while improving user experience and network performance.

SON approach was initially introduced by the NGMN Alliance [19, 20] and subsequently standardized by 3GPP [21], which classified it into three categories: self-configuration, self-optimization, and self-healing as depicted 2.13. The purpose of each group is as follows:

- Self-configuration. It involves the automated configuration of network elements and their parameters. This process encompasses the automatic detection of new elements, the establishment of connections, and the configuration of these new nodes. The primary objective of this process is twofold: first, to reduce the time and cost associated with deployment, and second, to minimize human error. Some functionalities that belong to this category are automatic neighbor finding [78, 79, 80], automatic cell planning [81, 82, 83], and automatic parameter configuration [84, 85, 86].

- Self-optimization. It encompasses the automatic adjustment of network parameters to enhance performance during operation. This process involves the optimization of QoS, the minimization of interference, the improvement of coverage, and the optimization of handovers. To this end, auto-tuning tasks are performed based on measurements reported by users and network nodes. Among tasks covered by this area are load balancing [87, 88, 89], mobility robustness optimization [90, 91, 92], and coverage and capacity optimization [93, 94, 95].

- Self-healing. It entails the automation of detection and repairing of network failures. It includes the identification of failures, the determination of the cause of the failure, and the application of compensatory actions to recover from the failure. The main objective of this approach is to minimize service disruptions and enhance the reliability of the network. This category comprises various functionalities including fault detection [96, 97, 98], failure compensation [99, 96, 100], and root cause analysis and diagnosis [101, 102, 103].

The development of SON techniques is fundamentally based on the measurements and information that can be gathered from the network. These measurements facilitate the assessment of the state of the network, thereby enabling the formulation of suitable actions. In this regard, measurements are categorized according to their source:

- Configuration management parameters (CM). It contains the current configuration of each network element.

- Performance management parameters (PM). It counts the number of times that a certain event occurs during a defined interval. It also kwon as counters.

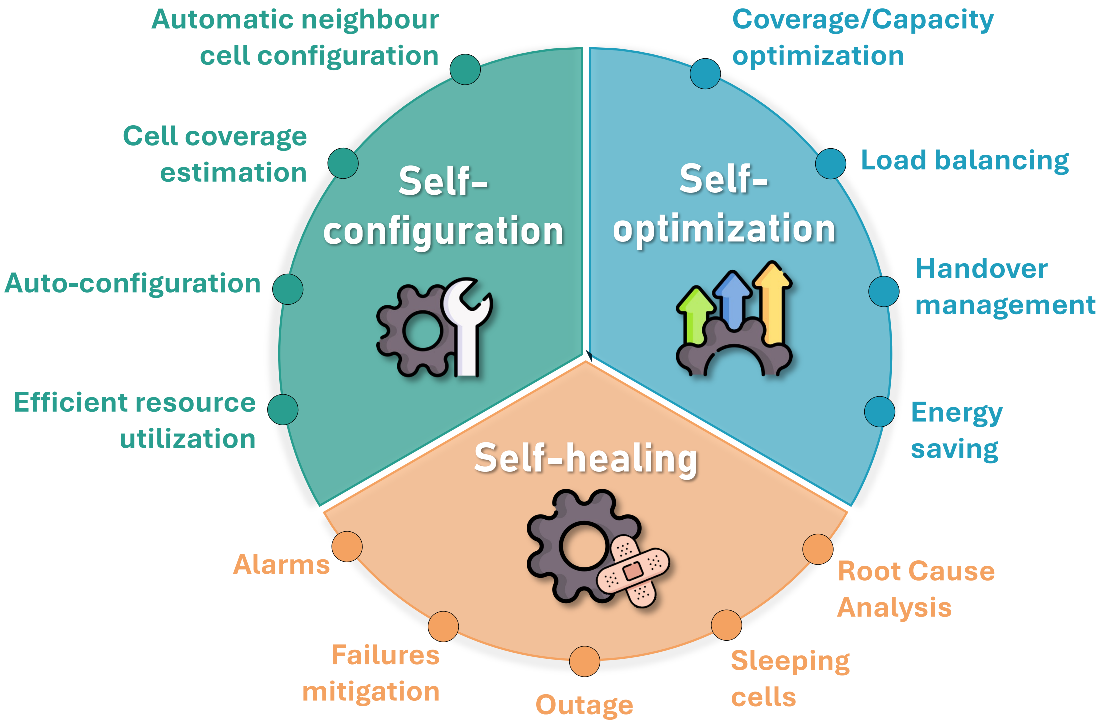


Figure 2.13: SON use case examples

- Alarm. It is message triggered when an element detects a malfunction.
- Key Performance Indicator (KPI). It represents meaningful performance measure, calculated as a combination of other measurements (e.g., counters).
- Drive tests. It involves the execution of field measurements with the utilization of specialized equipment. Given the elevated costs and time-consuming nature of the process, 3GPP defined Minimization of Drive Tests (MDT) to address these challenges by performing measurements directly in the UEs and taking into account the localization of it [104].
- Mobile traces. It refers to detailed measurements related to messages transmitted between a specific UE and the network. This facilitates comprehensive analysis of the communication; however, its utilization is typically limited due to its substantial resource consumption and storage requirements.

The SON concept has undergone a parallel evolution with the progression of mobile networks, with an evolution of it emerging for 5G, known as NG-SON [105]. This evolution entails the integration of AI and ML as the primary mechanisms for automating network operations. A similar development is observed in the O-RAN architecture [12], which introduces a novel element, known as the RIC, designed to bring intelligence to the radio part of a mobile network.

2.3 AI/ML-based approaches

The advent of AI and ML has precipitated a paradigm shift in the management of networks [106, 107]. Incorporating these technologies into SON has enabled the automation of network functions, leading to more efficient and reliable mobile networks.

ML is a branch of AI that focuses on developing algorithms that identify patterns and make predictions based on data. In contradistinction to conventional rule-based systems, machine learning models enhance their performance through experience, adjusting their parameters as more information is processed. In this regard, ML is subdivided into three categories as illustrated in Figure 2.14:

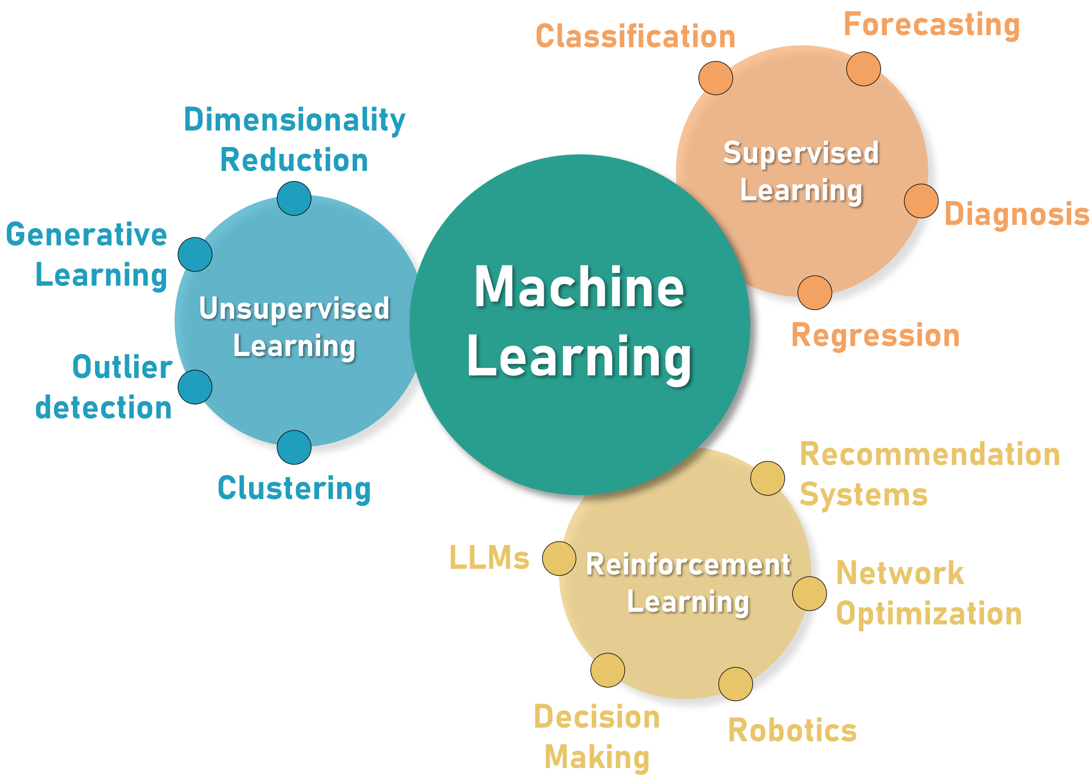


Figure 2.14: ML use case examples

- Supervised learning. It involves the process of training an algorithm on labeled data, enabling the model to learn the relationship between input and output data. Trained models estimate the correct output label for new input values with minimal error. With respect to the nature of the outputs, two primary applications are postulated:

  - Regression. It considers outputs that are continuous values, such as the estimation of a numeric value based on input data.
  - Classification. It involves outputs that are discrete values, such as the categorization of input data into predefined classes.

- Unsupervised learning. It entails the training of a model with unlabeled data, thereby supporting algorithms that explore and identify patterns and relationships within the data. This approach facilitates the acquisition of valuable information and the discovery of intrinsic relations between input variables with no prior knowledge. The primary applications of unsupervised learning are:

  - Clustering. It consists of categorizing data into distinct clusters based on their similarities.
  - Dimensional reduction. It refers to the process of reducing the number of input variables by selecting the most relevant features.

- Reinforcement learning. It involves training a model to make decisions based on the environment. Based on its actions, the model learns by trial and error and receives rewards or penalties. In this regard, it learns to maximize rewards by choosing the most appropriate actions. While the training of these models is time-consuming, their applications are highly effective when sequential and adaptive decision-making is required.

2.4 Conclusions of the chapter

This chapter has introduced the fundamental elements of cellular networks. In particular, the architectures and features of LTE, 5G, and O-RAN have been described. Within these capabilities, the advances in wireless communications such as NR and beamforming have been reviewed. Finally, an in-depth study has been conducted on the role of SON and ML in enhancing network intelligence to ensure more efficient and reliable networks.

Part II

Publications

Chapter 3

Research outline

Content

This chapter consists of two sections. The first one presents the research methodology followed during the course of this thesis. The second one provides an integral view of the thesis, detailing the relationship between the challenges faced, the objectives pursued and the results achieved.

3.1 Research Methodology

The research conducted for the development of this thesis was based on a structured methodology consisting of several steps. Figure 3.1 illustrates the different phases of the approach, which are described below:

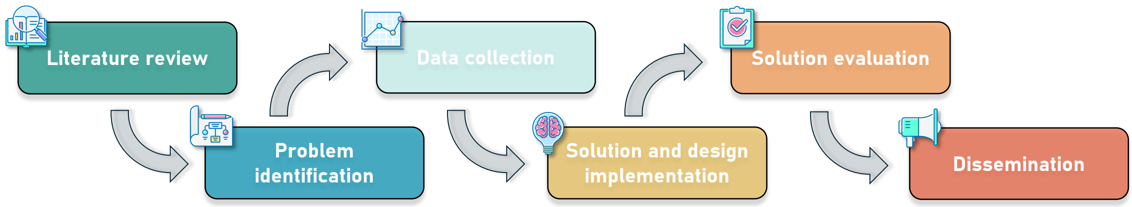


Figure 3.1: Research methodology followed in this thesis.

1. **Literature review:** The initial phase of the methodology is a comprehensive study of mobile networks, specifically the technologies used in this thesis (LTE, 5G and O-RAN), examining their characteristics and use cases. Additionally, a state-of-the-art review is carried out with a special focus on fault management in new generation mobile networks. In this manner, the main challenges to be addressed in this thesis are identified.

2. **Problem identification:** Based on the literature review, the principal challenges in fault management for next-generation networks were identified. These challenges are the basis for the research objectives of this thesis, which are defined in detail in this phase. Concurrently, strategies to address these objectives are formulated.

3. **Data collection:** The third stage of this methodology consists of collecting and pre-processing data that will be used to validate and evaluate the proposed solutions. During the development of this thesis, data from both real mobile networks and simulated scenarios have been employed.

    - **Simulated data:** used in cases where real data is not available or where the scenario needs to be controlled to validate and evaluate the proposed solution. A 5G system-level simulator implemented in MATLAB, an evolution of [56], is used. In particular, a scenario involving beamforming functionalities and the use of millimeter frequencies has been designed and implemented, described in detail in Appendix B.

- **Real data:** During the development of this thesis, commercial network data has been used. In particular, data from LTE-A networks provided by the company Tupl has been used within the NEREA project, while LTE/LTE-A data from Danish operators has been used for another objective of this thesis. Both datasets consist of counters, KPIs and context information from the different cells comprising the networks.

Some Python libraries like Pandas [108] or Scikit-Learn [109] were used to pre-process the data.

4. **Solution design and implementation:** During this phase, an exhaustive analysis of the possible solutions to the challenges previously identified is performed. A meticulous examination of diverse techniques and algorithms is undertaken, considering the potential difficulties, limitations, risks and capabilities of each alternative, in order to determine the most appropriate and suitable option. This comprehensive analysis resulted in the design and implementation of solutions capable of achieving important and impactful results.

5. **Solution evaluation:** This step is crucial in the methodology adopted as it involves a thorough evaluation of the solutions designed and implemented. It allows to assess the functionality and effectiveness of the solutions in addressing the aforementioned identified problems. The evaluation is carried out by performing a series of tests to validate the performance of the implemented solution. This meticulous procedure ensures that the proposed solution is in accordance with the defined objectives.

6. **Dissemination:** The final step involves the dissemination of the main results and contributions of the research carried out. This dissemination encompasses the presentation of the principal results obtained in technical reports, projects, national and international conferences, and publications in scientific journals.

3.2 Description of publications

In this section, the various publications that support this thesis are presented, addressing the different challenges and objectives identified in Section 1.3. Figure 3.2 illustrates the relationship between challenges, objectives, and outcomes obtained, represented by the various papers published in international conferences or journals included in the Journal Citation Reports (JCR).

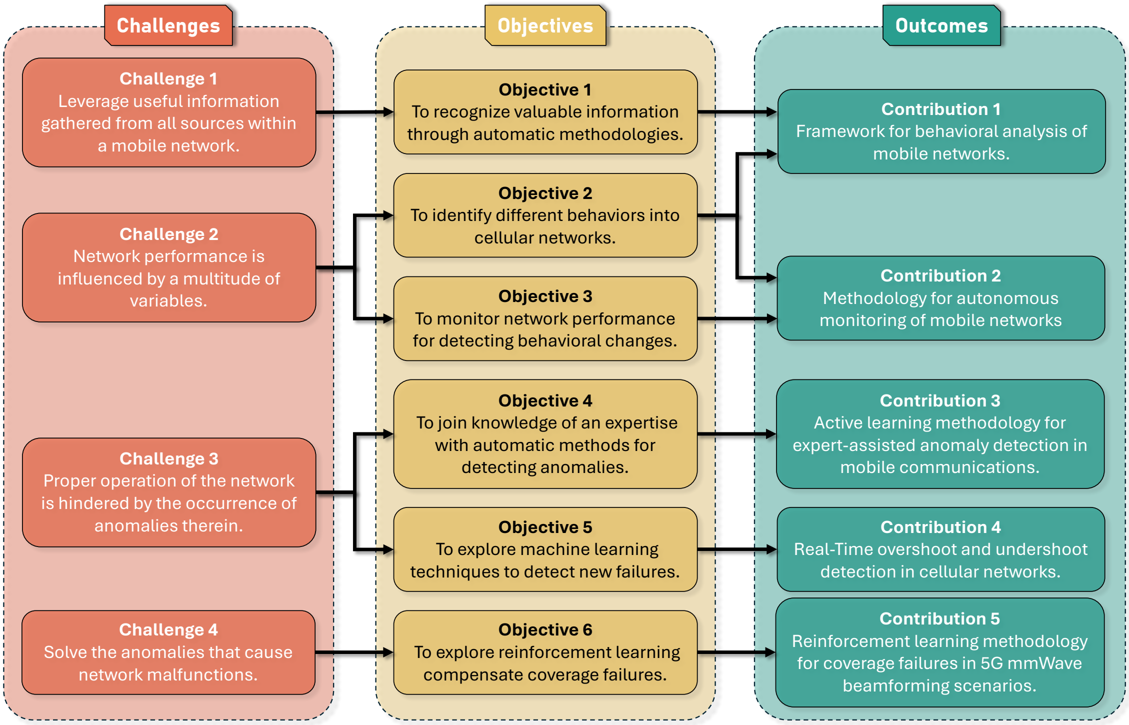


Figure 3.2: Challenges, objectives and outcomes.

The subsequent subsections summarize the individual papers that supported this thesis.

3.2.1 Framework for behavioral analysis of mobile networks

This paper introduces Chapter 4, which is dedicated to developments related to network performance analysis (Objectives 1, 2, and 3). In particular, this work proposes a novel framework for behavioral analysis and monitoring of a cellular network. The proposed framework integrates unsupervised and supervised ML algorithms in a same architecture. The proposed system is capable of analyzing the behavior of cells and monitoring them, finding behavioral changes over time. The information obtained by the framework helps to improve the subsequent management and optimization task.

As delineated in Objective 1, the framework provides the ability to analyze large amounts of data from commercial networks, focusing on different aspects of the network (traffic, radio conditions, quality). A variety of mathematical and automatic techniques are used to preprocess the database and extract valuable information. The unlabeled nature of this database poses a significant challenge in the characterization of the diverse behavior patterns inherent in mobile networks. To address this challenge, the unsupervised learning algorithm Self-Organizing Map (SOM) [110] identifies different behaviors and assigns labels to cells with similar patterns.

Once identified behavior patterns are discovered and covered the Objective 2, it is feasible to train supervised learning algorithms such as Random Forest (RF) [111]. This approach establishes the basis for an autonomous methodology to monitor network performance in real time and to detect behavioral changes in the network, according to Objective 3 that is completed in the work introduced in Subsection 3.2.2.

Finally, the effectiveness of the proposed methodology has been evaluated using a commercial LTE network database with promising results. Furthermore, the framework developed may provide valuable information that is relevant to other self-healing or self-optimization tasks.

3.2.2 Methodology for autonomous monitoring of mobile networks

According to the previous section, the second work of Chapter 4 also deals with Objective 3. Particularly, it proposes an approach to detect and analyze deviations of the recent performance of a mobile network.

The proposed framework aims to characterize the recent behaviors and performance of a cellular network using historical data from their KPIs. This component constitutes an offline phase, wherein recent behaviors of each KPI are identified and some threshold is established to determine if there is a deviation from these behaviors. Subsequently, an online phase is initiated, during which current data is evaluated in real time and its impact on the overall performance is analyzed.

The methodology is further enhanced by the incorporation of a configuration change analysis, encompassing the hours after the modification. This approach enables the extraction of valuable information about the deviations detected in the

KPIs and the performance of the network, facilitating the decision to perform self-optimization or self-healing tasks. Conversely, trend variations are analyzed to update the recent behavior of KPIs if these variations are considered as new behavior of the network.

Finally, the efficacy of the methodology is demonstrated by testing it on a commercial LTE database. Furthermore, this work fulfills Objective 3, which aims to establish a monitoring methodology that detects behavior changes and provide valuable information to MNOs efficiently apply management automatic optimization and self-healing task in their commercial networks.

3.2.3 Active learning methodology for expert-assisted anomaly detection in mobile communications

Chapter 5 started with this work, which contains all those challenges related to anomaly detection in next-generation cellular network technologies (Objectives 4 and 5).

The principal objective of this work is to reduce the time required by an engineer specialized in cellular networks to analyze a possible anomaly in the network. To this end, this work proposes the use of active learning by incorporating the feedback of an expert in the anomaly detection algorithms. In particular, the proposed methodology uses the knowledge of an expert engineer to optimize the hyperparameters of an anomaly detection algorithm based on the results of the anomaly detection algorithm. This collaborative approach, in line with Objective 4, enables an expert engineer to decide whether the anomaly detected by the algorithm is in fact an anomaly, or whether it may not be an anomaly, or doubts whether it is an anomaly. The algorithm will be optimized accordingly, so that its ability to detect anomalies will eventually converge with that of an expert engineer.

To evaluate the proposed methodology, a commercial LTE network dataset has been employed, firstly applying the anomaly detection algorithm alone. Subsequently, the same dataset has been introduced but applying the methodology proposed in this article, which includes feedback from an expert engineer on the potential anomalies detected by the algorithm. The findings demonstrate that the proposed methodology enhances the efficacy of the algorithm, thereby improving its performance.

MNOs often demonstrate reluctance in deploying automatic algorithms in their commercial networks because of the fear of causing problems to their users. To address this challenge, the proposed approach incorporates a human "interface" that facilitates the optimization of the automatic algorithm by integrating expert feedback and knowledge. This approach ensures that operators can have confidence in the effectiveness of the automatic algorithms as monitored by an expert network engineer.

3.2.4 Real-time overshoot and undershoot detection in mobile networks

The contribution delineated in this section serves to conclude Chapter 5. Considering the heterogeneity and density of networks in next-generation networks, the paper aims at detecting anomalies related to network coverage problems, in alignment with Objective 5.

The proposed methodology is built on ML algorithms for detecting network coverage problems, in particular overshoot and undershoot situations, which include possible effects such as coverage holes or interferences. The proposed framework involves the analysis of several KPIs obtained from counters that consider different aspects of the network. Furthermore, the integration of multiple algorithms is employed to leverage the strengths of each, thereby ensuring the optimal functioning of the methodology. Specifically, the following ML algorithms are employed for the purpose of detecting failures in real time: Logistic Regression (LR), Naive Bayes (NB), Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and RF.

In order to assess the efficacy of the proposed methodology, the algorithms have been trained using a database composed of commercial LTE and LTE-A networks. The results indicate that certain algorithms work better with overshoot cases and others with undershoot cases, confirming that the proposed methodology combines the ability to detect both situations simultaneously in the same framework.

In conclusion, the present study establishes the foundations for the development of automated methodologies to address these coverage challenges. The work also provides valuable information for operators in terms of network management and network planning.

3.2.5 Reinforcement learning methodology for coverage failures in 5G mmWave beamforming scenarios

This paper constitutes Chapter 6 of this thesis, which includes whatever is related to self-healing and its tasks. In particular, a methodology based on Reinforcement Learning (RL) is proposed to address coverage problems in next generation networks.

In accordance with Objective 6, the proposed methodology involves the analysis of novel ML techniques, including reinforcement learning, for the purpose of compensating for network failures. The methodology employs a gradient-based policy algorithm, namely Proximal Policy Optimization (PPO) [112], a RL algorithm that is widely utilized. The proposed methodology is further augmented by its application to scenarios involving novel technologies, including beamforming and millimeter frequencies. The methodology is designed to evaluate the KPIs in order to re-configure the beamwidths and azimuths of the unaffected beams to compensate for the drop of a pair of beams. This approach enables the expeditious and effective maintenance of service and coverage.

The methodology has been tested using the system-level network simulator developed by the research group. Within this simulator, a NR scenario has been configured, incorporating beamforming and millimeter frequencies. The scenario has been designed to simulate failures in specific beams. The outcomes demonstrate that the proposed methodology is capable of efficiently and expeditiously compensating for these failures.

The results conclude that the methodology is quite flexible and adaptable to different scenarios and networks, even adapting to diverse and emerging network architectures such as O-RAN. Notably, the proposed methodology facilitates the resolution of problems without the need for large, time-consuming, and costly deployments.

3.3 Conclusions of the chapter

In this chapter, a detailed overview of the research methodology employed throughout the thesis has been presented, from the establishment of the objectives to the dissemination of the results. In the following section, each of the contributions underpinning this thesis has been presented in relation to the research objectives, providing a cohesive structure for understanding their relevance and application to the line of research.

Chapter 4

Network analysis and valuable information extraction

Content

This section contains the work related to the objectives of the thesis enumerated as 1, 2, and 3. Concretely, it comprises two papers that focus on the analysis of behavioral patterns in mobile networks and the design of a methodology for autonomous monitoring of mobile networks.

4.1 Framework for Behavioral Analysis of Mobile Networks

[1] José A. Trujillo, I. de-la-Bandera, D. Palacios, R. Barco, "Framework for Behavioral Analysis of Mobile Networks", in *Sensors* 2021, 21, 3347. https://doi.org/10.3390/s21103347

Abstract: The arrival of the Fifth Generation (5G) entails a significant evolution in the context of mobile communication networks. This new technology will bring heterogeneous scenarios with new types of services and an increasingly high number of users and nodes. The efficient management of such complex networks has become an important challenge. To address this problem, automatic and efficient algorithms must be developed to facilitate operators' management and optimization of their networks. These algorithms must be able to cope with a very high number of heterogeneous data and different types of scenarios. In this paper, a novel framework for a cellular network behavioral analysis and monitoring is presented. This framework is based on a combination of unsupervised and supervised machine learning techniques. The proposed system can analyze the behavior of cells and monitor them, searching for behavior changes over time. The information extracted by the framework can be used to improve subsequent management and optimization functions. Despite the existence of studies in the literature, certain limitations are found, some works are only focused on specific aspects of the network such as a certain type of traffic. Other works are limited to the analysis of historical data but do not include a real-time stage for network monitoring. Finally, many of them are based on only one ML method, not taking advantage of the benefits of combining unsupervised and supervised algorithms.

4.2 Methodology for autonomous monitoring of mobile networks

[6] José A. Trujillo, I. de-la-Bandera, J. Burgueño, D. Palacios, and R. Barco, "Methodology for autonomous monitoring of mobile networks", in *IEEE Workshop on Complexity in Engineering (COMPENG)*, Florence, Italy, 2022, pp. 1-5, doi: 10.1109/COMPENG50184.2022.9905449.

Abstract: The arrival of a new generation of mobile networks as Fifth Generation (5G), brings with it greater complexity in the management of the network due to new services and scenarios. In this context, Self-Organising Networks (SON) becomes a key factor, given its ability for automate tasks and reduce human workload. Monitoring the network turns out be a crucial task, as it acts as the basis for the other SON functions. This paper proposes a methodology for automate monitoring of mobile networks based on their Key Performance Indicator (KPI). While most related works are typically designed to address specific monitoring objectives or target a narrow set of network indicators, the approach presented in this thesis aims to provide a more general and flexible monitoring tool. This allows the proposed methodology to be applied to a wide range of KPIs, making it adaptable to diverse operational needs and network scenarios.

4.3 Conclusions of the chapter

This chapter has thoroughly reviewed the scientific contributions related to the analysis and deployment of a mobile network behavioral analysis framework. The initial paper expounds on a novel framework for behavioral analysis and monitoring of mobile networks based on a combination of unsupervised and supervised machine learning techniques. This framework is capable of classifying new data and identifying the behavioral pattern that characterized it. The second paper proposes a methodology for autonomous monitoring of mobile networks based on their KPIs. This methodology is intended to detect potential deviations that affect network performance. In contrast to the initial paper, which is better suited for long-term analysis, this framework is designed for real-time implementation, establishing the foundations for a system that addresses the identified deviations. In this sense, the information extracted by the framework can be used to improve subsequent management and optimization functions. This methodology is a pivotal element within the SON framework, given its capacity to automate tasks and alleviate the workload of human operators. The monitoring of the network is a crucial task, as it serves as the foundation for the other SON functions.

Chapter 5

Anomaly Detection Methodologies

Content

This section encompasses the work associated with objectives 4 and 5 of the thesis. In particular, it consists of two papers that propose methodologies for anomaly detection in cellular networks. The initial paper introduces an active learning methodology for expert-assisted anomaly detection in mobile communications, while the second paper proposes a methodology for real-time detection of overshoot and undershoot situations in cellular networks.

5.1 Active learning methodology for expert-assisted anomaly detection in mobile communications

[2] José A. Trujillo, I. de-la-Bandera, J. Burgueño, D. Palacios, E. Baena, R. Barco, "Active Learning Methodology for Expert-Assisted Anomaly Detection in Mobile Communications", in *Sensors* 2023, 23, 126. https://doi.org/10.3390/s23010126

Abstract: Due to the great complexity, heterogeneity, and variety of services, anomaly detection is becoming an increasingly important challenge in the operation of new generations of mobile communications. In many cases, the underlying relationships between the multiplicity of parameters and factors that can cause anomalous behavior are only determined by human expert knowledge. On the other hand, although automatic algorithms have a great capacity to process multiple sources of information, they are not always able to correctly signal such abnormalities. In this sense, this paper proposes the integration of both components in a framework based on Active Learning that enables enhanced performance in anomaly detection tasks. A series of tests have been conducted using an online anomaly detection algorithm comparing the proposed solution with a method based on the algorithm output alone. The obtained results demonstrate that a hybrid anomaly detection model that automates part of the process and includes the knowledge of an expert following the described methodology yields increased performance. Concurrent research employs active learning methodologies in environments that are considerably less sophisticated than mobile networks. In a similar manner, the specialized expertise of experts is often simplified into rudimentary statistical methods.

5.2 Real-Time overshoot and undershoot detection in cellular networks

[3] José A. Trujillo, R. Lykke, I. de-la-Bandera, S. Søndergaard, Troels B. Sønrensen, R. Barco, P. Mogensen, "Real-Time Overshoot and Undershoot Detection in Cellular Networks," in *IEEE Access*, vol. 13, pp. 22325-22341, 2025, doi: 10.1109/ACCESS.2025.3537327.

Abstract: One of the most crucial aspects of cellular networks is coverage, as it determines the areas where users can connect to the network and utilize its services. In the past, the use of planning tools was common practice for the establishment of coverage areas and network capacity prior to the deployment of a network. However, issues with coverage, such as interference or coverage gaps, may arise due to equipment malfunctions, suboptimal configurations, or alterations in the propagation environment. In particular, an inadequate antenna tilt configuration can result in overshoot or undershoot situations on the network, which in turn can give rise to the aforementioned problems. This paper proposes a methodology for the real-time detection of overshoot and undershoot situations. To achieve this goal, KPI are analyzed using machine learning techniques. Given the difficulty of detecting coverage problems in mobile networks, the results obtained suggest that the methodology provides a consistent knowledge base for optimizing the antenna tilt, thereby improving network performance. Literature concerning coverage failures primarily concentrates on the identification of specific problems, such as sleeping cells and coverage holes. Additionally, the term undershoot is not frequently employed in the extant literature, as this concept is more appropriate for the nowdays heterogeneous mobile network scenarios.

5.3 Conclusions of the chapter

This chapter has included contributions related to the analysis of anomaly detection in cellular networks. This analysis considers the utilization of expert knowledge as an additional source of information to improve the performance of automatic anomaly detection algorithms. Additionally, the chapter deals with the analysis of coverage problems in heterogeneous networks, considering the use of machine learning techniques to detect these types of problems.

To this end, the efficacy of active learning in embedding the knowledge of an expert in the anomaly detection process has been thoroughly examined. This methodology demonstrates the impact that the integration of expert knowledge can have on the performance of automatic anomaly detection algorithms. The findings have demonstrated that the proposed hybrid model, which integrates the knowledge of an expert with an automatic algorithm, exhibits superior performance in comparison to the automatic algorithm when utilized in isolation.

Additionally, the analysis of coverage problems in heterogeneous networks has been undertaken, with consideration given to overshoot and undershoot failures. To address these challenges, a methodology has been formulated for the real-time detection of such problems using machine learning techniques. The findings have demonstrated that the proposed methodology can provide a consistent knowledge base for detecting failures in the network and lay the foundation for self-healing and self-optimization mechanisms that can solve the detected problems.

Chapter 6

Self-healing methodologies

Content

This section is dedicated to the work related to objective 6 of the thesis. Particularly, a paper is presented that proposes a methodology for self-healing in cellular networks. In this regard, novel methodologies for compensating coverage failures in emerging scenarios and technologies, such as mmWave and beamforming, are considered.

6.1 Reinforcement learning methodology for coverage failures in 5G mmWave beamforming scenarios

[4] José A. Trujillo, M. Martínez, I. de-la-Bandera, R. Barco, "Reinforcement learning methodology for coverage failures in 5G mmWave beamforming scenarios", under review in *EEE Open Journal of the Communications Society*.

Abstract: The advent of Fifth Generation (5G) technology has introduced novel challenges in the area of mobile network management, particularly with regard to beamforming and mmWave frequencies. This paper presents a reinforcement learning-based methodology to address coverage failures in 5G mmWave beamforming scenarios. The methodology utilizes the Proximal Policy Optimization (PPO) algorithm to dynamically adjust the configuration of operational beams in the presence of beam failures, thereby ensuring the maintenance of optimal coverage and capacity. The efficacy of this approach is substantiated through simulations, which demonstrate its capacity to restore network performance to its pre-failure levels. This approach offers a rapid and efficient means of mitigating beam failures, ensuring continuous service to users without the need for extensive network reconfiguration. Despite a thorough review of the extant literature, it is evident that there is an absence of relevant works that combine reinforcement learning techniques with beamforming scenarios where failures occur. Furthermore, there is an absence of literature addressing the resolution of beamforming issues from a network perspective.

6.2 Conclusions of the chapter

This chapter has presented the scientific contributions related to self-healing methodologies in cellular networks. Particularly, a reinforcement learning-based methodology has been proposed to address coverage failures in 5G mmWave beamforming scenarios. The methodology utilizes the PPO algorithm to dynamically adjust the configuration of operational beams in the presence of beam failures, thereby ensuring the maintenance of optimal coverage and capacity. The efficacy of this approach is substantiated through simulations, which demonstrate its capacity to restore network performance to its pre-failure levels. This approach offers a rapid and efficient means of mitigating beam failures, ensuring continuous service to users without the need for extensive network reconfiguration.

Part III

Conclusions

Chapter 7

Conclusions

Content

This chapter summarises the research carried out during this thesis. To that end, the chapter is structured into two sections. Firstly, Section 7.1 provides an overview of the objectives pursued in this thesis, outlining the main contributions of each of them. Secondly, Section 7.2 proposes potential future lines of research arising from this thesis.

7.1 Contributions

The central objective of this thesis has been to investigate the potential of ML and AI in the development of self-healing techniques that address the challenging failures of next-generation networks. To this end, a set of challenges has been identified, defining the objectives that can solve these problems. The identified challenges has been addressed by a set of six objectives, which were distributed across the various sections of this thesis.

Objectives 1, 2, and 3 pertained to the analysis of a substantial volume of data collected in a mobile network. In particular, the focus was on the automatic analysis of the networks, which allowed to discover the behavioral patterns within a cellular network. Based on this, performance monitoring was identified as an enabler to establish the basis for self-optimization and self-healing approaches.

Second, objectives 4 and 5 of this thesis were related to the detection of anomalies in cellular networks. To that end, this section addressed two specific approaches. The first approach involved leveraging expert knowledge to improve the performance of existing anomaly detection algorithms. Conversely, the analysis of coverage problems in next-generation networks and the development of techniques to detect them were considered as goals.

Finally, objective 6 of this thesis corresponds to the failure management and compensation section, where novel ML/AI algorithms were investigated in order to compensate failures in 5G and beyond networks.

Regarding these objectives, the contributions of this thesis are:

- **Objective 1. To analyze and extract valuable information from vast amounts of data collected in next-generation mobile networks.**
  - In relation to this objective, a study was conducted into the various measurements that are available on the substantial amount of data connected to cellular networks. To this end, a comprehensive statistical analysis was performed, encompassing the construction of a correlation matrix and the examination of data distributions, among other methods. This analytical approach was undertaken to understand the characteristics of the different parts and aspects of the cellular networks (traffic, quality, radio part, and so on).

- A thorough case-specific examination was conducted in order to select the most suitable indicators for each scenario and use case, thus ensuring that as much valuable information as possible would be available for automated functions.
- Finally, certain cases, the KPIs provided by the network may prove to be inadequate or may not accurately reflect a particular aspect or performance of the network. To address this potential shortcoming, a thorough examination of the relevant CMs and PMs has been undertaken to identify the most pertinent indicators for a given scenario or use case. This analysis has yielded the development of novel indicators, which have been designed to provide more meaningful information for the specific scenario or use case.

- **Objective 2. To characterize the different behavioral patterns existing in a mobile network through automated techniques.**
  - In order to address this objective, a framework has been developed for the identification of the inherent behavior patterns in cellular networks. Specifically, the methodology is founded on the employment of an unsupervised learning (i.e., SOM) that analyzes the KPIs associated to several aspects of the network and identifies the cells that have a similar behavior. This approach facilitated the utilization of unlabeled data, which constitutes the majority of data collected in mobile networks, and implemented a classifier (i.e., Random Forest) that assigns a label to new cells based on the knowledge acquired from the initial phase of the framework.
  - For the evaluation of this approach, a database of different commercial LTE networks was analyzed and used for training the framework. The findings demonstrated a promising performance, enabling an interesting tool for MNOs to understand the different behaviors manifested in their networks. This tool could also serve as a basis for monitoring systems, due to its ability to characterize the networks and the possibility to assign new labels once the framework has been trained.

- **Objective 3. To provide an autonomous monitoring methodology capable of detecting behavioral changes in network elements.**

  - The monitoring of mobile networks poses a significant challenge due to the large amount of data produced in them. Knowing which indicators better represent the performance of a network is therefore important. To this end, a couple of techniques has been developed to address this objective. On the basis of the classifier implemented to address the previous objective, a methodology to detect changes in pattern behavior was implemented. This methodology involved the continuous monitoring of KPI reported by a cellular network. It was designed to alert the user if the label assigned to a cell differs during a specified interval from the previously assigned label.
  - The second approach involved the implementation of a monitoring methodology, which detects deviations in the KPIs within a cellular network. This methodology has been implemented to analyze the recent behavior of the KPIs in conjunction with the current data and notify in case of a deviation. Additionally, the configuration of specific input parameters facilitated the assessment of the impact of these deviations on the performance of the network. This approach was designed to be adaptable to different trends that emerge in mobile networks.
  - The efficacy of both approaches has been demonstrated through empirical testing using data collected from a commercial LTE network. The findings indicated that both methods can achieve a satisfactory efficiency in monitoring the network and detecting behavioral changes or deviations. While the first proposal is more appropriate for long-term analysis (i.e., weeks or months), the second can be applied in real-time for more specific tasks (e.g., monitoring and analyzing the potential impact of deviations caused by a configuration change). It is noteworthy that these methodologies are scalable and adaptable to any mobile network technology, given that each evolution in this field brings the possibility to access more information (KPIs, counters, information context, and others).

- **Objective 4. To enable ML/AI algorithms to not only learn from the data generated by mobile networks, but also to integrate the knowledge of expert network management engineers.**
  - From the perspective of MNOs, the automation of time-consuming

tasks, such as anomaly detection, is a subject of interest. Moreover, MNOs have access to a large team of technical experts who have a wealth of knowledge in the area of network management. This expertise frequently encompasses insights that are challenging for algorithms to discern. To address this challenge, an approach based on the concept of active learning has been developed. This approach enabled the seamless integration of the feedback from the engineer expert within the anomaly detection loop, thereby enhancing the performance of the algorithm in detecting failures. This strategy has been successful in achieving both objectives: reducing the time requirement of an expert to detect anomalies and improving the efficiency and reliability of the anomaly detection algorithm.

  - The proposed approach was evaluated using a dataset of a commercial LTE network with anomalies. The findings of this study demonstrated the importance of incorporating the feedback of an expert engineer to enhance the performance of automatic anomaly detection algorithms. It was noteworthy that the time required for an expert to detect anomalies was considerably reduced compared to fully manual detection, achieving the same or even better results. Furthermore, the results indicated that the performance of the algorithms could be improved within a few days with respect to the efficiency achieved without implementing the proposed approach.

- **Objective 5. To explore new techniques for anomaly detection to address novel failures that may emerge in the scenarios and use cases of the new generations of mobile networks.**

  - Coverage problems have historically been a cornerstone in mobile networks. In response to the continuous evolution of technologies, mobile networks have evolved towards denser scenarios, characterized by a high density of users and base stations. In this regard, a methodology has been proposed to detect coverage problems (i.e., overshoot and undershoot) in real time. The methodology was designed to ensure comprehensive representation of failures by first examining the impacts of these situations in different aspects of the network and reflecting them in the measurements. The proposed approach employed a range of ML algorithms, leveraging the strengths of each to generate a unique output.

- This approach was evaluated through a database of commercial LTE and LTE-A networks, including data from base stations operating in different frequency bands (from 800 MHz to 2600 MHz). The experimental results have demonstrated the efficacy of the proposed approach in identifying anomalies and coverage issues in mobile networks. The approach provided valuable information for further deployment, where the overshoot and undershoot situations detected will be addressed.

- **Objective 6. To investigate novel ML/AI techniques to provide a framework for suggesting possible actions to be taken in the network to solve the detected problems.**
  - The advent of next-generation mobile networks brings with it challenging failures associated with the new capabilities of these networks. However, these capabilities also provide opportunities to successfully compensate for these failures. Additionally, ML techniques are undergoing continuous evolution, thereby opening up a world of possibilities. In this regard, this thesis has developed a framework for the compensation of coverage failures in 5G NR scenarios using beamforming capabilities. The proposed framework utilized a reinforcement learning algorithm, which determines the optimal configuration for non-affected beams, with the objective of compensating the failures of other beams within the same cell.
  - In order to assess the efficacy of the proposed methodology, a system-level simulator with NR capabilities (i.e., beamforming and mmWave) has been implemented and utilized. In particular, a scenario of mmWave cells with a set of beams was simulated, including failures in random beams. Two scenarios were considered: beams could be partially affected or completely damaged. The proposed algorithm has been demonstrated to restore service levels to the usual thresholds of the cell quickly, providing a similar performance only with the non-affected beams.

7.2 Future work

As a result of this thesis, a variety of research lines and potential applications have been identified. These involve not only further improvements based on the current research, but also additional developments and broader areas of application derived from this research. The following summarizes these future work lines:

- The advent of the innovative O-RAN architecture contemplates the integration of AI and ML directly into its elements, introducing the RIC. Consequently, a primary focus of future research should be the implementation of the methodologies and algorithms outlined in this thesis within this novel architecture. To this end, the approaches will be adapted as xApps or rApps both test beds and real deployments will assess the performance and efficiency of these in other technologies and networks. Additionally, it will be relevant to explore a wider range of scenarios and technologies to measure the scalability and adaptability of the proposed methodologies. In this regard, a range of network configurations, traffic profiles, services, and capabilities, including network slicing, will be considered for deployment to validate the efficacy of these methodologies.

- As mobile networks evolve towards 6G, future research should align with its key trends, such as AI-native architectures, autonomous network management, and energy-efficient operation. In this regard, the AI-based methodologies presented in this thesis provide a solid foundation to be further extended towards fully intelligent and sustainable network functionalities, particularly in the areas of anomaly detection and self-healing.

- Regarding the advancement of mobile network generations, the data sources and the amount of data have been growing. It has resulted in a considerable interest in the evolution of ML/AI, exploring techniques such as deep learning and reinforcement learning. In this regard, a possible future line of research to consider is the exploration of new algorithms that enable the development of more complex mechanisms in the context of self-healing in mobile networks, improving functionalities such as prediction of potential anomalies and sophisticated techniques to compensate for failures. In this context, federated learning and energy-efficient AI techniques are particularly promising to enable distributed intelligence while preserving user privacy and reducing the computational and energy costs of large-scale model training.

- This thesis explores the integration of automatic algorithms and contextual information (i.e., expert knowledge) in the same approach. In this regard, another future line of research could be to consider including other contextual information (i.e., localization, environment, traffic patterns, etc.) or predictions to enhance the performance of existing anomaly detection algorithms.

- The advent of next-generation mobile networks has given rise to a proliferation of heterogeneous networks, accompanied by a novel failure that was previously unseen. This thesis has sought to address coverage-related failures by deploying methodologies to detect and compensate for them. However, it is essential to observe that there are other aspects of mobile networks that are also susceptible to anomalies. In this regard, two future lines of research can be delineated. Firstly, the methodologies proposed could be adapted to focus their functionality on failures related to other aspects of the network, such as traffic, quality, and latency. To this end, a comprehensive analysis of these failures and their effects on the indicators is imperative, followed by the implementation of the required modifications to the proposed methodology. Conversely, a comprehensive analysis could be expanded to identify the most suitable ML/AI technique to address a particular novel failure.

Chapter 8

Research activities

Content

This section presents the research activities performed during the course of this thesis. This includes the dissemination of the results, the projects in which the author has contributed and the research stays that have been part of this thesis.

8.1 Dissemination

The results of this thesis have been disseminated through various publications in prestigious scientific journals and conferences, as referenced at the beginning of the manuscript. Nevertheless, the dissemination activities were not limited to the scientific publications, but also included demonstrations and assistance at various events in the technological field. These events fostered a valuable exchange of knowledge and experience with the academic and professional community.

- Mobile Week Málaga 2021, organised by Palacio de Ferias y Congresos de Málaga, December 2021.
- 13th European Meeting on Science, Technology, and Innovation, organised by Transfiere (Foro Europeo para la Ciencia, Tecnología e Innovación), in Málaga (Spain), March 2024.
- 14th European Meeting on Science, Technology, and Innovation, organised by Transfiere (Foro Europeo para la Ciencia, Tecnología e Innovación), in Málaga (Spain), March 2025.

8.2 Related projects

The work developed in this thesis has contributed to the following projects:

- **NEREA**: Network Strategy And Evolution Advisor, funded by Spanish Ministry of Economy and Competitiveness and European Regional Development Fund (ERDF), project number: RTC-2017-6661-7.
- **DAMA-5G**: Detección de Anomalías Multivariable Asistida, funded by Junta de Andalucía and ERDF, project number: UMA-CEIATECH-12.
- **PENTA**: Provisión de servicios PPDR a través de Nuevas Tecnologías de Acceso radio, funded by Junta de Andalucía and ERDF, project number: PY18-4647.
- **MAORI**: Massive AI for the OpenRadIo b5G/6G network. Project number TSI-063000-2021-53, receiving funds from Ministerio de Asuntos Económicos y Transformación Digital and European Union - NextGenerationEU within the framework "Recuperación, Transformación, y Resiliciencia".

Additionally, the author has contributed to the work performed in the following projects:

- **ESCUDO**: Desarrollo de casos de uso para el diseño, optimización y dimensionado de redes móviles, funded by Ericsson España.
- **OPTIRAN**: Optimización Multipropósito de la Red de Acceso Radio 5G, funded by Junta de Andalucía, FEDER, project number: UMA18-FEDERJA-174.

8.3 Research stays

This thesis involved a stay as a visiting researcher at Wireless Communications Section (WCN) Section, Department of Electronic Systems, of Aalborg University (AAU), between February and July 2023. This stay was supervised by Associate Professor for the receiving institution Troels B. Sønrensen and the CEO of 2Operate, Søren Søndergaard.

José Antonio Trujillo Saborido

Málaga, Spain, 2025.

Part IV

Appendices

Appendix A

Summary (Spanish)

Content

El siguiente apéndice ofrece un resumen en español de la tesis, abordando aspectos clave como la motivación que impulsó la investigación, los objetivos establecidos, una descripción detallada de los resultados obtenidos, las conclusiones extraídas del estudio y un resumen de las contribuciones científicas realizadas durante el desarrollo de la investigación.

A.1 Motivación

En las últimas décadas, las redes móviles han evolucionado a un ritmo asombroso, lo que ha dado lugar a una revolución en las comunicaciones. En las primeras generaciones de redes móviles, las funcionalidades elementales de un teléfono móvil se limitaban a las llamadas de voz y los mensajes de texto. En la actualidad, los teléfonos móviles no solo permiten la comunicación interpersonal, sino que también ofrecen acceso a Internet, lo que ha dado lugar a una amplia gama de aplicaciones y funcionalidades, tales como la transmisión de vídeo, el comercio electrónico, la banca online y la navegación web. La continua evolución de las redes móviles ha dado lugar a un paradigma en el que la conectividad está presente en todos los ámbitos de la sociedad, conectando todo tipo de dispositivos y a todas las personas. En este contexto, las comunicaciones móviles se han convertido en un elemento clave de la transformación social y económica.

La llegada de la quinta generación de redes móviles (5G) representa un hito en la evolución de las telecomunicaciones, dando lugar a una notable expansión de los servicios y funcionalidades ofrecidos por esta nueva generación [15]. Considerando este nuevo paradigma, las redes 5G no solo surgen con el objetivo de proveer servicios mejorados de banda ancha (eMBB), sino que también buscan dar cabida a otros servicios y escenarios estandarizados por el 3GPP [16]. Más allá del mencionado eMBB, las redes 5G contemplan un par de casos de uso adicionales: URLLC y mMTC. El primero de estos, URLLC considera aquellas aplicaciones que necesitan comunicaciones críticas que deben cumplir con estrictos requisitos de latencia y fiabilidad, como la conducción autónoma o la telecirugía. Por su parte, mMTC contempla aplicaciones como IoT, que abarcan escenarios con una gran cantidad de dispositivos conectados que consumen poca potencia y no necesitan demasiado ancho de banda, como la industria 4.0 o la monitorización ambiental entre otros.

No obstante, las demandas tecnológicas siguen evolucionando, lo que impulsa la investigación acerca de las redes de sexta generación (6G). Esta nueva generación no solo ampliará las capacidades de las redes 5G, sino que también introducirá nuevos casos de uso que probablemente transformarán los paradigmas actuales. Entre las innovaciones propuestas, se destacan la comunicación holográfica en tiempo real, la integración de sistemas de inteligencia artificial nativa dentro de la red y la implementación de sistemas no terrestres. Gracias a estos avances, se están abriendo nuevos horizontes en los ámbitos de la conectividad y la automatización. En este contexto, la arquitectura Open RAN (O-RAN) surge como una tecnología fundamental para facilitar estas innovaciones, ya que permite disponer de redes más flexibles, interoperables y programables. El enfoque O-RAN, fundamentado en la virtualización y las interfaces abiertas, posibilita la implementación eficiente de los servicios URLLC y mMTC, permitiendo optimizar los recursos de red en tiempo real y adaptarlos dinámicamente a los requisitos de los futuros casos de uso 6G.

La constante evolución de las redes móviles, en combinación con la proliferación de dispositivos conectados y servicios ofrecidos, aumenta la complejidad de las tareas de gestión de las redes. En consecuencia, los operadores de redes móviles están explorando vías de automatización para hacer frente a estos desafíos. Este enfoque permite optimizar la red y la gestión de sus recursos, al tiempo que se evita el aumento de los gastos de capital (CAPEX) y de operación (OPEX).

Ante la necesidad de automatizar estas tareas, el concepto de redes auto-organizadas (SON) fue introducido por la NGMN en 2008 [19, 20]. Posteriormente, el 3GPP estableció los requisitos para las redes SON [21], categorizando sus funcionalidades en tres áreas: *self-configuration* [22], *self-optimization* [22], y *self-healing* [23]. *Self-configuration* se refiere a la capacidad para incorporar de forma automática nuevos elementos a la red [24, 25, 26]. Por su parte, *self-optimization* abarca actividades relacionadas con la reconfiguración de la red para adaptarse a las variaciones del entorno, garantizando un funcionamiento adecuado [27, 28, 29, 30]. Por último, *self-healing* implica tareas relacionadas con la detección de anomalías [31, 32, 33] y sus posibles causas [34, 35, 36, 37], así como tareas que permiten recuperar la red frente a estas anomalías como la búsqueda de posibles acciones que permitan compensarlas [38, 39, 40].

Al mismo tiempo, los avances en las funcionalidades de SON han generado un gran interés entre la comunidad científica, dando lugar a una proliferación de propuestas de algoritmos de gestión de redes [41]. En consecuencia, el aprendizaje automático (ML) [42] emerge como un elemento clave para hacer frente a la complejidad inherente de la diversidad de servicios y la cantidad de usuarios conectados a una red móvil [43]. Este enfoque se pone de manifiesto mediante la integración de ML/AI en la evolución de SON para 5G, conocida como NG-SON, que sentará las bases para la automatización de tareas de gestión y orquestación de redes [44]. Este enfoque hace un uso de la proliferación de datos generados por las redes móviles, dotándolas de escalabilidad, flexibilidad y resistencia [46, 47]. El hecho de que se acumule una gran cantidad de información procedente de las redes móviles presenta problemas relacionados con el ruido, la redundancia y los posibles sesgos, que pueden afectar considerablemente al rendimiento de los modelos ML. En consecuencia, se hace indispensable la implementación de un proceso riguroso de selección de datos, preprocesamiento y *feature engineering*, con el fin de asegurar la precisión, la imparcialidad y la generalizabilidad de los modelos de ML, mejorando así las capacidades de *self-management* de la red, especialmente en funciones críticas como la optimización de recursos en tiempo real y *self-healing*.

Considerando el contexto anteriormente mencionado, *self-healing* surge como un componente fundamental dentro de las redes SON para garantizar la fiabilidad y la continuidad del servicio. Tradicionalmente, se ha recurrido al monitoreo y análisis de datos de la red para la identificación de anomalías o fallos [48]. No obstante, los avances en las redes móviles no solo aportan beneficios, sino que también introducen nuevos fallos y problemas en la red [49, 50]. Para hacer frente a esta situación, se han desarrollado metodologías más complejas y enfoques proactivos cuyo objetivo es anticiparse a los fallos antes de que se produzcan [51, 52]. Estos métodos de autorreparación siguen siendo un tema de investigación de gran relevancia, especialmente a medida que surgen paradigmas de red como O-RAN y la transición a 6G. De este modo, la adopción de arquitecturas abiertas y basadas en software como el O-RAN proporciona una mayor flexibilidad y adaptabilidad. No obstante, se evidencia la necesidad de contar con mecanismos de autorreparación más avanzados, capaces de adaptarse dinámicamente a entornos de red heterogéneos y altamente distribuidos [53]. Se prevé una necesidad similar de soluciones avanzadas de gestión de fallos en las redes 6G, que se basarán en la automatización impulsada por la inteligencia artificial y en una conectividad ultradensa. Dichas redes requerirán soluciones de gestión de fallos aún más sofisticadas para mantener un rendimiento y una fiabilidad óptimos [54, 55].

A.2 Preámbulos

Esta tesis ha sido desarrollada en el grupo de investigación Mobile and Aerospace Networks Lab (*MobileNet*), que pertenece al Instituto Universitario Telecomunicaciones de la Universidad de Málaga (*TELMA*).

(*MobileNet*) fue creado como resultado de una colaboración entre el grupo TIC-

102 y *Nokia Networks* en la creación del Centro de Investigación en Comunicaciones Móviles en el Parque Tecnológico de Andalucía (PTA) en Málaga en el año 2000.

Una de las principales líneas de investigación del grupo es la aplicación de técnicas de ML/AI a las redes móviles. En colaboración con *Nokia Networks* - España, uno de los proyectos iniciales del grupo fue desarrollar una herramienta automática para la solución de problemas en la parte radio de la red (RAN). Este proyecto sentó las bases para la integración del conocimiento de un ingeniero experto con datos de un red móvil comercial, desarrollando una solución autónoma para la resolución de problemas.

Desde entonces, el desarrollo de aplicaciones SON ha sido una temática constante en el grupo de investigación, participando en proyectos de investigación y colaboraciones con empresas líderes en el secto tanto a nivel nacional como internacional. Entre estas iniciativas, el proyecto NEREA tenía como objectivo el desarrollo de una herramienta autónoma de gestión de red. Fundamentalmente, se trata de una herramienta basada en los datos obtenidos de los contadores y los KPI para dar soporte a diversas funcionalidades, en las que los modelos de aprendizaje automático desempeñan un papel fundamental. Entre sus funcionalidades se encuentran la detección y predicción de anomalías, un simulador del impacto generado por los cambios de configuración y el soporte para la toma de decisiones de los ingenieros de red.

Asimismo, *MobileNet* contribuyó a un proyecto llamado DAMA-5G, en el que se diseñaron métodos automáticos para identificar degradaciones en el rendimiento de la red. Esta iniciativa incorporó la experiencia de un ingeniero para mejorar la eficacia del proceso de detección. Por otro lado, *MobileNet* también participó en el proyecto PENTA, centrado en el aprovechamiento de las funcionalidades de SON en escenarios de emergencia. Este proyecto se centró en la aplicación de mecanismos de autorreparación para mitigar las interrupciones de la red causadas por situaciones de emergencia y en la optimización del rendimiento de URLLC en entornos afectados por catástrofes.

De acuerdo con esta trayectoria, *MobileNet* ha participado en el proyecto MAORI, que pretende implantar metodologías y algoritmos de ML para la gestión inteligente de redes móviles de nueva generación. Un punto central del proyecto es la implementación de mecanismos de *self-optimization* y *self-healing* dentro de la parte radio de la red. El proyecto incluye trabajos de investigación en funcionalidades como la identificación de fallos de radio enlaces o la optimización del rendimiento de la red mediante el uso de información de contexto. Colectivamente, estos proyectos establecen la base de esta tesis, además del desarrollo de aspectos seleccionados dentro de esta tesis.

La infraestructura de *MobileNet* desempeña un papel crucial en el desarrollo de estos proyectos, entre los que se encuentra un simulador de red LTE a nivel de sistema, desarrollado dentro del grupo [56]. Esta herramienta constituye un componente esencial de la presente tesis doctoral, habiendo sido objeto de una actualización a la tecnología 5G NR y utilizada como método de evaluación de algoritmos y funcionalidades de red.

A.3 Objetivos

El objetivo principal de esta tesis es explorar el potencial de las técnicas de ML/AI para incorporar funcionalidades de *self-healing* en las redes de próxima generación. La llegada de estas redes avanzadas aportará numerosos beneficios, pero también introducirá nuevos retos y problemas que deberán abordarse. En este sentido, la presente tesis se centra en todo el ciclo que comprende la selección de información relevante, la monitorización de la red, la detección de anomalías y la propuesta de soluciones pertinentes. Para abordar estas funcionalidades dentro del ciclo completo, se han establecido ciertos objetivos, que representan hitos en el camino hacia la consecución del objetivo final de esta tesis.

Los recientes avances en las redes móviles han propiciado la proliferación de servicios, casos de uso y funcionalidades, dando lugar a nuevos escenarios que deben ser considerados desde la perspectiva de la gestión de redes. Esta proliferación de novedades genera inevitablemente un volumen sustancial de datos que puede resultar útil para evaluar el estado de la red. No obstante, esta abundancia de datos plantea un desafío, ya que no todos los datos son útiles para gestionar la red y sus recursos. Este desafío constituye la premisa fundamental del primer objetivo específico de la presente tesis (Objetivo 1), que busca identificar la información relevante a partir de la información irrelevante. En este sentido, el propósito de este estudio es examinar qué aspectos de la red favorecen la automatización de distintas funcionalidades de la misma.

En el contexto actual de las redes móviles, se observa una marcada tendencia a la heterogeneidad, consecuencia de la coexistencia de diversas tecnologías de acceso y de una gran variedad de dispositivos con capacidades y requisitos diferentes. Esta heterogeneidad da lugar a una gran variedad de comportamientos de red de naturaleza dinámica y compleja, lo que dificulta la identificación de anomalías y la gestión eficaz de los recursos. En consecuencia, comprender los patrones de comportamiento de estas redes es indispensable para anticipar fallos potenciales y optimizar los mecanismos de *self-healing*. En este contexto, el objetivo de esta tesis (Objetivo 2) es analizar y categorizar metódicamente dichos patrones, lo que contribuirá a mejorar el conocimiento de la red y permitirá una mejor detección de anomalías, así como el desarrollo de soluciones adaptativas que permitan a la gestión de la red operar con mayor eficiencia y autonomía. No obstante, para garantizar la eficacia del conocimiento de patrones de comportamiento en redes heterogéneas, es fundamental integrarlo en un sistema de monitorización en tiempo real. Tomando en consideración las características dinámicas de las redes móviles, se hace evidente que la monitorización constante de las condiciones de la red resulta indispensable para la detección óptima de anomalías y, en el mejor de los casos, para la anticipación proactiva de posibles fallos, garantizando así una calidad de servicio óptima. La integración de este conocimiento en un sistema de monitorización continua no solo facilita una detección más precisa, sino que también potencia la implementación de mecanismos de *self-healing* capaces de proporcionar respuestas autónomas y adaptativas.En este sentido, otro de los objetivos clave de esta tesis (Objetivo 3) es el desarrollo de una monitorización en tiempo real capaz de identificar cambios en el comportamiento de la red, proporcionando así a los operadores la información necesaria para detectar anomalías o realizar ajustes proactivos en la configuración de la red. Este enfoque no solo facilitará la detección temprana de problemas, sino que también permitirá la optimización continua del rendimiento de la red, lo que facilita su adaptación a las condiciones cambiantes y mejora la calidad del servicio para los usuarios.

A pesar de los avances en automatización y de la aparición de la inteligencia artificial en la gestión de redes móviles, los operadores de redes continúan manifestando una actitud de precaución respecto a la implementación de algoritmos totalmente autónomos ya que estos podrían afectar potencialmente a la calidad de servicio percibida por los usuarios. Tradicionalmente, la configuración de redes, la optimización y la resolución de problemas han sido responsabilidades de ingenieros expertos, cuyas competencias y experiencia son fundamentales para la toma de decisiones cruciales. No obstante, la tendencia hacia una mayor automatización es innegable, como lo demuestran los avances en la estandarización 3GPP y la incorporación de AI en nuevos elementos O-RAN. En este sentido, el RIC emerge como un componente clave introducido por la O-RAN Alliance para integrar estos algoritmos automáticos en la arquitectura de red. Consciente de ello, otro de los objetivos de esta tesis (Objetivo 4) es integrar el conocimiento humano en los algoritmos ML/AI para que estos no solo aprendan de los datos, sino que también incorporen el razonamiento y las estrategias de los ingenieros. Este enfoque tiene como propósito generar sistemas más fiables y transparentes, manteniendo la estabilidad y el rendimiento de la red.

En consonancia con lo anteriormente mencionado, la mayor complejidad de las redes móviles de nueva generación ha dado lugar al planteamiento de nuevos retos derivados de las nuevas capacidades y funcionalidades que introducen estas redes. Una de las principales ventajas de la tecnología 5G es la optimización de la cobertura y la disponibilidad de diversos servicios, incluyendo funcionalidades como *beamforming*, *network slicing* y el uso de frecuencias milimétricas. Sin embargo, la implementación de estas funciones avanzadas conlleva nuevos retos. En escenarios caracterizados por una variabilidad creciente, una multitud de patrones de tráfico y una variedad de dispositivos cada vez mayor, el enfoque convencional para la detección de anomalías puede resultar ineficaz. En este contexto, la presente tesis tiene como objetivo explorar técnicas de ML avanzadas para la detección de anomalías (Objetivo 5). Estas técnicas aprovecharán la valiosa información contenida en amplias cantidades de datos para identificar problemas latentes. A diferencia de los enfoques convencionales, estas técnicas facilitarán una detección más precisa y adaptable, permitiendo así la toma de decisiones automatizada sin comprometer la estabilidad de la red.

En resumen, los objetivos de la tesis son los siguientes:

- **Objetivo 1.** Analizar y extraer información valiosa de grandes volúmenes de datos recogidos en las redes móviles de nueva generación. En este contexto, se exploran diversas técnicas automáticas para identificar la información relevante para una funcionalidad determinada.

- **Objetivo 2.** Caracterizar los diferentes patrones de comportamiento existentes en una red móvil mediante el uso de técnicas automatizadas. El propósito de este estudio es desarrollar una metodología que permita determinar, a partir de métricas de red como contadores, estadísticas o KPI, si los patrones de comportamiento de dos celdas son similares o diferentes. Este enfoque metodológico permite identificar las distintas clases de celdas que componen la red, contribuyendo así a una comprensión más profunda y precisa de su estructura y funcionamiento.

- **Objetivo 3.** Proporcionar una metodología de monitorización autónoma que sea capaz de detectar cambios de comportamiento en los elementos de la red. El propósito de esta monitorización es proporcionar el estado de la red en tiempo real para que se puedan llevar a cabo tareas de *self-healing* o *self-optimization* y generar información valiosa sobre si existen cambios de comportamiento en la red monitorizada.

- **Objetivo 4.** Integrar a los algoritmos ML/AI con el conocimiento de ingenieros expertos en gestión de redes. Este enfoque tiene como objetivo garantizar que los algoritmos no solo aprendan de los datos generados por las redes móviles, sino que también integran los razonamientos y conocimientos de ingenieros expertos en redes. Esto garantiza algoritmos más fiables para un rendimiento de red eficiente y robusto.

- **Objetivo 5.** Explorar nuevas técnicas de detección de anomalías para hacer frente a fallos emergentes en los escenarios y casos de uso de las nuevas generaciones de redes móviles. En concreto, se investigarán los problemas de cobertura causados por la heterogeneidad de la red y la elevada densidad de elementos en las mismas.

- **Objetivo 6.** Investigar técnicas novedosas de ML/AI que proporcionen un framework para recomendar posibles acciones que se podrían llevar a cabo en la red para solucionar los problemas detectados. Más concretamente, se abordarán escenarios que integren funcionalidades y características innovadoras, como *beamforming* o el uso de frecuencias milimétricas.

A.4 Descripción de los resultados

En esta sección se presentan las diferentes publicaciones que sustentan la tesis, abordando los distintos desafíos y objetivos identificados en la Sección A.3. La Figura 3.2 muestra la relación entre los distintos desafíos, objetivos y resultados obtenidos, representados en forma de artículos publicados en conferencias internacionales o revistas científicas incluidas en el JCR.

Los artículos de esta tesis se han organizado para cubrir tres capítulos bien definidos. En primer lugar, el Capítulo 4 abarca el análisis de los datos generados por una red móvil, y la exploración de algoritmos que permitan extraer información útil de estos para monitorizar la red. Luego, el Capítulo 5 engloba todo el trabajo relacionado con la detección de anomalías de la presente tesis. Por un lado, las técnica para utilizar el conocimiento de los expertos y mejorar el rendimiento de los algoritmos; y por otro lado el desarrollo de métodos para la detección de problemas de cobertura. Finalmente, el Capítulo 6 se centra en la parte de solución de estos problemas, explorando las diferentes opciones de técnicas de ML que podrían usarse para abordar esta tarea. A continuación, se resumen los distintos artículos que respaldan esta tesis en las subsecciones siguientes.

A.4.1 Framework for behavioral analysis of mobile networks

Este trabajo inicia el capítulo 4, dedicado a los desarrollos relacionados con el análisis del comportamiento en las redes móviles (objetivos 1, 2 y 3). En particular, propone un enfoque innovador para el análisis y la supervisión de una red móvil, integrando algoritmos supervisados y no supervisados en un mismo sistema. Dicho sistema es capaz de analizar el comportamiento de las celdas y monitorizarlas, detectando cambios en su comportamiento a lo largo del tiempo. La información obtenida por la metodología ayuda a mejorar la gestión de la red y sentar las bases para futuras optimizaciones de esta.

Como se describe en el objetivo 1, esta metodología posee la capacidad de analizar grandes volúmenes de datos en redes comerciales, centrándose en diferentes aspectos de la red (tráfico, condiciones radio o calidad). Con el fin de extraer información valiosa, se realiza un preprocesado de los datos haciendo uso de distintas técnicas matemáticas y automatizadas. La naturaleza no etiquetada propia de este tipo de bases de datos plantea un importante reto a la hora de caracterizar los diversos patrones de comportamiento inherentes a las redes móviles. Para hacer frente a este reto, se utiliza el algoritmo de aprendizaje no supervisado SOM [110] que identifica los distintos comportamientos y asigna etiquetas a las celdas con patrones de funcionamiento similares.

Una vez los patrones de comportamiento han sido identificados y por tanto, se ha cubierto el Objetivo 2, es posible entrenar algoritmos de aprendizaje supervisado, como RF [111]. Este planteamiento sienta las bases de una metodología autónoma para monitorizar el rendimiento de la red en tiempo real y detectar cambios de comportamiento en ella, según lo establecido en el objetivo 3 (que se completa en el siguiente apartado A.4.2.

Por último, se ha evaluado la eficacia de la metodología propuesta utilizando una base de datos de redes LTE comerciales, con resultados prometedores. Además, el enfoque desarrollado puede proporcionar información valiosa para otras tareas de *self-healing* o *self-optimization*.

A.4.2 Methodology for autonomous monitoring of mobile networks

De acuerdo con el apartado anterior, el segundo trabajo del capítulo 4 también se encarga de cubrir el objetivo 3. Concretamente, propone un enfoque para detectar y analizar las desviaciones del rendimiento reciente de una red móvil.

El modelo propuesto tiene como objetivo caracterizar los comportamientos y el rendimiento recientes de una red celular a partir de datos históricos. Este componente constituye una fase off-line, en la que se identifican dichos comportamientos y se establecen umbrales para determinar si existe una desviación de los mismos. Posteriormente, se inicia una fase online, durante la cual se evalúan los datos en tiempo real y se analiza su impacto en el rendimiento global de la red.

La metodología se ve reforzada por la incorporación de un análisis de los cambios de configuración que abarca las horas posteriores a la modificación de parámetros de configuración. Este enfoque permite extraer información valiosa y facilita la decisión de realizar tareas de *self-optimization* o *self-healing*. Por otro lado, se analizan las variaciones de tendencia para actualizar el comportamiento reciente si se considera que estas variaciones constituyen un nuevo comportamiento de la red.

Finalmente, se demuestra la eficacia de la metodología mediante su aplicación a una base de datos comercial LTE. Además, con este trabajo se cumple el objetivo 3, que pretende establecer una metodología de monitorización que detecte cambios de comportamiento y proporcione información valiosa para que los MNOs apliquen eficientemente la gestión automatizada de la optimización y las tareas de *self-healing* en sus redes comerciales.

A.4.3 Active learning methodology for expert-assisted anomaly detection in mobile communications

El capítulo 5 que contiene este trabajo, abarca todos los desafíos relacionados con la detección de anomalías en redes de nueva generación (objetivos 4 y 5).

El objetivo principal de este artículo es reducir el tiempo que un ingeniero especializado en redes móviles necesita para analizar una posible anomalía en la red. Para ello, propone el uso de *active learning*, incorporando la retroalimentación de un experto en los algoritmos de detección de anomalías. En concreto, la metodología propuesta utiliza el conocimiento de un ingeniero experto para optimizar los hiperparámetros de un algoritmo de detección de anomalías basándose en los resultados del propio algoritmo. Este enfoque colaborativo, en línea con el Objetivo 4, permite a un ingeniero experto decidir si la anomalía detectada por el algoritmo es efectivamente una anomalía o en cambio sí puede que esta no lo sea, o incluso si existen dudas de que lo sea. En consecuencia con esta retroalimentación, el algoritmo se optimizará, de modo que su capacidad para detectar anomalías converja con la de un ingeniero experto.

Para evaluar la metodología propuesta, se ha empleado un conjunto de datos de redes LTE comerciales. En primer lugar, se ha aplicado el algoritmo de detección de anomalías por sí solo. Posteriormente, se ha introducido el mismo conjunto de datos, pero aplicando la metodología propuesta en este artículo, que incluye la opinión de un ingeniero experto sobre las posibles anomalías detectadas por el algoritmo. Los resultados demuestran que dicha metodología aumenta la eficacia del algoritmo y, por tanto, su rendimiento.

Los operadores de redes móviles suelen mostrarse reacios a implantar algoritmos automáticos en sus redes comerciales por temor a causar problemas de servicio a sus usuarios. Para hacer frente a este desafío, la propuesta incorpora una interfaz amigable que facilita la optimización del algoritmo automático integrando los comentarios y conocimientos de los ingenieros expertos. Este enfoque garantiza que los operadores puedan confiar en la eficacia de los algoritmos automáticos, ya que están supervisados por un ingeniero experto en la gestión de redes.

A.4.4 Real-Time overshoot and undershoot detection in cellular networks

La contribución descrita en esta sección sirve para concluir el capítulo 5. Teniendo en cuenta la heterogeneidad y densidad de dispositivos de las redes de próxima generación, el trabajo pretende detectar anomalías relacionadas con problemas de cobertura de red, en consonancia con el Objetivo 5.

La metodología propuesta se basa en algoritmos para la detección de problemas de cobertura, en particular situaciones de overshoot y undershoot, que incluyen posibles efectos como huecos de cobertura o interferencias. El enfoque propuesto implica el análisis de varios KPIs obtenidos a partir de contadores que tienen en cuenta diferentes aspectos de la red. Además, se integra una combinación de múltiples algoritmos para aprovechar las fortalezas de cada uno y garantizar el funcionamiento óptimo de la metodología propuesta. En concreto, se emplean los siguientes algoritmos de ML para la detección de fallos en tiempo real: LR, NB, SVM, kNN y RF.

Para evaluar la eficacia de la metodología propuesta, se han entrenado los algoritmos utilizando una base de datos compuesta por redes comerciales LTE y LTE-A. Los resultados indican que ciertos algoritmos funcionan mejor con casos de overshoot y otros con situaciones de undershoot, lo que confirma que la metodología propuesta combina la capacidad de detectar ambas situaciones simultáneamente.

En conclusión, este estudio sienta las bases para el desarrollo de metodologías automatizadas que aborden estos retos de cobertura. El trabajo también proporciona información valiosa a los operadores en términos de gestión y planificación de la red.

A.4.5 Reinforcement learning methodology for coverage failures in 5G mmWave beamforming scenarios

Este trabajo constituye el capítulo 6 de esta tesis, en el que se aborda todo lo relacionado con *self-healing* y sus funcionalidades. En particular, se propone una metodología basada en RL para solucionar problemas de cobertura en redes de nueva generación.

De acuerdo con el Objetivo 6, la metodología propuesta implica el análisis de técnicas de ML novedosas, como el *reinforcement learning*, con el fin de compensar los fallos de red. La metodología emplea un algoritmo de política basado en gradientes, llamado PPO [112]. Este algoritmo es una variante de RL ampliamente utilizado. El enfoque propuesto amplía su radio de acción dada su aplicación a escenarios que implican tecnologías novedosas, como *beamforming* y el uso de frecuencias milimétricas. La metodología está diseñada para evaluar los KPIs y reconfigurar los *beamwidths* y los azimuths de los haces que no se han visto afectados, con el fin de compensar el fallo en los otros *beams*. Este enfoque permite mantener el servicio y la cobertura de forma rápida y eficaz.

La metodología se ha probado utilizando el simulador de red a nivel de sistema desarrollado en el grupo de investigación. En este simulador se ha configurado un escenario que incorpora *beamforming* y frecuencias milimétricas. El escenario está diseñado para simular fallos en *beams* específicos. Los resultados demuestran que la metodología propuesta es capaz de compensar estos fallos de forma eficiente y rápida.

Los resultados concluyen que la metodología es bastante flexible y se puede adaptar a diferentes escenarios y redes, incluso a arquitecturas de red diversas y emergentes como O-RAN. Cabe destacar que el enfoque propuesto permite resolver problemas sin necesidad de grandes despliegues que suelen ser costosos tanto económicamente como en tiempo invertido.

A.5 Conclusiones

El objetivo de esta tesis doctoral es examinar la capacidad de las tecnologías ML y AI en la creación de métodos de *self-healing* que aborden los problemas y fallos emergentes en las redes de última generación. Para ello, se ha identificado un conjunto de desafíos, definiendo los objetivos que pueden resolver estos retos. Los desafíos identificados se abordan mediante un conjunto de seis objetivos, que se distribuyen a lo largo de las distintas secciones de esta tesis.

Los objetivos 1, 2 y 3 se centran en el análisis de grandes volúmenes de datos recopilados en una red móvil. En particular, se enfatiza en el análisis automático de las redes, que permite identificar patrones de comportamiento dentro de una red móvil. A partir de este análisis, se identifica la monitorización del rendimiento como un elemento que permite sentar las bases de enfoques de *self-optimization* y *self-healing*.

En segundo lugar, los objetivos 4 y 5 de esta tesis están relacionados con la detección de anomalías en redes celulares. Para ello, esta sección aborda dos enfoques específico siendo el primero de ellos el que se centra en la utilización de conocimientos de ingenieros especializados para optimizar el desempeño de los algoritmos de detección de anomalías existentes. Por otro lado, se plantean como objetivo el análisis de los problemas de cobertura en las redes de nueva generación y el desarrollo de técnicas para detectarlos.

Por último, el objetivo 6 de esta tesis corresponde al apartado de *self-healing*, donde se investigan algoritmos innovadores de ML y RL para compensar fallos en redes de nueva generación.

En relación con estos objetivos, las aportaciones de esta tesis se resumen en los siguientes puntos:

- **Objetivo 1. Analizar y extraer información valiosa a partir de las enormes cantidades de datos recogidos en las redes móviles de nueva generación.**
  - En relación con el objetivo planteado, se analizaron las diversas medidas disponibles sobre la gran cantidad de datos generados por las redes celulares. Para ello, se ha llevado a cabo un análisis estadístico exhaustivo que ha incluido la construcción de matrices de correlaciones y el análisis de las distribuciones de los datos, entre otros métodos. Este enfoque analítico se emprendió con el propósito de comprender las características de las distintas partes y aspectos de las redes celulares (tráfico, calidad, parte radio, etc.).
  - Para seleccionar los indicadores más adecuados para cada escenario y caso de uso, se ha estudiado en profundidad cada caso específico, garantizando así que se dispusiera de la mayor cantidad posible de información valiosa para la automatización de funciones.
  - En última instancia, los KPIs proporcionados por la red pueden no ser adecuados o no reflejar con exactitud un aspecto o rendimiento concreto de la red. Para abordar esta posible limitación, se ha realizado un análisis exhaustivo de los CM y los PM pertinentes para identificar los

indicadores más relevantes desde el punto de vista del escenario o caso de uso específico. Este análisis ha dado lugar al desarrollo de nuevos indicadores, diseñados para proporcionar información más significativa para el escenario o caso de uso específico.

- **Objetivo 2. Caracterizar los diferentes patrones de comportamiento existentes en una red móvil mediante técnicas automatizadas.**
  - Para abordar este objetivo, se ha desarrollado un método para identificar los patrones de comportamiento inherentes a las redes celulares. Concretamente, la metodología se fundamenta en el uso de un algoritmo de aprendizaje no supervisado (es decir, SOM), que analiza los KPIs asociados a varios aspectos de la red e identifica las celdas con un patrón de comportamiento similar. Este enfoque facilita la utilización de datos no etiquetados, que constituyen la mayoría de los datos recogidos en las redes móviles, e implementa un clasificador (basado en Random Forest) que asigna una etiqueta a las nuevas celdas basándose en los conocimientos adquiridos en la fase inicial de este enfoque.
  - Para la evaluación de este enfoque, se ha utilizado una base de datos de diferentes redes LTE comerciales, que ha servido para entrenar la metdología propuesta. Los resultados obtenidos evidencian un rendimiento prometedor, lo que confiere a la herramienta un potencial significativo para los operadores de redes móviles, permitiéndoles comprender los diversos patrones de comportamiento que se manifiestan en sus redes. Además, se ha observado que esta herramienta podría servir como fundamento para sistemas de monitorización, debido a su capacidad para caracterizar las redes y a la posibilidad de asignar nuevas etiquetas una vez entrenado el modelo.
- **Objetivo 3. Proporcionar una metodología de monitorización autónoma capaz de detectar cambios de comportamiento en elementos de red.**
  - La monitorización de las redes móviles constituye un desafío importante debido a la gran cantidad de datos que se generan en ellas. En consecuencia, resulta esencial identificar los indicadores que mejor reflejan el rendimiento de una red. En este sentido, se han desarrollado

un par de técnicas destinadas a lograr este objetivo. Sobre la base del clasificador implementado para abordar el objetivo anterior, se implementa una metodología para detectar cambios en el comportamiento de los distintos patrones de comportamiento. Esta metodología se centra en la supervisión continua de los KPIs que reporta una red móvil. Su diseño tiene como finalidad notificar al operador si la etiqueta asignada a una celda difiere de la etiqueta previamente asignada durante un intervalo de tiempo concreto.

– El segundo enfoque se centra en la implementación de una metodología de monitorización, que tiene como objetivo la detección de desviaciones en los KPIs dentro de una red móvil. Esta metodología ha sido implementada con el propósito de analizar el comportamiento reciente de los KPIs en conjunto con los datos actuales y notificar en caso de desviación. Además, la configuración de parámetros de entrada específicos facilita la evaluación del impacto de las mencionadas desviaciones en el rendimiento de la red. Este enfoque se ha concebido para ser adaptable a las diversas tendencias que emergen en las redes móviles.

– La eficacia de ambos enfoques ha sido demostrada empíricamente mediante el análisis de datos recopilados de una red LTE comercial. Los resultados obtenidos indican que ambos métodos pueden lograr una eficacia satisfactoria a la hora de monitorizar la red y detectar cambios o desviaciones de comportamiento. Si bien la primera propuesta se muestra más apropiada para análisis a largo plazo (es decir, semanas o meses), la segunda puede aplicarse en tiempo real para tareas más específicas por ejemplo, monitorizar y analizar el impacto potencial de las desviaciones causadas por un cambio de configuración. Es relevante destacar la capacidad de adaptación y escalabilidad de estas metodologías a diversas tecnologías de red móvil, lo que permite aprovechar las mejoras tecnológicas para acceder a más información relevante para la toma de decisiones.

- **Objetivo 4. Permitir que los algoritmos ML/AI no sólo aprendan de los datos generados por las redes móviles, sino que también integren los conocimientos de ingenieros expertos en gestión de redes.**

- Tanto la automatización de tareas que necesitan mucho tiempo, como la detección de anomalías, es un tema que suscita un gran interés desde la perspectiva de los MNOs. Normalmente, los MNOs cuentan con el respaldo de un extenso equipo de ingenieros expertos, quienes poseen un amplio conocimiento en el ámbito de la gestión de redes. Con frecuencia, estos conocimientos incluyen perspectivas que pueden resultar difíciles de captar por los algoritmos. Para abordar este desafío, se ha formulado un enfoque basado en el concepto de *active learning*. Este enfoque posibilita la integración fluida de las observaciones del ingeniero experto en el proceso de detección de anomalías, lo que mejora el rendimiento del algoritmo en la detección de fallos. Esta estrategia ha logrado alcanzar dos objetivos principales: reducir el tiempo que necesita un experto para detectar anomalías y mejorar la eficacia y la fiabilidad del algoritmo de detección de anomalías.
- El enfoque propuesto ha sido evaluado mediante el análisis de un conjunto de datos procedente de una red comercial LTE con anomalías. Los resultados de este estudio han demostrado la importancia de incorporar la opinión de un ingeniero experto para mejorar el rendimiento de los algoritmos de detección de anomalías. Además, cabe destacar que el tiempo necesario para que un experto detecte anomalías se reduce considerablemente en comparación con la detección totalmente manual, consiguiendo los mismos resultados o incluso mejores. Además, los resultados indican que el rendimiento de los algoritmos puede mejorarse en pocos días con respecto a la eficacia alcanzada sin aplicar el enfoque propuesto.

• **Objetivo 5. Explorar nuevas técnicas de detección de anomalías para hacer frente a fallos novedosos que puedan surgir en los escenarios y casos de uso de las nuevas generaciones de redes móviles.**

  - Los problemas de cobertura han sido históricamente un problema fundamental en las redes móviles. En respuesta a la continua evolución de las tecnologías, las redes móviles han experimentado una transición hacia entornos más densos, caracterizados por una alta densidad de usuarios y estaciones base. En este contexto, se ha planteado una metodología destinada a la detección en tiempo real de problemas de cobertura, tales como overshoot y undershoot. La metodología propuesta está diseñada para garantizar una representación exhaustiva de los fallos, examinando primero los efectos de estas situaciones en distintos aspectos de la red y reflejándolos en las mediciones. El enfoque propuesto implementa una serie de algoritmos de ML, aprovechando las fortalezas inherentes a cada uno de ellos para generar un resultado único.

  – Para evaluar este método, se ha utilizado una base de datos de redes comerciales LTE y LTE-A que contiene datos de estaciones base que operan en diferentes bandas de frecuencia (de 800 MHz a 2600 MHz). Los resultados de los experimentos han demostrado la eficacia del enfoque propuesto para identificar anomalías y problemas de cobertura en redes móviles. El enfoque proporciona información valiosa para abordar las situaciones de overshoot y undershoot detectadas en un posterior despliegue.

- **Objetivo 6. Investigar técnicas novedosas de ML/AI que proporcionen un marco para sugerir posibles acciones a realizar en la red para solventar los problemas detectados.**

  – La llegada de las redes móviles de nueva generación trae consigo problemas de funcionamiento asociados a las nuevas capacidades de estas redes. No obstante, dichas capacidades también ofrecen oportunidades para compensar con éxito dichos fallos. Además, es pertinente mencionar que las técnicas de ML están en constante evolución, lo que abre un amplio espectro de posibilidades. En este contexto, la presente tesis ha elaborado un modelo para la compensación de fallos de cobertura en redes 5G NR utilizando capacidades de *beamforming*. El enfoque propuesto emplea un algoritmo de RL para determinar la configuración óptima de los *beams* no afectados con el fin de compensar los fallos de otros *beams* dentro de la misma celda.

  – Con el fin de evaluar la eficacia de la metodología propuesta, se ha utilizado un simulador a nivel de sistema LTE disponible en el grupo de investigación, que ha sido mejorado para incluir capacidades NR (es decir, beamforming y mmWave) durante el desarrollo de esta tesis. Concretamente, se ha simulado un escenario de celdas mmWave con un conjunto de *beams*, incluyendo fallos aleatorios en algunos de los *beams*. Se han considerado dos escenarios: en el primero, los haces pueden verse parcialmente afectados, mientras que en el segundo los *beams* se ven completamente dañados. Los resultados obtenidos han demostrado que el algoritmo propuesto tiene la capacidad de restablecer con rapidez los niveles de servicio a los umbrales habituales de la celda, proporcionando un rendimiento similar solo con los *beams* no afectados.

A.6 Actividades de investigación

A.6.1 Difusión de resultados

Los resultados de la presente tesis han sido divulgados mediante diversas publicaciones en revistas y congresos científicos de prestigio, como se ha mencionado en la introducción del manuscrito. Sin embargo, las actividades de difusión no se limitaron a las publicaciones científicas, sino que también incluyeron demostraciones y asistencia a diversos eventos del ámbito tecnológico. Estos eventos propiciaron un valioso intercambio de conocimientos y experiencias con la comunidad académica y profesional.

- Mobile Week Málaga 2021, organizado por el Palacio de Ferias y Congresos de Málaga, diciembre de 2021.
- 13ª European Meeting on Science, Technology, and Innovation, organizado por Transfiere (Foro Europeo para la Ciencia, Tecnología e Innovación), en Málaga (España), marzo de 2024.
- 14º European Meeting on Science, Technology, and Innovation, organizado por Transfiere (Foro Europeo para la Ciencia, Tecnología e Innovación), en Málaga (España), marzo de 2025.

A.6.2 Proyectos relacionados

El trabajo desarrollado en esta tesis ha contribuido a los siguientes proyectos:

- **NEREA**: Network Strategy And Evolution Advisor, financiado por el Ministerio de Economía y Competitividad y el Fondo Europeo de Desarrollo

Regional (FEDER), número de proyecto: RTC-2017-6661-7.

- **DAMA-5G**: Detección de Anomalías Multivariable Asistida, funded by Junta de Andalucía and ERDF, project number: UMA-CEIATECH-12.
- **PENTA**: Provisión de servicios PPDR a través de Nuevas Tecnologías de Acceso radio, financiado por la Junta de Andalucía y el FEDER, número de proyecto: PY18-4647.
- **MAORI**: Massive AI for the OpenRadIo b5G/6G network. Número de proyecto TSI-063000-2021-53, recibiendo fondos del Ministerio de Asuntos Económicos y Transformación Digital y la Unión Europea - NextGenerationEU en el marco de "Recuperación, Transformación, y Resiliciencia".

Además, el autor ha contribuido al trabajo realizado en los siguientes proyectos:

- **ESCUDO**: Desarrollo de casos de uso para el diseño, optimización y dimensionado de redes móviles, en colaboración con Ericsson España.
- **OPTIRAN**: Optimización Multipropósito de la Red de Acceso Radio 5G, financiado por la Junta de Andalucía, FEDER, número de proyecto: UMA18-FEDERJA-174.

A.6.3 Estancias de investigación

Esta tesis incluyó una estancia como investigador visitante en el departamento de Comunicaciones inalámbricas de la Universidad de Aalborg, entre febrero y julio de 2023. Esta estancia fue supervisada por el profesor asociado de la institución receptora Troels B. Sønrensen, y por el CEO de 2Operate, Søren Søndergaard.

Appendix B

Enhancements and modifications to the simulation tool

Content

This appendix delineates the enhancements introduced in the mobile communication simulation tool utilized throughout this research. The initial section provides a comprehensive overview of the simulator, subsequently accompanied by an exposition of the newly integrated functionalities.

B.1 Simulation tool description

The system-level simulator implemented in MatLab [56] serves as the baseline tool utilized throughout this thesis. A summary of the main functionalities and characteristics of the tool is provided below:

- It is a system-level simulator that represents a network with LTE as the access radio technology.
- The simulator encompasses the primary functionalities that are characteristic of LTE at the link and network levels. It has been determined that certain functions are subject to dynamic adaptation, including link adaptation, admission control, and resource planning.
- The simulator is a versatile instrument that can be configured to accommodate a variety of scenarios and situations. These parameters include the azimuth and tilt of the antennas, the distribution and mobility of the users, and the traffic patterns.

B.1.1 Simulator operating cycle

The operating cycle of the simulator initiates with the configuration of the scenario and parameters for the simulation. During the course of a simulation, the functions that execute network management and the functions that emulate different network elements are simulated. Upon the culmination of the simulation, a set of statistics and results are generated as output, thereby facilitating the analysis of the behavior of the network for the configured situation. As illustrated in Figure B.1, the block diagram depicts the primary functions incorporated within the simulator. A comprehensive description of these functions is provided below:

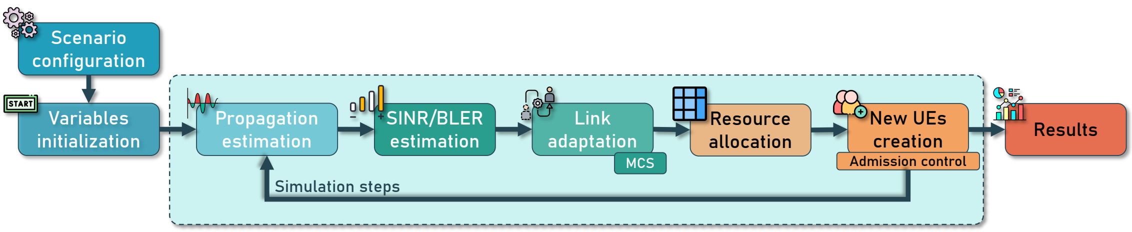


Figure B.1: Simulation tool flowchart

- **Scenario configuration.** It defines the scenario that will be simulated. It is imperative to configure certain parameters, including those pertaining to antenna characteristics, bandwidth, and traffic patterns.

- **Variables initialization.** The initialization process involves the establishment of various variables that delineate the scenario, in addition to the determination of the characteristics that define the components of the network.

Subsequent to the initialization of the variables, the simulation loop is initiated. The duration of this loop is specified as n steps, determined through previous configuration. The temporal resolution of each step is 100 ms. At the initiation of each step, the simulator performs a series of verifications. These include the determination of the number of active users in the network, the identification of the type of traffic, and the assessment of the status of the connection.

- **Propagation estimation.** This function is responsible for calculating the propagation losses experienced by each active user, incorporating the slow fading component. It is therefore possible to estimate the signal strength and quality received by each user based on these losses.

- **Signal to Interference plus Noise Ratio (SINR) and Block Error Rate (BLER) estimation.** It calculates the level of SINR perceived by each user, taking into account the interferences. Furthermore, the estimation of BLER and throughput can be derived from estimated SINR values.

- **Link adaptation.** Utilizing the SINR estimation calculated in the preceding functions, the CQI can be ascertained for each user, thereby enabling the execution of AMC (Adaptative Modulation and Coding) to determine the optimal Modulation and Coding Scheme (MCS) for each user.

- **Resource allocation.** At this stage, various algorithms are implemented to allocate resources dynamically to different users. The simulator is capable of simulating different algorithms, including round robin or proportional fair.

- **New UEs creation.** Prior to the finalization of the simulation step, new connections are generated, and admission and congestion control algorithms are applied.

- **Results.** Subsequent to the execution of all simulation steps, statistical calculations are performed based on the performance indicators of the network.

B.2 Enhancements and modifications implemented

This section provides a detailed exposition of the modifications introduced to evolve the LTE-based simulator towards supporting 5G functionalities, building on the information provided in Section . These modifications were necessary to ensure that the simulation environment was aligned with the fundamental aspects of 5G technology, thereby facilitating more precise analysis and validation of the mechanisms explored in this thesis.

B.2.1 Deployment of 5G base stations

The simulator has been enhanced to accommodate the deployment of 5G base stations, specifically gNBs. This enhancement allows for the simulation of various deployment scenarios, including the integration of 5G base stations with existing LTE infrastructure. The simulator is capable of simulating both 5G and LTE cells, enabling a comprehensive analysis of their coexistence and interaction.

To adequately deployment of 5G base stations, the simulator has been modified to incorporate two main functionalities: new patterns of radiation for the antennas and the beamforming capabilities of the antennas. In accordance with the 3GPP Technical Specification 38.901 [14], the radiation pattern model of a single antenna element was updated in the simulator. The modifications entailed the incorporation of standardized equations for the azimuth and elevation radiation patterns (see Table 7.3-1 of the aforementioned standard), thereby facilitating a more precise depiction of antenna behavior in 5G scenarios. These updates ensure compliance with 3GPP-recommended propagation modelling practices and improve the realism of the simulated radio environment.

The simulator was extended to support beamforming capabilities by enabling the definition of multiple antenna elements within the same site. This enhancement facilitates the modeling of directional transmissions, a characteristic of 5G systems. Additionally, the implementation incorporates a directional gain component that dynamically adjusts based on the steering angle of the beam, thereby capturing the effects of angular alignment between the transmitter and receiver. The estimation of the directivity gain provided by beamforming entails a comparison of antenna radiation patterns with different horizontal beamwidths, representing scenarios with and without beamforming. The narrower beamwidth in the beamforming state results in a theoretical increase in antenna directivity. However, in practical scenarios, users are not always perfectly aligned with the main lobe of the directed beam. To model this misalignment, the simulation includes an angular offset. The resulting gain is then adjusted linearly based on the reduction in antenna gain caused by the angular deviation of the user from the beam center. This computation is reflected in Equations B.1. These modifications are intended to provide a more realistic representation of antenna array behavior and spatial selectivity in beamformed transmissions.

$$\begin{aligned}
\text{Gain}_{\text{Max}} &= \text{Directivity}_{\text{Max Beam}} - \text{Directivity}_{\text{Omnidirectional}} \\
\text{Gain}_{\text{Offset Direction}} &= \text{Directivity}_{\text{Max Beam}} - \text{Directivity}_{\text{Offset Beam}} \\
\text{Gain}_{\text{Beam}} &= \text{Gain}_{\text{Max}} - \text{Gain}_{\text{Error Direction}}
\end{aligned} \tag{B.1}$$

where $Gain_{\text{Max}}$ is defined as the maximum gain that a beam can achieve when measured in relation to an omnidirectional antenna. $Gain_{\text{Offset Direction}}$ denotes the gain when taking into account a deviation between the direction of maximum gain and the actual position of the user. The gain of the beam is represented by $Gain_{\text{Beam}}$ and is the difference between the two previous beams.

B.2.2 Integration of 5G pathloss models

One of the fundamental challenges in adapting the LTE-based simulator to 5G requirements is the necessity of updating the propagation loss models to reflect the expanded frequency range available in 5G networks. In contrast to LTE, which predominantly operates below 6 GHz, 5G introduces support for considerably higher frequencies, encompassing millimeter-wave bands. These higher frequencies manifest distinct propagation characteristics, including augmented pathloss, susceptibility to obstruction, and constrained diffraction. Consequently, the existing LTE propagation models have been updated in accordance with 3GPP standards.

To support a wide range of frequencies in the simulator, two standardized deployment scenarios have been implemented: UMa and UMi. The two scenarios are delineated in the 3GPP Technical Specification 38.901 [14], which aims to model realistic urban environments with different base station placements and user distributions. These models facilitate the simulation of radio propagation characteristics across a broad spectrum, ranging from 0.5 GHz to 100 GHz, rendering them suitable for both sub-6 GHz and millimeter-wave frequency bands utilized in 5G networks.

According to the aforementioned document, the UMa propagation model has been implemented. This environment typifies a densely populated urban area, wherein base stations are customarily installed on rooftops or elevated structures that surpass the rooftop level. This scenario is distinguished by relatively large inter-site distances and significant building clutter, which result in complex propagation conditions. The implementation encompasses both Line of Sight (LOS) and Non-Line of Sight (NLOS) conditions, incorporating parameters such as pathloss, and shadow fading, which vary with frequency, height, and distance. The configuration of this scenario has been designated for FR1, encompassing frequencies below 6 GHz. The equations implemented in the simulator for this pathloss are listed in Table B.1. The aforementioned equations have been demonstrated to be applicable in scenarios where the base station is situated at a height of 25 meters (h_{BS}) and the UE is positioned at an elevation ranging from 1.5 to 22.5 meters (h_{UT}).

In accordance with the methodology employed for UMa, the UMi has been incorporated into the simulator. The UMi is designed to represent dense urban areas where base stations are deployed below rooftop level, typically mounted on building walls, street furniture, or small towers. This low-height deployment results in shorter communication distances and distinct propagation characteristics compared to macrocell scenarios. In a manner analogous to the UMa model, the LOS and NLOS scenarios are taken into account in the UMi model. In this particular instance, UMi has been incorporated for the utilization of FR2 use cases, thereby facilitating the implementation of mmWave frequencies scenarios. A list of the equations implemented in the simulator for this pathloss can be found in Table B.2. In contrast with the pathloss experienced in UMa, the height of the base station in UMi pathloss is lower (10 meters). Meanwhile, the height of the UE can be situated within the same range as UMa.

Table B.1: Pathloss model for UMa scenario (Table 7.4.1-1 [14])

LOS/NLOS	Pathloss (dB)	Shadow fading (dB)
LOS	$PL_{\text{UMa-LOS}} = \begin{cases} PL_1 & 10\,\text{m} \leq d_{2D} \leq d'_{BP} \\ PL_2 & d'_{BP} \leq d_{2D} \leq 5\,\text{km} \end{cases}$ $PL_1 = 28.0 + 22\log_{10}(d_{3D}) + 20\log_{10}(f_c)$ $PL_2 = 28.0 + 40\log_{10}(d_{3D}) + 20\log_{10}(f_c)$ - $9\log_{10}((d'_{BP})^2 + (h_{BS} - h_{UT})^2)$	$\sigma_{SF} = 4$
NLOS	$PL_{\text{UMa-NLOS}} = \max(PL_{\text{UMa-LOS}}, PL'_{\text{UMa-NLOS}})$ for $10\text{m} \leq d_{2D} \leq 5km$ $PL'_{\text{UMa-NLOS}} = 13.54 + 39.08\log_{10}(d_{3D})$ + $20\log_{10}(f_c) - 0.6(h_{UT} - 1.5)$	$\sigma_{SF} = 6$

Table B.2: Pathloss model for UMi scenario (Table 7.4.1-1 [14])

LOS/NLOS	Pathloss (dB)	Shadow fading (dB)
LOS	$PL_{\text{UMi-LOS}} = \begin{cases} PL_1 & 10\,\text{m} \leq d_{2D} \leq d'_{BP} \\ PL_2 & d'_{BP} \leq d_{2D} \leq 5\,\text{km} \end{cases}$ $PL_1 = 32.4 + 21\log_{10}(d_{3D}) + 20\log_{10}(f_c)$ $PL_2 = 32.4 + 40\log_{10}(d_{3D}) + 20\log_{10}(f_c)$ - $9.5\log_{10}((d'_{BP})^2 + (h_{BS} - h_{UT})^2)$	$\sigma_{SF} = 4$
NLOS	$PL_{\text{UMi-NLOS}} = max(PL_{\text{UMi-LOS}}, PL'_{\text{UMi-NLOS}})$ for $10\text{m} \leq d_{2D} \leq 5km$ $PL'_{\text{UMi-NLOS}} = 22.4 + 35.3\log_{10}(d_{3D})$ + $21.3\log_{10}(f_c) - 0.3(h_{UT} - 1.5)$	$\sigma_{SF} = 7.82$

B.2.3 SINR to BLER estimation for 5G

In order to enhance the precision of throughput estimation in the simulator, the SINR-to-BLER mapping curves have been recalibrated. These curves are instrumental in translating signal quality conditions into link-level performance indicators, such as throughput. The new mappings were implemented based on the 3GPP standard [113], which defines the physical layer procedures for 5G NR systems. As demonstrated in Figure B.2, each curve corresponds to a distinct CQI level, thereby reflecting the relationship between SINR and BLER. This ensures that realistic performance modeling can be achieved across a wide range of radio conditions.

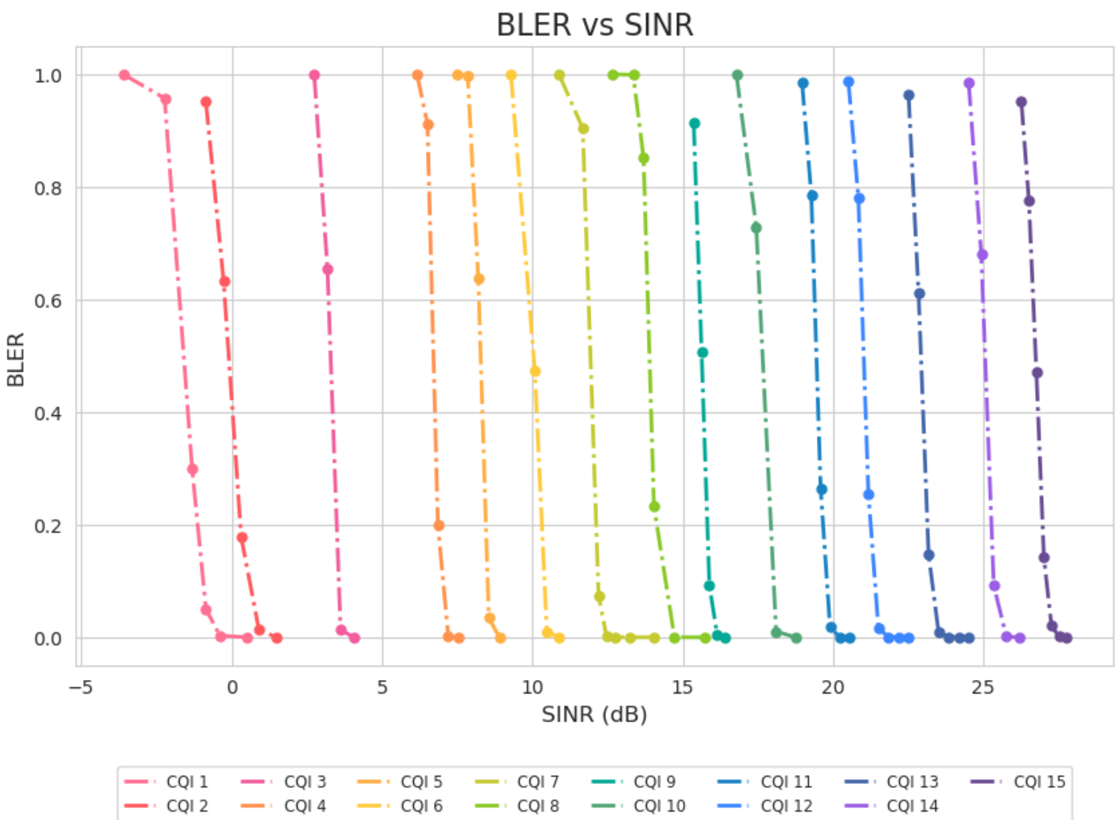


Figure B.2: BLER and SINR estimation for 5G CQI levels

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