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Machine Learning for Spectrum Sharing: A Survey

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Contents

Machine Learning for Spectrum Sharing: A Survey

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ABSTRACT

The 5th generation (5G) of wireless systems is being deployed with the aim to provide many sets of wireless communication services, such as low data rates for a massive amount of devices, broadband, low latency, and industrial wireless access. Such an aim is even more complex in the next generation wireless systems (6G) where wireless connectivity is expected to serve any connected intelligent unit, such as software robots and humans interacting in the metaverse, autonomous vehicles, drones, trains, or smart sensors monitoring cities, buildings, and the environment. Because of the wireless devices will be orders of magnitude denser than in 5G cellular systems, and because of their complex quality of service requirements, the access to the wireless spectrum

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will have to be appropriately shared to avoid congestion, poor quality of service, or unsatisfactory communication delays. Spectrum sharing methods have been the objective of intense study through model-based approaches, such as optimization or game theories. However, these methods may fail when facing the complexity of the communication environments in 5G, 6G, and beyond. Recently, there has been significant interest in the application and development of data-driven methods, namely machine learning methods, to handle the complex operation of spectrum sharing. In this survey, we provide a complete overview of the state-of-the-art of machine learning for spectrum sharing. First, we map the most prominent methods that we encounter in spectrum sharing. Then, we show how these machine learning methods are applied to the numerous dimensions and sub-problems of spectrum sharing, such as spectrum sensing, spectrum allocation, spectrum access, and spectrum handoff. We also highlight several open questions and future trends.

1

Introduction

Due to the rapidly increasing number of mobile data subscriptions and the continuous increase in the average data volume per mobile broadband subscription, the demand for wireless services and applications has been experiencing a large growth in recent years. Users of enhanced mobile broadband (eMBB), Internet of Things (IoT), smart factory, remote health care, connected unmanned aerial vehicle (UAV) (drone), urban air mobility applications, intelligent transportation, and smart home services demand high functional safety and rely on the exchange of large amount of data with low latency and often with high reliability. To meet these requirements, 5$^{\text{th}}$ generation (5G) systems are deployed to support 10-100 times more connected devices, transmit 100 times more data, and support 1000 times the capacity compared with the capabilities of 4$^{\text{th}}$ Generation (4G) systems [193]. For 6$^{\text{th}}$ generation (6G) systems, meeting new requirements on data volumes, coverage and capacity, as well as on the massive number of connected devices means that spectrum management will be even more challenging and important [7, 191].

Recognizing the increasing demands for wireless services, and thereby for spectrum resources in cellular and local area networks, several previous works have suggested that the static assignment of spectrum to mobile network operators (MNOs) and/or specific wireless technologies confine the utilization of spectrum resources. The key observation of these works is that a certain geographical area, such as a single cell of a cellular network, may occasionally be populated by users – including connected vehicles, drones or IoT devices – belonging to different MNOs [231]. In such scenarios, spectrum sharing among multiple players is a flexible and efficient paradigm, which enables to better utilize the spectrum, avoid spectrum shortage in sub millimeter-wave (mmWave) bands, and enhance the return-of-investment in spectrum resources by MNOs [198], [263]. Following these early works on spectrum sharing, several technical and economical aspects of spectrum sharing have been discussed in the literature [53, 57, 60, 64, 71]. One of the practical results of these ideas is the protocols and mechanisms standardized by the 3GPP and implemented by MNOs for sharing spectrum between 4G and 5G networks [28, 198].

Massive machine type communications (MTC), eMBB enablers and ultra-reliable low-latency communication (URLLC) are technology components that aim to fulfill the aforementioned 5G and emerging 6G requirements [204, 205]. The MTC and a part of eMBB implementation should be deployed in sub-6 GHz band due to cost reduction, since sub-6 GHz bands have favourable propagation characteristics [86]. However, this spectrum is heavily used by other wireless systems, including cellular and local area wireless networks using licensed and unlicensed spectrum bands.

To accommodate the emerging 5G and the upcoming 6G services an appealing alternative is to utilize mmWave frequencies, which operate between 10 and 300 GHz. Unfortunately, even this spectrum range has availability problems, due to other service requirements, which are already allocated in these frequencies [231]. Due to the pressing demand for efficient ways to allocate and access spectrum, the concept of dynamic spectrum sharing (DSS) has attracted significant research attention [76, 123, 228, 294]. Currently, MNOs have to refarm their available cellular frequency bands either to enable exclusive 5G operations or to support shared operations of 4G and 5G infrastructures in the same or overlapping frequency bands [4, 37]. As a natural step beyond currently available spectrum sharing solutions designed for 4G and 5G systems, the more general concept of DSS facilitates the coexistence of cellular and other technologies such as WiFi, UAV networks and cognitive radio networks (CRNs), as illustrated in Figure 1.1. Indeed, DSS will enable to share the same spectrum resources across multiple radio access technologies allowing to gradually deploy new services that are best served by different access technologies.

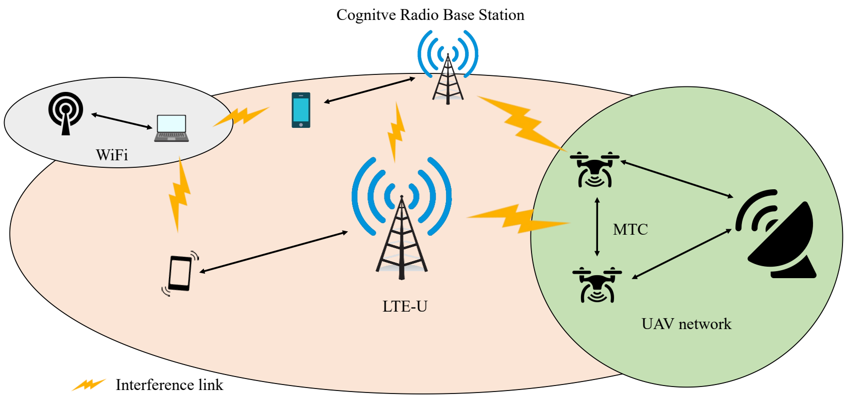

Figure 1.1: Coexistence of different technologies in a spectrum sharing scenario.

To serve a growing number of users and applications by spectrum sharing between 4G and 5G systems – while maintaining high spectrum utilization and meeting capital and operational expenditure constraints – comes at the cost of considerable complexity. While operating 4G and 5G systems in dedicated bands allows use of a wide range of self-optimizing network (SON) functionalities, introducing DSS between 4G and 5G systems increases the number of parameters to tune considerably. However, this increasing complexity makes it difficult to continue using the current resource allocation and optimization techniques. To cope with such complexity, the 3GPP and the research community have started to explore the use of machine learning (ML) and artificial inteligence (AI) for spectrum sharing.

With an ML-based SON, the network self-adjusts and fine-tunes a range of parameters according to the prevailing radio and traffic conditions, alleviating the burden of manual optimization by the MNOs.

While SON algorithms are not standardized in 3GPP, SON implementations may be assisted by various ML algorithms, including those employing supervised learning, unsupervised learning and reinforcement learning (RL)-based schemes [30].

1.1 Spectrum Sharing State-of-the-Art Surveys

Spectrum sharing can be performed either in a centralized or distributed manner. The former is characterized by a central unity, often called spectrum server, which is responsible for optimizing the spectrum usage among all users. In the latter, all network users participate in the spectrum optimization process. It is a more practical solution for high spectral demand since the computational complexity at the central unity increases with the number of spectrum requests [152].

In a spectrum sharing scenario, the coexistence of different wireless systems are supported by four mechanisms:

1. *Spectrum sensing*: in this mechanism, signal features are extracted from the environment to determine the radio frequency occupancy condition, i.e., which channels are in use and which ones are free.

2. *Spectrum allocation*: receives the channel characterization from sensing mechanism or directly from the environment in case of frequency planing. The main goal is to assign users on available channels for data transmission.

3. *Spectrum access*: the user assignment is used in this stage to provide channel access for allocated users in order to guarantee the data transmission.

4. *Spectrum handoff*: responsible for user channel switching whenever necessary. It sends a request to the spectrum allocation mechanism to check and to assign a new channel to the user so it can continue to access the medium sending its data.

This relationship between the four spectrum sharing mechanisms is shown in Figure 1.2.

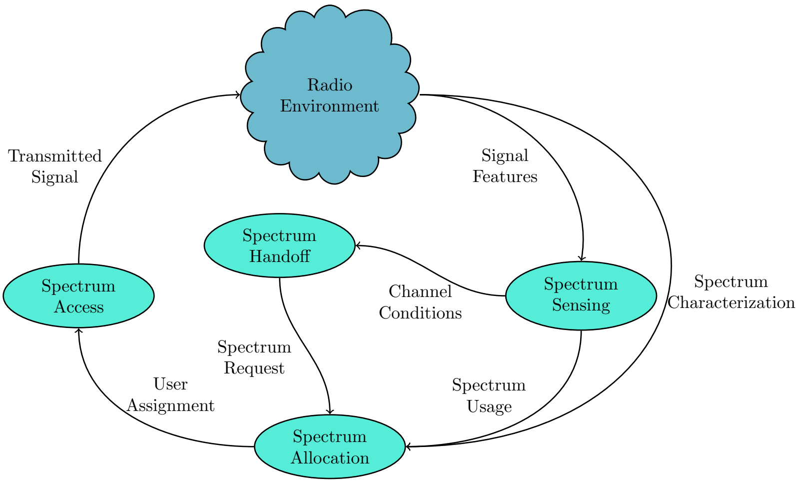

Figure 1.2: Relationship among spectrum sharing mechanisms.

The use of ML solutions as a tool for spectrum sharing has been investigated by recent surveys [5, 13, 48, 59, 66, 94, 104, 118, 169, 206, 222, 245, 249, 269, 275, 309, 310].

Agrawal *et al.* [5], Arjoune *et al.* [13], Fernando *et al.* [66], and Syed *et al.* [245] cover the state-of-the-art of spectrum sensing for cognitive radio (CR). The main focus of [13] is the classification and review of different sensing techniques using traditional and ML schemes, while Syed *et al.* [245] provide a deep learning (DL) detailed survey for spectrum sensing. Agrawal *et al.* [5] discuss recent spectrum sensing and dynamic spectrum access (DSA) schemes and topics related to CR including ML solutions. The authors highlight the efficiency, limitations and implementation challenges of both narrowband and wideband sensing approaches. On the other hand, Fernando *et al.* [66] present spectrum sensing in IoT context, giving a brief discussion of recent papers in the area. These works also discuss the open issues related to spectrum sensing and the way how CR can be used to solve spectrum sharing problems in next generation networks. However, these references do not discuss ML issues in detail. To bridge this research gap, in this survey we provide an overview of spectrum sensing ML works that address narrowband and wideband spectrum sharing schemes, and present a mathematical formulation of the ML-assisted spectrum sensing problem.

Wang *et al.* [275] present a survey on spectrum allocation using RL algorithms for CRNs. The authors analyze the advantages and disadvantages of each RL algorithm by dividing them into two groups: minor and major implementation improvements. They also address challenges and open issues related to spectrum allocation for CRNs and RL algorithms. However, the usage of ML methods for other spectrum sharing networks such as long-term evolution on unlicensed spectrum (LTE-U), UAV networks and non-orthogonal multiple access (NOMA) systems, are not investigated in that paper.

Zhang *et al.* [310] present a survey on spectrum sharing techniques that address the basic principles and state-of-the-art for CR, device-to-device (D2D), in-band full-duplex (IBFD), NOMA and LTE-U technologies. The authors also discuss the challenges related to deploying each of these techniques, as well as how they can be integrated into 5G networks. Spectrum access is also the focus for Zhang *et al.* [309]. It presents the basic principles and spectrum sharing solutions for the most popular IoT technologies applicable in both licensed and unlicensed spectrum. That paper also identifies future challenges of IoT systems and suggests research directions for next generation technologies. However, none of these references address ML solutions for spectrum access. Differently from both works, in this survey we describe the DSA problem and discuss ML solutions by surveying the most relevant recent works in this area.

Tehrani *et al.* [249] study various scenarios on licensed cellular networks with different topologies in order to demonstrate the importance of spectrum sharing for future networks. That paper provides an analysis of spectrum sharing involving MNOs using licensed shared access for wide area broadband services. The main concepts of spectrum sharing are explained, and open issues for future research are suggested. However, such a paper does not discuss the potential and challenges related to ML schemes for spectrum sharing.

Puspita *et al.* [206] focus on recent RL-based surveys for CRNs. The work discusses how ML algorithms can be used to solve spectrum sharing problems for CR. It also presents future research directions and network solutions for upcoming CR technologies. The authors, however, dedicate only a small section to discuss RL for CRN. Other ML schemes such as supervised and unsupervised learning are not addressed.

Janu *et al.* [104] address the usage of ML for cooperative spectrum sensing and DSS. The authors characterized the surveyed papers based on the applied ML methods (supervised, unsupervised or RL) and on the evaluation performance metrics of the adopted approaches, showing their advantages and limitations. It also addresses DSS scenarios providing useful discussion on spectrum allocation and spectrum access. However, the authors did not survey ML papers on these topics, which are covered in Samanta *et al.* [222]. In this work, the authors provide an overview of ML techniques focusing on addressing 5G network issues such as resource allocation, spectrum access and security aspects. Although relevant spectrum sharing topics are discussed in this work, a spectrum sensing discussion is missing.

Hu *et al.* [94] and Kaur *et al.* [118] provide an extensive review of works related to spectrum sensing, allocation, access and handoff in the context of CRNs. They also present a summary of existing survey works on CRN and discuss design aspects of CR control mechanisms and energy efficiency. Although the former includes a large set of spectrum sharing works, ML papers are out of the scope of that survey. On the other hand, the latter presents a comprehensive review of ML works for spectrum sharing, however beamforming and security are not addressed.

Since mmWave has arisen as a key technology to accommodate new services in next generation systems, ElHalawany *et al.* [59] presented an extensive survey on ML-based beamforming for mmWave scenario. The authors provided an overview and applicability of ML techniques, summarized mmWave beamforming strategies and provided insightful discussion about ML usage for mmWave beamforming. Although sub 6GHz frequencies were out of the scope, there are important recent references not covered by the authors. In our work, we cover relevant ML works for beamforming design in all range of frequencies.

The exponential growth of data traffic in next generation networks motivates recent surveys to explore spectrum sharing security. Lu *et al.* [169] surveyed RL strategies for the physical layer, focusing on jammers, eavesdroppers, spoofers and inference attackers. Although the authors provided a large overview of security techniques and defense strategies, unsupervised and supervised learning classification strategies were not considered. Falsification attacks, for example, rely on camouflaging the attacker as an authorized node. Classification methods were proved to be efficient to combat this strategy [48, 269]. Wang *et al.* [269] review spectrum sharing for various types of network frameworks. They also investigate the state-of-the-art ML of security threats and defensive strategies in different network layers. Instead of considering all network aspects, Dangi *et al.* [48] address security issues focusing on network slice lifecycle. The authors present insightful discussions on ML strategies for network slicing and an existing related surveys mapping. Although Dangi *et al.* [48] and Wang *et al.* [269] have many contributions in the security field, they did not survey works related with spectrum sharing mechanisms.

To summarize the above discussion on recent related works, Table 1.1 presents the main aspects and Table 1.2 summarizes the main contributions covered by each work. Differently from other surveys, our work covers the fundamentals of ML methods, which are prevalent in the topic of spectrum sharing and are expected to play a key role in emerging 6G systems. The main reason for this is that 6G systems will cope with the increasing traffic demands, complexity and scalability requirements by employing cognitive and learning technologies, as inherent parts of both lower and upper layers of the system. Also, we provide a mathematical description of ML methods, highlight the conceptual differences among them, and discuss spectrum sharing applications for which ML techniques have already been successfully applied. We also provide an in-depth comparison of the proposals available in the literature, identify research gaps in the existing solutions, and discuss open questions related to spectrum sharing that will be important in the upcoming generation of wireless systems.

Another point also provided by our survey is the evaluation of the most active keywords in the recent literature. We provide in Figure 1.3 a density illustration of the works cited in this survey, showing the most relevant topics (keywords) considered in the surveyed literature. The darker the color where the keyword is being shown the more frequent the keyword is in the considered database. The neighborhood of the keywords is related to their joint occurrence in the references and therefore the figure allows us to see which topics are more correlated. Finally,

Table 1.1: Spectrum sharing surveys aspects overview.

Work	Spectrum Sharing				Additional Aspects		
	Sensing	Allocation	Access	Handoff	ML	Beamforming	Security
[13]	✓	–	–	–	✓	–	–
[245]	✓	–	–	–	✓	–	–
[5]	✓	–	✓	–	✓	–	–
[66]	✓	–	✓	–	✓	–	–
[275]	–	✓	–	–	✓	–	–
[310]	–	–	✓	–	–	–	–
[309]	–	–	✓	–	–	–	–
[249]	✓	✓	✓	–	–	–	–
[206]	–	–	✓	–	✓	–	–
[104]	✓	–	–	–	✓	–	–
[222]	–	✓	✓	–	✓	–	✓
[94]	✓	✓	✓	✓	–	–	–
[118]	✓	✓	✓	✓	✓	–	–
[59]	–	–	–	–	✓	✓	–
[169]	–	✓	–	–	✓	–	✓
[269]	–	✓	–	–	✓	–	✓
[48]	–	–	–	–	✓	–	✓
Our work	✓	✓	✓	✓	✓	✓	✓

only the keywords that are mentioned in at least 5 (five) references are displayed in the density map.

The major contributions of the present survey are summarized as follows:

- We cover the recent spectrum sharing surveys state-of-the-art addressing the strong points and pointing out the main gaps of each work, providing a comparison among various ML papers on spectrum sensing, allocation, access and handoff scenarios highlighting the main contributions of each work.
- We outline ML methods providing a general discussion and a mathematical formulation in the context of spectrum sharing networks describing the benefits of these approaches.
- We discuss the contributions of ML to fundamental aspects on spectrum sharing security and beamforming applications.
- We identify existing challenges on spectrum sharing and we point out how ML can be used as a potential solution to overcome those issues. We also point to future open research on spectrum sharing using ML applications.

Table 1.2: Spectrum sharing surveys key contributions summary.

Work	Key Contribution
[13]	A survey on narrowband and wideband spectrum sensing schemes for CRNs.
[245]	A survey on DL spectrum sensing schemes for CRNs.
[5]	A review on spectrum sensing and DSA for cognitive radar networks. It provides a detailed spectrum sensing classification and a spectrum management framework.
[66]	A systematic review on the relationship between spectrum sensing, clustering algorithms, and energy-harvesting for CRNs in IoT context.
[275]	An overview of the state-of-the-art of RL algorithms for spectrum allocation on CRNs.
[310]	A brief discussion on spectrum sharing techniques for CR, D2D, IBFD, NOMA and LTE-U technologies.
[309]	Discussion of spectrum sharing solutions for popular IoT technologies.
[249]	Study of potential scenarios that can benefit from spectrum sharing.
[206]	Brief survey on RL works for spectrum sharing on CRNs, including the discussion of efficient spectrum management on 5G technology.
[104]	A survey on ML algorithms in the cooperative spectrum sensing (CSS) and DSS domain for CRNs.
[222]	A deep learning discussion to tackle 5G and beyond wireless systems issues.
[94]	A survey on spectrum sharing for CR towards 5G networks, including a taxonomy from the perspective of Wider-Coverage, Massive-Capacity, Massive-Connectivity, and Low-Latency.
[118]	Provides a classification and a survey for ML techniques on spectrum sharing scenario.
[59]	Provides an overview of mmWave beamforming design with ML.
[169]	Surveys RL techniques for physical layer attacks in 6G systes.
[269]	Investigates the state-of-the-art ML defensive strategies, such as primary user emulation, spectrum sensing data falsification, jamming and eavesdropping attacks.
[48]	A survey on security issues for 5G networking slicing.
Our work	An extensive up to date survey on ML for spectrum sharing. Particularly, 1. We present several works that use ML as a tool for spectrum sharing problem, including beamforming and security aspects. 2. We include a ML review section and summary tables that provide useful insights on ML techniques for spectrum sharing. 3. We also highlight spectrum sharing challenges and future research directions.

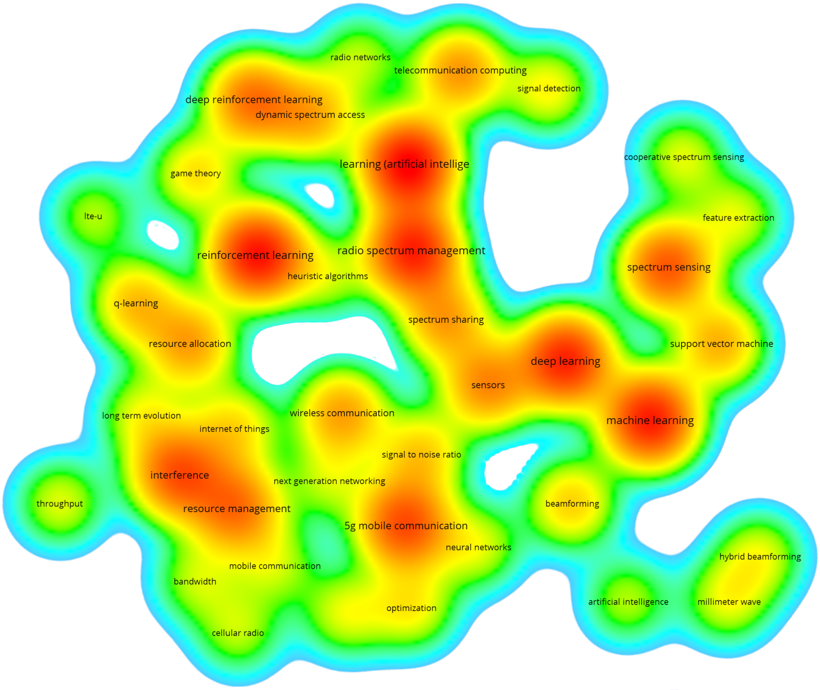

Figure 1.3: Density of the keywords presented in the cited references of this survey.

This survey is structured as follows. Section 2 introduces ML schemes which can be used in the context of spectrum sharing. More than just a recall about the main ML methods, the goal is to provide a more suitable description of the methods for the applications of spectrum sharing. Although the literature has a high number of introductory texts about machine learning and the topics covered in Section 2 could be just assumed to be known by the reader, the section is intended to be a self-contained introduction to the most important ML methods. This will allow the unfamiliar reader to see the details of some of the strategies available in the literature to be able to understand the underlying concepts that are used for the solution of the spectrum sharing problems. Hence, the reader already familiar with the ML strategies and models can skip Section 2 without any loss of continuity. Sections 3, 4 and 5 review the most relevant works in the literature covering ML solutions for spectrum sensing, allocation and access, respectively. Section 6 addresses ML usage on spectrum handoff, beamforming and spectrum sharing security. Subsequently, Section 7 discusses the main issues and challenges on spectrum sharing and highlights important points on spectrum sharing for future research. Finally, Section 8 concludes this survey. A list of key acronyms and abbreviations used throughout the survey is given in Table 1.3.

Table 1.3: List of key acronyms.

Acronym	Definition	Acronym	Definition
AE	Autoencoder	LRMM	Log-Rayleigh Mixture Model
AI	Artificial Intelligence	LSTM	Long Short-Term Memory
ANN	Artificial Neural Network	MAB	Multi-Armed Bandit
BS	Base Station	MARL	Multi-Agent Reinforcement Learning
BF	Beamforming	MDP	Markov Decision Process
CBF	Coordinated Beamforming	ML	Machine Learning
CSI	Channel State Information	MM	Mixture Model
CSIT	Channel State Information at the Transmitter	mmWave	Millimeter-Wave
CNN	Convolutional Neural Network	NOMA	Non-Orthogonal Multiple Access
CRN	Cognitive Radio Network	NR	New Radio
CSS	Cooperative Spectrum Sensing	PU	Primary User
DDQN	Double Deep Q Network	PR	Primary Receiver
DL	Deep Learning	PSO	Particle Swarm Optimization
DNN	Deep Neural Network	QoE	Quality of Experience
DRL	Deep Reinforcement Learning	QoS	Quality of Service
DSA	Dynamic Spectrum Access	RAN	Radio Access Network
DSS	Dynamic Spectrum Sharing	RAT	Radio Access Technology
eMBB	Enhanced Mobile Broadband	RF	Random Forest
eNB	Evolved Node B	RNN	Recurrent Neural Network
FDA	Fisher Discriminant Analysis	RL	Reinforcement Learning
GMM	Gaussian Mixture Model	ROC	Receiver Operating Characteristics
HBF	Hybrid Beamforming	RSS	Received Signal Strength
HMM	Hidden Markov Model	SAE	Stacked Autoencoder
IBFD	In-Band Full-Duplex	SGD	Stochastic Gradient Descent
IDS	Intrusion Detection System	SINR	Signal-to-Interference-plus-Noise Ratio
IoT	Internet of Things	SU	Secondary User
ITU	International Telecommunication Union	SVM	Support Vector Machine
k-NN	k-Nearest Neighbor	UAV	Unmanned Aerial Vehicle
KPI	Key Performance Indicator	UE	User Equipment
LTE	Long-Term Evolution	URLLC	Ultra-Reliable Low-Latency Communication
LTE-U	Long-Term Evolution on Unlicensed Spectrum	VUE	Vehicular User Equipment

1.2 Summary

In this section, we introduced the spectrum sharing problem. Specifically, we contextualized the need for the use of spectral sharing in 5G and beyond networks and we pointed out ML as one of the enables to do it efficiently. We also presented the state of the art of recent spectrum sharing surveys, along with the contributions of our work.

In the next section, we will discuss the ML approaches and common algorithms used by spectrum sharing ML works in literature.

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