Enabling Spatial Reuse in Future Wireless Local Area Networks: a Machine Learning & Game Theoretic Proposal

Francesc Wilhelmi Roca

TESI DOCTORAL UPF / ANY 2020

Director de la tesi
Boris Bellalta, Cristina Cano & Anders Jonsson
Departament of Information and Communication Technologies

Universitat Pompeu Fabra Barcelona

Write here your dedication

Acknowledgments

Abstract

The Spatial Reuse (SR) operation is gaining momentum in the newest IEEE 802.11 family of standards due to the overwhelming requirements posed by next-generation wireless networks. In particular, the increasing traffic capacity and number of concurrent devices compromise the efficiency of Wireless Local Area Networks (WLANs) and throw into question their decentralized nature. The SR operation, initially introduced by the IEEE 802.11ax-2020/21 amendment and further studied in IEEE 802.11be-2024, is aimed at increasing the number of concurrent transmissions in an Overlapping Basic Service Set (OBSS), thus improving spectral efficiency.

The SR operation has been initially defined as a distributed mechanism, but it is evolving towards coordinated schemes. Nevertheless, coordination entails communication and synchronization procedures that have not been defined yet. The necessary overhead to carry out coordination has implications on the performance of WLANs and remains unknown. Moreover, the coordinated scheme is not compatible with IEEE 802.11 devices not implementing it.

Given the SR-related problems faced by future WLAN deployments, Artificial Intelligence (AI) emerges as a promising solution able to overcome the challenges arisen from the complex and varying spatial interactions among devices. In particular, due to the challenges posed by coordination, in this thesis, we study the feasibility of Reinforcement Learning (RL)-based methods to overcome the SR problem in a decentralized manner.

... [TO BE COMPLETED]

Resum

List of Publications

1. Wilhelmi, F., Muñoz, S. B., Cano, C., Selinis, I., & Bellalta, B. (2019). *Spatial Reuse in IEEE 802.11 ax WLANs.* arXiv preprint arXiv:1907.04141.

2. Wilhelmi, F., Barrachina-Muñoz, S., & Bellalta, B. (2019, October). *On the Performance of the Spatial Reuse Operation in IEEE 802.11 ax WLANs.* In 2019 IEEE Conference on Standards for Communications and Networking (CSCN) (pp. 1-6). IEEE.

3. Wilhelmi, F., Bellalta, B., Cano, C., & Jonsson, A. (2017, October). *Implications of decentralized Q-learning resource allocation in wireless networks.* In 2017 ieee 28th annual international symposium on personal, indoor, and mobile radio communications (pimrc) (pp. 1-5). IEEE.

4. Wilhelmi, F., Cano, C., Neu, G., Bellalta, B., Jonsson, A., & Barrachina-Muñoz, S. (2019). *Collaborative spatial reuse in wireless networks via selfish multi-armed bandits.* Ad Hoc Networks, 88, 129-141.

5. Wilhelmi Roca, F., Barrachina Muñoz, S., Bellalta, B., Cano Sandín, C., Jonsson, A., & Neu, G. (2019). *Potential and pitfalls of multi-armed bandits for decentralized spatial reuse in WLANs.* Journal of Network and Computer Applications, 2019, 127.

6. Barrachina-Muñoz, S., Wilhelmi, F., Selinis, I., & Bellalta, B. (2019, April). *Komondor: a wireless network simulator for next-generation high-density WLANs.* In 2019 Wireless Days (WD) (pp. 1-8). IEEE.

7. Wilhelmi, F., Barrachina-Munoz, S., Bellalta, B., Cano, C., Jonsson, A., & Ram, V. (2020). *A Flexible Machine-Learning-Aware Architecture for Future WLANs. IEEE Communications Magazine, 58(3), 25-31.*

8. Wilhelmi, F., Carrascosa, M., Cano, C., Ram, V., & Bellalta, B. (2020). *Usage of Network Simulators in Machine-Learning-Assisted 5G/6G Networks.*

Contents

1 INTRODUCTION **1**

2 SPATIAL REUSE IN IEEE 802.11 WLANS: TECHNOLOGY **3**
2.1 Related Work . . . 3
2.2 Spatial Reuse in IEEE 802.11ax . . . 4
2.2.1 OBSS/PD-based Spatial Reuse . . . 4
2.2.2 Parametrized Spatial Reuse . . . 5
2.3 Spatial Reuse in Future IEEE 802.11 WLANs . . . 6

3 MACHINE LEARNING IN IEEE 802.11 WLANS **9**
3.1 Computation paradigms . . . 10
3.2 Multi-Armed Bandits for Decentralized Spatial Reuse: Between ML and Game Theory . . . 11
3.2.1 The MAB Framework . . . 11
3.2.2 MAB in Communications . . . 12
3.2.3 MAB-based Decentralized Spatial Reuse . . . 13

4 METHODOLOGY AND ENABLERS **17**
4.1 Spatial Reuse through Continuous Time Markov Networks . . . 17
4.1.1 IEEE 802.11ax OBSS/PD-based Spatial Reuse . . . 18
4.1.2 IEEE 802.11be Coordinated Spatial Reuse . . . 18
4.2 System-level Simulation of Spatial Reuse . . . 18
4.3 Architectural Aspects of Machine-Learning-Aware Networks . . . 18

5 MAIN FINDINGS **21**

6 OPEN CHALLENGES AND FUTURE WORK **23**

7 PUBLICATIONS **39**
7.1 Spatial Reuse in IEEE 802.11 ax WLANs . . . 39
7.2 On the Performance of the Spatial Reuse Operation in IEEE 802.11 ax WLANs 39
7.3 Implications of decentralized Q-learning resource allocation in wireless networks 39
7.4 Collaborative spatial reuse in wireless networks via selfish multi-armed bandits 39
7.5 Potential and pitfalls of multi-armed bandits for decentralized spatial reuse in WLANs . . . 39
7.6 A Flexible Machine-Learning-Aware Architecture for Future WLANs. IEEE Communications Magazine . . . 39

7.7 Komondor: a wireless network simulator for next-generation high-density WLANs 39
7.8 Usage of Network Simulators in Machine-Learning-Assisted 5G/6G Networks . 39

Chapter 1

INTRODUCTION

The Institute of Electrical and Electronics Engineers (IEEE) 802.11 family of protocols for wireless local area networks (WLANs) was first released in 1997 as a novel solution for physical (PHY) and medium access control (MAC) layers. Since that date, the standard has evolved to sustain the increasingly user requirements in terms of capacity, load, and coverage, as well as to serve for different purposes (e.g., mesh networking, security-enhanced communications, channel measurement, etc.). The set of novel and improved capabilities have been captured along the time in the plethora of amendments that followed the initial 802.11-1997 standard (e.g., 802.11b, 802.11g, 802.11h, etc.).

Looking forward, the next generation of WLAN standards is expected to revolutionize the telecommunications and converge along with 5G systems and beyond to expand to multiple domains, such as light communications (IEEE 802.11bb), Internet of Things (IEEE 802.11ah), vehicle-to-everything (IEEE 802.11bd), or next-generation positioning (IEEE 802.11az).

One of the most influential amendments is the IEEE 802.11ax-2021 (11ax) amendment for High Efficiency (HE) WLANs [1–3], which primary goal is to enhance network efficiency in ultra-dense deployments, thus providing high capacity (up to 10 Gbps). The 11ax (commercially known as WiFi 6) includes a set of unprecedented techniques, such as Orthogonal Frequency Division Multiple Access (OFDMA), Downlink/Uplink Multi-User Multiple-Input-Multiple-Output (DL/UL MU-MIMO), and Spatial Reuse (SR), to address the broad range of issues arisen from high-density scenarios [4].

This thesis focuses on the SR operation that was initially conceived for IEEE 802.11ax WLANs and that is now evolving in the IEEE 802.11be. SR is meant to enhance spectral efficiency by increasing the number of parallel transmissions in high-dense deployments. To this end, SR proposes a mechanism to improve the probability of ignoring transmissions which source is a device belonging to a different Basic Service Sets (aka inter-BSS transmissions). This can be done by applying a less restrictive carrier sense threshold for inter-BSS transmissions, which is referred to as Overlapping BSS Packet Detect (OBSS/PD) threshold. To promote fairness, SR also incorporates a mechanism that limits the transmit power of the new transmissions that result from using a less restrictive OBSS/PD threshold (so that the primary transmissions are not affected). Table 1.1 summarizes the potential effects and implications of adjusting the sensitivity threshold and the transmit power in WLANs.

The SR operation included in the 11ax has shown significant gains for cell-center devices but lacks applicability in cell-edge users. As a result, the 11be is working on Coordinated SR (CSR), a cooperative scheme whereby BSSs exchange information (e.g., the acceptable level

Table 1.1: Effects and implications of adjusting the sensitivity threshold and the transmit power in IEEE 802.11 WLANs.

	Data rate	**Channel access probability**	**Generate starvation probability**	**Hidden-node probability**	**Exposed-node probability**
Sensitivity ↑	-	↑	↑	↑	↓
Tx. power ↑	↑	-	↑	↓	↑

of interference supported by the different devices) to further enhance the quality of the parallel transmissions achieved through SR. Apart from that, the convergence with other technologies such as OFDMA and beamforming/null steering is also being studied to shape the future of SR.

In light of the importance of SR for future IEEE 802.11 WLANs, in this thesis, we study the potential of Machine Learning (ML) on addressing the challenges raised by the sensitivity and transmit power adjustment mechanisms inherent in SR. ML is revolutionizing telecommunications due to its ability for solving problems that can be barely understood and modeled due to their underlying complex patterns, which is the case of SR.

This thesis, therefore, aims to shed light on the potential gains of the SR operation, study its projected future, and devise its intersection with Artificial Intelligence (AI). The contributions of this thesis are summarized next:

- We study state-of-the-art solutions to improve spectral efficiency in wireless networks.
- We provide an in-depth overview of the IEEE 802.11ax SR operation and devise its potential evolution path in the IEEE 802.11be and beyond.
- We analytically model and study the new kind of inter-device interactions resulting from the novel SR operation for WLANs.
- We provide simulation-based results on the performance gains of SR for future WLANs.
- We propose several RL-based solutions to address the SR problem in decentralized WLAN deployments.
- We delve into architectural aspects to enable future ML-aware networks.

This thesis is a compendium of articles resulting from the research activity related to the application of ML to address SR in IEEE 802.11 WLANs. Besides the list of publications (attached at the end of this documents), a monograph is provided to introduce the research topic and provide some background on it. This document is structured as follows. Chapter 2 surveys SR techniques in wireless networks, overviews the IEEE 802.11ax SR operation, and discusses the evolution of the same in future amendments. Chapter 3 provides insights on the intersection of ML in wireless communications and describes the proposed MAB-based approach to address SR in decentralized WLANs. Then, Chapter 4 introduces the analytical and simulation tools used for performance evaluation. Besides, it delves into architectural considerations for realizing the proposed ML-based mechanisms. The main finding of this thesis are summarized in Chapter 5 and final remarks are provided in Chapter 6.

Chapter 2

SPATIAL REUSE IN IEEE 802.11 WLANS: TECHNOLOGY

In this Chapter, we describe the SR operation and survey the related work, ranging from solutions for sensitivity and transmit power in wireless networks, to specific IEEE 802.11 technology. Then, we overview of the IEEE 802.11ax SR operation and discuss the next steps being taken by the Task Group 802.11be (TGbe) to make this technology evolve.

2.1 Related Work

Improving medium utilization through SR has been extensively studied for both sensitivity and transmit power adjustment in different domains such as multi-hop networks [5, 6], cellular networks [7], and IEEE 802.11 WLANs [8]. Several SR techniques have been applied in different manners to address multiple problems (improve capacity, boost fairness, save energy, etc.). Figure 2.1 shows a categorization of SR techniques according to the optimization goal and their implementation.

Concerning IEEE 802.11ax SR, the Dynamic Sensitivity Control (DSC) scheme [53] was the first proposal for adapting the sensitivity of devices in an OBSS, but it was never incorporated in any amendment. Roughly, the DSC mechanism iteratively increases or reduces the sensitivity of an STA in a decentralized manner, based on the average perceived RSSI. Intuitively, DSC aims at increasing the sensitivity level at STAs that are close to the AP (avoid contention), while reducing this threshold for STAs at the cell edge (avoid collisions by hidden node). While DSC was initially meant for tuning the physical carrier sense threshold (PCS), it was later proposed as a method for tuning the OBSS/PD [54]. Due to its promising potential, the performance of DSC has been extensively studied in multiple scenarios and in combination with other mechanisms [55–65].

Apart from DSC, other solutions for tuning the sensitivity have been proposed in [66–69]. First, [66] proposed tuning the transmission power based on the Expected Transmission Count (ETX) metric, which has been widely used in wireless sensor networks. The authors in [67] provided an iterative method whereby the OBSS/PD is progressively updated, based on the received signal strength indicator (RSSI) at STAs. Similarly, [68] proposed the RSSI to OBSS threshold (RTOT) method, whereby the OBSS/PD value used by an STA is derived from the RSSI received from its AP (which is used as an indicator of the distance). Despite this method is meant to deal with network dynamics (the OBSS/PD varies according to the RSSI), a static

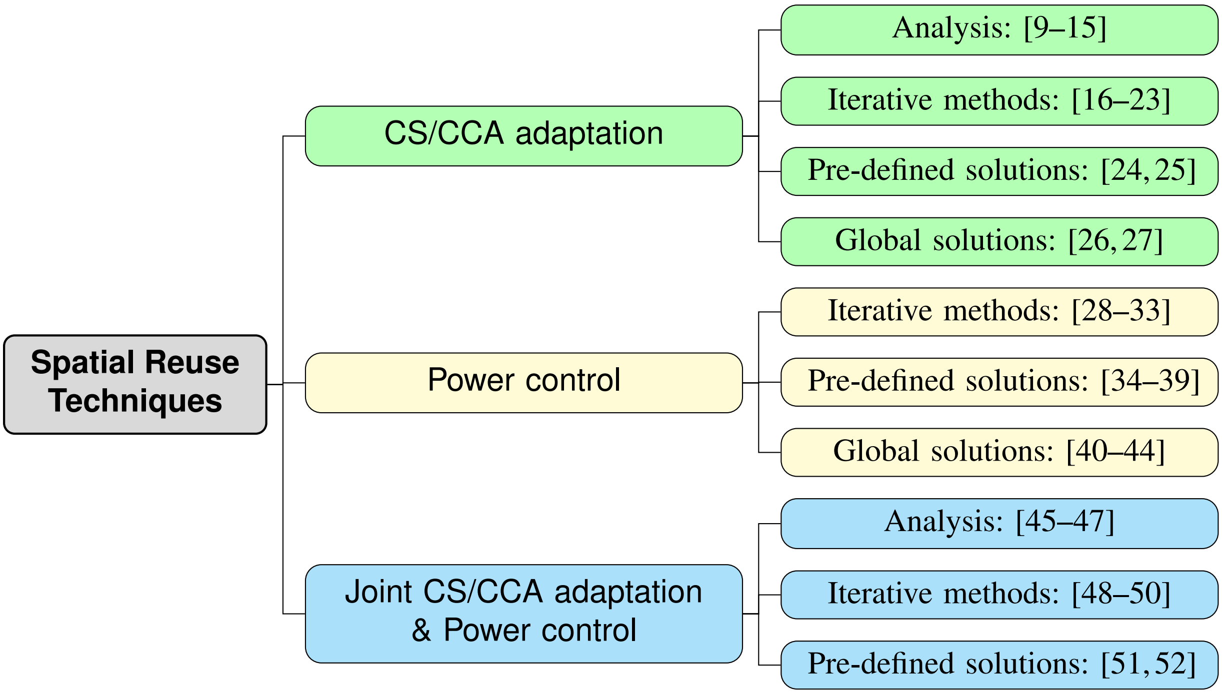

Figure 2.1: Spatial reuse techniques in wireless networks.

margin value is included used for selecting the OBSS/PD. As for DSC, the rigidity of the margin value may lead to not finding the optimal solution in some scenarios. Finally, the interference-based dynamic channel algorithm (IB-DCA) was proposed in [69], whereby STAs exchange the expected RSSI so that the transmit power is globally adjusted, rather than applying the OBSS/PD.

2.2 Spatial Reuse in IEEE 802.11ax

The IEEE 802.11ax SR operation includes two different mechanisms: *i)* **OBSS/PD-based SR**, for decentralized settings, and *ii)* **Parametrized SR (PSR)**, for scheduled uplink transmissions. Both mechanisms are based on BSS coloring, whereby HE devices can quickly determine whether the channel is occupied by another device belonging to the same BSS (intra-BSS transmission, same color) or from a different one (inter-BSS transmission, different color).

2.2.1 OBSS/PD-based Spatial Reuse

In OBSS/PD-based SR, an HE STA can use a less restrictive OBSS/PD threshold when detecting inter-BSS transmissions, thus increasing the probability of ignoring them and accessing the channel. In case of initiating a transmission due to OBSS/PD-based SR (an SR-based TXOP is obtained), an HE STA must regulate the transmit power it uses. The maximum allowed transmission power is given by:

$$\text{TX\_PWR}_{\text{max}} = \text{TX\_PWR}_{\text{ref}} - (\text{OBSS/PD} - \text{OBSS/PD}_{\text{min}})$$

Figure 2.2 sketches an example of the OBSS/PD-based SR mechanism in which an HE device (i.e., AP_A) ignores inter-BSS transmissions (i.e., AP_B) by applying the OBSS/PD threshold, which allows it initiating a simultaneous transmission with limited transmit power.

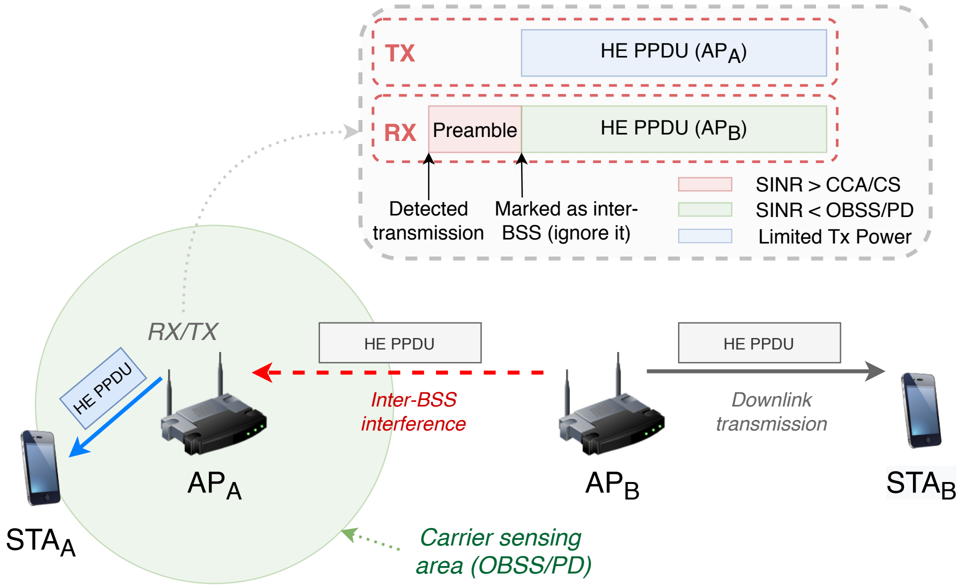

Figure 2.2: Example of OBSS/PD-based SR in a toy scenario.

The performance gains of OBSS/PD-based SR operation have been previously analyzed in [70–73].

2.2.2 Parametrized Spatial Reuse

Unlike for OBSS/PD-based SR, the PSR operation attempts to exploit triggered-based (TB) UL transmissions to carry out SR. Depending on the role of nodes participating in the PSR operation, we find two types of devices: *sharing* (the ones initiating TB transmissions and indicating support for the PSR operation) and *shared* (the ones taking advantage of the PSR opportunities from detected TB transmissions).

To detect PSR opportunities, shared devices must check whether their intended transmit power meets the requirements indicated in TB PPDUs from sharing devices. These requirements are based on the maximum level of interference supported by the sharing device. In particular, the minus the intended transmit power cannot exceed the following value:

$$\text{TX\_PWR}_{\text{max}} = \text{TX PWR}_{\text{AP}} + \text{I}_{\text{AP}}^{\text{max}} - RPL,$$

where $\text{TX PWR}_{\text{AP}}$ is the normalized transmit power in dBm at the output of the antenna connector, $\text{I}_{\text{AP}}^{\text{max}}$ is a normalized value in dB that captures the maximum allowed interference at the sharing device,[1] and Received Power Level (RPL) is measured from the legacy portion of the TF (i.e., from PHY headers).

The PSR operation is sketched in Figure 2.3 for a toy scenario. As shown, the sharing device (i.e., AP_B) schedules an UL TB transmission by sending a TF, which is inspected by the shared device (i.e., AP_B) to detect a PSR-based TXOP.

The potential latency gains of PSR have been analyzed in [74].

[1] $\text{I}_{\text{AP}}^{\text{max}}$ is computed as the target RSSI indicated in the TF minus the minimum SNR granting a 10% PER (a

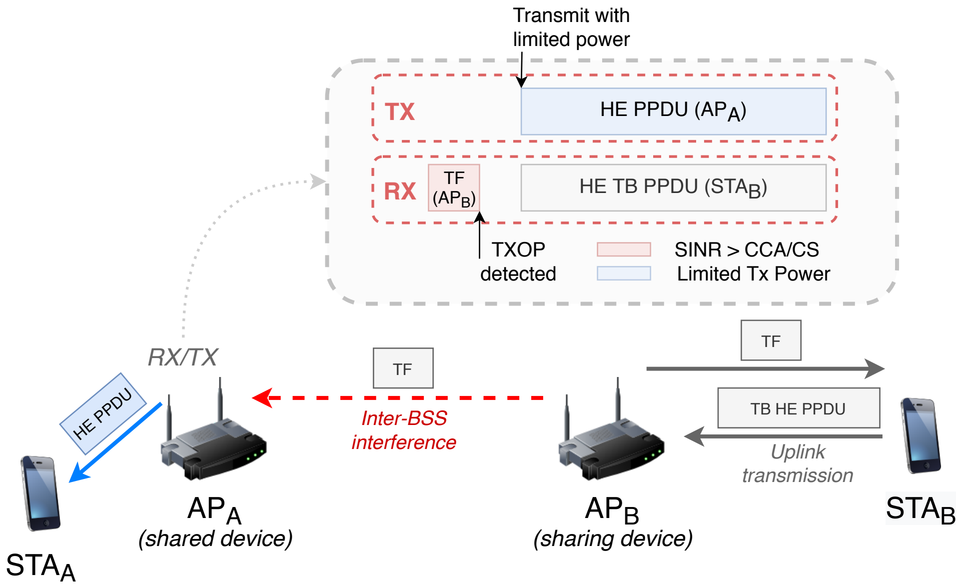

Figure 2.3: Example of PSR in a toy scenario.

2.3 Spatial Reuse in Future IEEE 802.11 WLANs

Currently, the TGbe is studying a new coordinated scheme for SR. Notice that Multi-AP coordination (e.g., coordinated and joint transmission) is one of the main topics that has been so far been discussed by members of TGbe for coordinated beamforming (CBF) [75], coordinated OFDMA [76], and coordinated SR (CSR) [77].[2]

Concerning CSR (or Co-SR), it aims to improve the quality of the simultaneous transmissions that can take place due to the SR operation. In particular, the transmit power of secondary transmissions take into account the maximum level of interference of the target devices to which transmissions are sought to be held. Co-SR is a natural extension of the SR scheme under the multi-AP operation framework and can be implemented with relatively low added complexity.

Beyond 11be SR, the integration of SR with other novel mechanisms remains unexplored and it is expected to provide further performance gains. Among the most important techniques, we highlight beamforming/null steering [78], OFDMA [79,80], multiple antenna systems [81], and scheduled transmissions [82]. For instance, the combination of SR with directional transmissions may lead to efficient and performance maximizing communications, where SR is applied on a per-beam basis. Similarly, SR can be further exploited through TB communications. In this case, users of a given BSS can be categorized into different types, so that different inter-BSS OBSS/PD values are assigned to them for the sake of scheduling joint transmissions. It is worth pointing out that users belonging to different groups can be scheduled together, provided that the most restrictive OBSS/PD threshold is used.

Finally, AI emerges as a potential solution to address SR because of the complexity of the problem and the characteristics of dense WLAN deployments, which are typically decentralized and highly varying in terms of users and channel dynamics. Through AI, it is possible

safety margin is also included not to exceed 5 dB).

[2]Approved initial draft of PAR: `https://mentor.ieee.org/802.11/dcn/18/11-18-1231-01-0eht-eht-draft-proposed-par.docx`

to capture and exploit complex information that cannot be predicted on before-hand (traffic demands, user behavior, varying interference regimes, etc.). As a result, a learning-based procedure can be conducted to further improve the performance of WLAN deployments.

Chapter 3

MACHINE LEARNING IN IEEE 802.11 WLANS

ML is meant to empower a computational system for learning automatically, based on experience, so that future situations can be properly managed without having been programmed explicitly. The actual utility of ML lies in those problems that are hard to solve by hand-programming due to their underlying complex patterns (e.g., network traffic prediction). Formally, a machine is said to learn if it improves the performance $\mathbb{P}$ obtained from undertaking task $\mathbb{T}$, based on the gathered experience $\mathbb{E}$ [88]. Different ML techniques have been categorized in multiple ways, but the most common taxonomy differentiates between supervised learning (labeled data is used for training), unsupervised learning (no labels are used on input data), and reinforcement learning (exploration-exploitation trade-off with label/unlabeled data).

Concerning wireless communications, the application of ML reveals a big potential because of the following aspects:

- First, there is a huge amount of unexploited data generated at both infrastructure and user levels, which could be extremely useful for learning patterns that help at improving network performance.

- Second, current models lack of accuracy and/or tractability for capturing non-linear complex phenomena of communications systems (e.g., channel effects, varying traffic requirements, hardware imperfections, etc.). In this regard, ML does not require a mathematically tractable model to operate and can be used to address such complexities.

- Apart from the underlying complex characteristics of problems (e.g., wireless channel), communications systems are built based on functional blocks, each executing well defined and isolated functions (e.g., rate selection, channel allocation, etc.). While individual functions can be separately optimized, their joint operation may lead to further improve end-to-end complexity, thus hindering global optimized solutions. ML can therefore help at optimizing end-to-end processes by getting rid of the modularization of communications systems.

Henceforth, ML is expected to overcome the systemic complexity inherited from novel use cases like Vehicle to Everything (V2X) communications, Machine Type Communications (mMTC), and Ultra-Reliable Low-Latency Communication (uRLLC). In particular, the inherent flexibility of ML for automatically learning diverse situations can address heterogeneous scenarios including mobility, a huge number of devices, and varying throughput and latency requirements. For those reasons, added to the ongoing softwarization of networks, ML is expected to be pervasively included beyond the fifth-generation (5G) of mobile communications systems, namely the sixth generation (6G) [89–91]. Because of its high potential on addressing complex problems in communications, ML has been applied to a plethora of fields. We address the interested reader to the surveys in [83–86, 92–96] and references therein.

3.1 Computation paradigms

Most popular ML approaches typically require a centralized architecture for training tasks on one point (e.g., a data center), which is useful for deriving global ML models encompassing data acquired from multiple sources (e.g., nodes in a network) and even from different domains (e.g., inter-operator data). This allows obtaining a general understanding of the target problem, but the accuracy of the output solution is tied to the characteristics of the training data; too diverse and complex patterns may lead to a high level of bias and model overfitting. Moreover, centralization requires certain perennity of data, thus lacking of responsiveness and not suiting real-time applications. Notice that training datasets are typically large and entail significant resource and time-consuming computational tasks. Centralized solutions are therefore very useful for problems related to the core of the network or involving higher layers of the protocols stack. For instance, DL approaches have been broadly applied for predicting periodical patterns of network traffic [97–99] or user mobility [100–102].

However, the access network and edge devices may face other kinds of challenges for PHY/MAC-related problems, thus requiring decentralized architectural solutions. First, end devices typically have highly-varying heterogeneous requirements and are subject to different environmental conditions. As a result, deriving a general model to properly fit all the cases can be difficult or even impossible. Second, data may fail to be integrated at a single point due to potential computation, storage or communication limitations (e.g., end devices may have low-throughput connections and be intermittently available). Third, time-consuming mechanisms requiring a heavy workload such as NNs can be barely applicable due to high non-stationarity (e.g., due to highly varying traffic demands, channel conditions, etc.), which would make trained ML models become obsolete very fast.

Decentralized approaches typically address complex and varying processes that cannot be fully learned (e.g., the learning curve is unfordable). In this regard, decentralization can provide on-time solutions rather than seeking for optimality (fast moderate improvement vs slow optimization). For that reason, techniques such as Reinforcement Learning or Sequential Learning are widely employed for PHY/MAC optimization. Some examples are resource allocation [103], edge computing [104, 105], or MIMO optimization [106].

Figure 3.1 summarizes the computational approaches and implications for different problem characteristics, including requirements, available resources, and purpose.

In-between centralized and decentralized systems, we find mixed architectures where other types of learning mechanisms can be applied. For instance, transfer learning (storing knowledge gained while solving one problem and applying it to a different but related problem) [107] and federated learning (collaborative training starting from a general model to better fit different

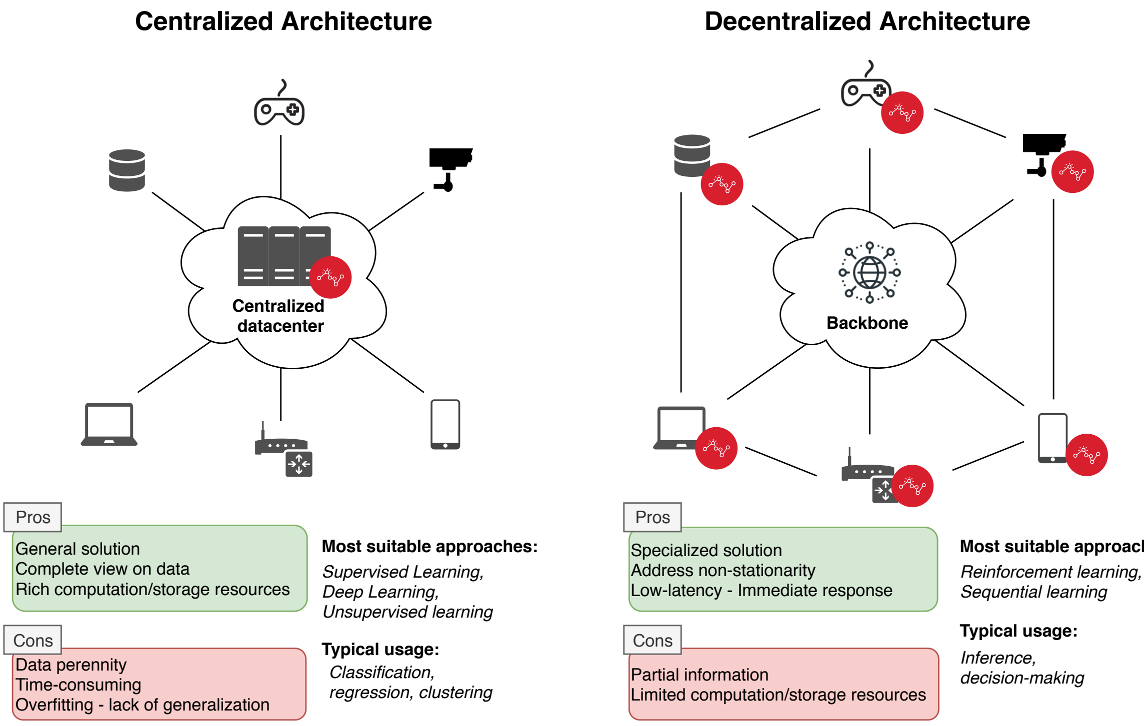

Figure 3.1: High-level representation of centralized and decentralized architectures.

contexts and situations) [108, 109] find a compromise that combines the power of centralized architectures and the flexibility of decentralized ones. However, the successful application of these kind of approaches is tightly tied to the communication capabilities of the implied devices, which defines the degree of cooperation among nodes in a network.

3.2 Multi-Armed Bandits for Decentralized Spatial Reuse: Between ML and Game Theory

The *learning by experience* characteristic of sequential learning suits well to the WLANs because it allows addressing complex partial information problems. The fact is that WLANs pose a set of specific challenges resulting from their multiple deployment modes (e.g., campus network, residential usage) and their typical decentralized nature. Despite WLANs can count with plenty of data to be used by ML methods in large and planned deployments, we find other residential-type scenarios that are decentralized and lack of powerful centralized equipment. Besides, as a consequence of the abovementioned lack of coordination, a high non-stationarity is to be addressed.

3.2.1 The MAB Framework

In the MAB problem, [110, 111], and as for classical RL formulations, an agent (or learner) interacts with the environment to accumulate knowledge that allows responding to unforeseen events, with the aim of finding an equilibrium between exploration (improve your knowledge) and exploitation (obtain the maximum profit based on your knowledge) [112].

Formally, a learner sequentially picks actions $a_t \in K$ and observes their reward vector r_t over a time horizon T. Typically, the reward is granted by what is known as the environment, which may be of diverse nature (e.g., stochastic distribution, adversarial payoff). In the bandits setting, the reward follows a hidden probability distribution, and it is only revealed once the arm is played. Bandits differ from *partial* and *full* information settings that reveal the reward of a set or all the possible actions, respectively.

The performance of a given action-selection strategy is typically measured by the regret R_T, which compares the performance achieved by the actual selected actions with the best action in hindsight granting the optimal reward (r_t^*). In general, an algorithm is said to learn if its regret grows sublinearly. Typical good performance is achieved for $R_T \in \mathcal{O}(\sqrt{T})$ or even $R_T \in \mathcal{O}(\log T)$.

In spite of its simplicity, the bandits framework stands as a very powerful solution for decision making problems. The main reason lies in its versatility, which allows bandits to model almost any problem. Because of this, the utilization of bandits is nowadays widely spread, and a plethora of applications are powered by such a framework. The most typical ones are web advertising, sales optimization, online recommendations, resource allocation, and packet routing, among many others. A plethora of bandits formulations exists according to multiple assumptions that extend the basic bandits game, which are based on the reward statistics (e.g., stochastic vs non-stochastic bandits), the dynamics of actions (e.g., sleeping bandits, mortal bandits), the type of Markovian settings (e.g., rested vs restless bandits), the nature of the environment (e.g., adversarial bandits), and a very long etcetera of variations. The bandits problem has been treated in detail by several books and surveys. Table 3.1 provides a high-level categorization of the most popular types of bandits. We encourage the interested reader to delve into the works in [113–117].

Table 3.1: High-level categorizations of most popular bandits types.

Cathegorization Criteria	**Bandits models**
Reward generation process	Stochastic, adversarial, Markovian (rested/restless)
Reward function	Discrete, continuum (linear/nonlinear), Lipschitz, Gaussian
Feedback type	Full information, bandit, semi-bandit, partial monitoring
State-awareness	Multi-armed bandit, contextual bandit

3.2.2 MAB in Communications

In wireless communications, many problems have statistical characteristics that can be approximated with mathematical models. In this regard, MAB-based applications have shown a great potential for optimizing a plethora of problems. Some examples are channel selection [118], spectrum access [119], transmission scheduling [120], or AP selection [121]. Table 3.2 provides an overview of some popular applications in communications that are based on the MABs framework.

Concerning the decentralized SR problem, it can be naturally defined as a multi-agent sys-

Table 3.2: Overview of bandit-based applications for communications

Problem	Modeling	Goals	Baseline algorithms	References
Opportunistic spectrum access & Channel selection	Stochastic, non-stochastic, restless, contextual, Markovian bandits	Decentralized optimal allocation, optimize number of secondary transmissions, ϵ-correct ranking	UCB, ϵ-greedy, calibrated forecasting	[118, 119, 122–125]
Power control	Non-stochastic bandits	Optimize SINR	Follow the perturbed leader, exponential weighted average	[126]
User association	Sleeping, Bernoulli, non-stochastic bandits	Energy saving, improve the throughput	UCB, ϵ-greedy	[127, 128]
Inter-cell coordination	Adversarial, stochastic, non-stochastic, contextual bandits	Optimize inter-cell frequency resources, energy saving, map SON configurations and operator objectives	EXP3, UCB, ϵ-greedy	[129–132]
Dynamic rate selection	Structured, Markovian bandits	Maximize the number of packets successfully transmitted, learn changes in the channel	UCB	[133, 134]
LTE/Wi-Fi coexistence	Convex bandits	Fair channel sharing	Online gradient descent	[135]

tem, where each individual (e.g., a BSS) has player-specific goals and rewards.[1] The multi-agent approach allows capturing the distributed nature of IEEE 802.11 WLANs and keeping dimensionality low for the SR problem. However, it may unleash a competition among players, thus revealing a nexus with game theory. In a single-agent system, a player attempts to maximize a long-term reward by interacting with an environment (which can be stochastic or non-stochastic) in isolation. Under this setting, performance guarantees can be straightforwardly provided, even if dealing with adversarial [136] or dynamic environments [137]. In contrast, weaker performance guarantees can be provided for multi-agent systems. The fact is that knowledge acquired by agents becomes easily outdated because of the non-stationarity produced by their concurrent operation.

Most of the current literature in multi-player MABs for wireless communications is based on the channel access problem in cognitive radio [84, 118, 122, 123, 138–142]. The characteristics of the cognitive radio make it a suitable and an attractive problem to be modeled with the bandits framework. In particular, each node attempting to access the channel represents a player, and channels are arms (or bandits). In general, rewards are granted to players in a binary fashion, being 1 if the channel can successfully be accessed, or 0 otherwise (two or more nodes select the same channel). Accordingly, each player has the same view on actions (different players playing the same bandit obtain to the same payoff), which makes the game smooth, i.e., the reward function of the players is continuous with respect to the entire strategy set. Table 3.3 analyzes the state-of-the-art approaches taken for modeling channel access in cognitive radio through multi-player MABs.

3.2.3 MAB-based Decentralized Spatial Reuse

In the MABs setting, optimal solutions can typically be provided only to tractable problems that are generally linear, stationary, and generated by independent stochastic processes (e.g., with underlying Gaussian statistics). This is not the case of the multi-agent SR problem, in which it is not possible to provide a distributed no-regret strategy that converges to an optimal equilibrium. The fact is that the set of correlated equilibria cannot be characterized in the SR problem with multiple concurrent players. In particular, the following properties differing from distributed channel access prevent to do so:

[1]The maximum achievable performance of a node depends on its transmission capabilities, the interference it senses, the traffic load it needs to serve and/or receive, etc.

Table 3.3: State-of-the-art multi-player MAB solutions for channel access in cognitive radio.

Work	Approach	Requirements	Results
[123]	Distributed mechanism that combines sensing with randomized access to learn channel statistics and the activity of other users	- The number of users is fixed and known - Channel sensing is perfect - All the players use the same strategy - Binary reward (free/collision)	Order-optimal regret with logarithmic lower bound
[143]	Decentralized time-division fair sharing of the best arms	- i.i.d. reward - Conditions of linearity, continuity, and density for unknown parameters - Binary reward (free/collision) - The number of users is fixed and known	Same logarithmic regret order as for collaborative approach where nodes exchange observations and make decisions jointly
[138]	Collaborative mechanism based on slotted periods (decision, sensing, transmission, communication)	- Channel sensing is done - CSMA/CA is used by secondary users - Rewards are broadcasted - Same channel conditions for all users	Linear regret improving random and greedy channel access schemes
[125]	Distributed no-regret learning with calibrated forecaster	- The joint action profile is known - All the players use the same strategy - Time-invariant average channel gains	Global optimal solution and convergence to correlated equilibria
[142]	Non-cooperative selfish approach based on ϵ-greedy exploration and CSMA/CA	- K $\geq$ N (K: channels, N: users) - The number of users is fixed and known	Sub-linear regret and convergence to system-optimal solution
[118]	Centralized method for combinatorial bandits with user-channel pairs	- K $\geq$ N (K: channels, N: users) - Throughput as an i.i.d. random variable - Coordination/synchronization	Upper bound regret that grows polynomially with the combinatorial number of users and channels

1. Spatial interactions inflict abrupt changes to the reward obtained by a BSS, which can be based, for instance, on the throughput. To put an example, increasing the sensitivity contributes to reducing contention, but it may lead to noticing a higher amount of interference during transmissions.

2. Apart from spatial interactions, devices do not transmit uniformly along the time, which is in fact an unrealistic assumption. Therefore, the social-cost of actions varies with time and according to the transmissions done on a per-packet-basis (where certain randomness is added due to many causes such as channel effects, retransmissions, the randomized backoff procedure, etc.).

In these situations, defining a shared learning goal in multi-agent systems is not trivial because rewards are not equally assigned to agents and each individual reward depends on the joint action profile. Nonetheless, MABs remain a powerful solution to address real-world problems with complex and even unpredictable phenomena behind reward distributions. This is the case of the multi-player setting (i.e., multiple agents attempt to learn concurrently), which entails the enormous challenge of non-stationary, but for which on-time improvements prevail over long-term optimality.

In the following subsections, we show the different settings that have been considered for applying concurrent SR through MABs, which are based on the cooperation degree among BSSs (selfish, collaborative, and social-aware). In cooperative scenarios, agents collaborate to optimize a common goal (e.g., a shared reward), which is attempted to be maximized jointly. When it comes to non-cooperative approaches, local rewards are employed to characterize selfish behaviors, i.e., each agent attempts to improve its own performance.

Selfish Setting

[TBD] Idea: formulate the problem and devise implications and opportunities.

Under the selfish setting, several concurrent agents attempt to improve their own performance, based on local information. In the case of SR, actions are defined as combinations of sensitivity and transmit power values.

While the selfish setting has been shown to provide fast learning rates [144], it may also provoke several undesired issues such as sub-optimal performance and unfairness [145]. Nevertheless, a collaborative behavior was shown to be achieved, thus leading to an equilibrium.

Collaborative Setting

[TBD] Idea: formulate the problem and devise implications and opportunities.

In this case, an environment-aware strategy is provided for deciding the best transmit power and sensitivity configuration, based on the performance of the overlapping networks into account. Despite a fair solution is shown to be achieved, certain limitations were revealed for maximizing the overall performance, thus showing that a shared reward is not enough in a decentralized setting.

Social-Aware Setting

[TBD] Idea: formulate the problem and devise implications and opportunities.

To overcome the issues raised by both selfish and shared reward settings, we focus on hybrid approaches by considering a social-aware cost function, which combines both local and collaborative rewards. In this regard, we highlight the work in [141], which includes transmission power control to the distributed channel access problem in cognitive networks. Given a proposed model for opportunistic spectrum access, the authors are able to provide distributed no-regret strategies that lead to the set of correlated equilibria. However, some assumptions are made to provide convergence guarantees. In particular, the reward function used by the players is continuous with respect to the strategy set, which is also bounded. Intuitively, this means that the social cost that any action incurs to the other players can be linearly quantified.

Chapter 4

METHODOLOGY AND ENABLERS

[TBD]

4.1 Spatial Reuse through Continuous Time Markov Networks

Characterizing the IEEE 802.11ax SR operation is crucial to fully understand its implications. However, it turns out to be a challenging task due to the complex (and still unknown) inter-WLAN interactions generated by adjusting the sensitivity and the transmission power. To the best of our knowledge, none of the previous works have attempted to model the 11ax SR operation. Nevertheless, with the aim of providing a thorough understanding of the SR operation, we introduce the CSMA/CA throughput model based on Continuous Time Markov Networks (CTMNs) [146, 147]. The CTMNs model aims to provide further insight into the effects of applying SR in next-generation WLANs.

The CTMN model captures the CSMA/CA operation used in IEEE 802.11 WLANs through states, which represent the set of WLANs that are active at a given moment. Transitions between states occur when WLANs become active (i.e., they gain access to the medium) or when they abandon the channel (i.e., their transmission is finished).

Analyzing inter-BSS MAC interactions is of great utility to deeply understand the implications of applying SR in WLANs. For that, we have modeled SR through Continuous Time Markov Networks (CTMN) [146, 147], based on the framework presented in [148].[1] Concerning this model, the following assumptions are done:

- Transmissions are downlink only.
- Uplink transmissions of control packets (e.g., ACKs) are only considered to compute the total transmission time. This implies that we do not consider uplink transmissions for modeling inter-BSS interactions.

First, the backoff procedure for accessing the medium is continuous in time. Thus, collisions due to backoff expiring at the same instant are not captured by the model. Second,

[1] The SFCTMN framework has been extended for the SR operation in `https://github.com/sergiobarra/SFCTMN/tree/single_channel_IEEE80211ax_spatial_reuse`

downlink traffic is considered. Accordingly, the model is focused on finding inter-AP interactions. It is important to highlight that additive interference is considered, which results from the combination of different simultaneous interfering transmissions. Accordingly, we are able to characterize real deployments where spatially-distributed interactions occur. Moreover, traffic is considered to be saturated in all the nodes, so that pure SR-based interactions become more apparent.

4.1.1 IEEE 802.11ax OBSS/PD-based Spatial Reuse

In order to model the 11ax SR operation, we have considered the generation of new states, which are related to the different sensitivity levels that each WLAN can use. Notice that using different sensitivity levels enables, on the one hand, to find new types of inter-WLAN interactions that could not exist without applying SR. On the other hand, increasing the sensitivity entails decreasing the transmission power. As a result, the capabilities of a given node vary according to the OBSS/PD threshold that is employed in every situation; a lower transmission power entails using a more robust Modulation and Coding Scheme (MCS).

4.1.2 IEEE 802.11be Coordinated Spatial Reuse

4.2 System-level Simulation of Spatial Reuse

In addition to the analytical model, we introduce the 11ax SR operation in the Komondor simulator. This simulator was conceived, among other purposes, to allow the low-cost integration of novel mechanisms included in new IEEE 802.11 standards. This is the case of the 11ax SR operation, which has not been yet fully implemented in any other well-known simulator. To the date of publishing this article, SR is still being developed for ns-3. By comparing our simulation results with the analytical model, we expect to shed some light on the effects of using 11ax SR, particularly with regard to inter-WLAN interactions. The analytical model will assist us in drawing conclusions regarding the network dynamics that can occur when applying the SR operation.

4.3 Architectural Aspects of Machine-Learning-Aware Networks

Finally, we delve into the architectural aspects for enabling ML-aware networking solutions. The fact is that the existing infrastructure is not yet prepared to accommodate ML-oriented tasks such as data collection, processing, and output distribution. Instead, current networking systems are typically meant for delivering content, without taking into account the underlying characteristics of the processes that generate it.

The first steps towards AI-enabled networking are currently being made in 5G through Network Function Virtualization (NFV). Unlike traditional hardware-based networks, NFV allows rapid elasticity and fast reconfiguration on assigning network resources. This is particularly useful to enable verticals such as autonomous driving in the automotive sector or smart manufacturing in industry 4.0. Besides, network virtualization is useful to boost inter-operator coordination and bringing the ML operation to a macro-scale level, counting with vast information and computation resources.

To conduct the evolution towards ML-aware networks, standardization is key to reach consensus between operators and manufacturers. In this regard, we find many initiatives held by standardization organizations, from which we highlight the Focus Group on Machine Learning for Future Networks including 5G (FG-ML5G), which belongs to the International Telecommunication Union Telecommunication Standardization Sector (ITU-T). The FG-ML5G aims to enable the convergence of future communications with ML technologies. To that end, the focus group has released a specification on a *Unified architecture for 5G and beyond*, recently turned into an ITU Recommendation [149]. Remarkably, ITU's standardized architecture provides a common nomenclature for ML-related mechanisms so that interoperability with other networking systems is achieved.

The module-based ITU's architecture allows adapting to the problem instance and the set of available resources, thus providing flexibility in terms of deployment heterogeneity. For instance, despite deep learning is a powerful solution that may improve the performance in multiple scenarios, it entails a set of computation, storage and communication requirements that may not be fulfilled in other deployments, or parts of the network

Apart from the ITU-T initiatives, other important standardization bodies such as the 3rd Generation Partnership Project (3GPP) or the European Telecommunications Standards Institute (ETSI) are currently working on the integration of data analytics to network functions. The 3GPP contemplates AI as one of the priority topics for shaping its upcoming release (Release 17) and architectural requirements are currently under study [150]. Furthermore, we highlight the ETSI groups on Experiential Networked Intelligence (ENI) and Zero-touch network and Service Management (ZSM), which actively study the integration of AI to networks [151]. Unlike the ITU's unified architecture, most of the work held by the 3GPP and the ETSI focuses on centralized data collection and data analytics solutions. Nevertheless, we understand that the works in [149–151] are complementary to each other.

Apart from the specific ML solutions to problems in communications, some efforts have been made towards enabling AI-aware networking in more general terms. In particular, several architectural proposals have been provided so far [152–154]. Most of the referenced works agree in the necessary steps for enabling big data analytics in cellular deployments: (1) data collection, (2) data preparation, (3) data analysis, and (4) decision making. Nevertheless, none of these works provide architectural guidelines to introduce ML to wireless networks. In this regard, the ITU's architecture looks deeper into the ML operation and targets the actual procedures involving information gathering, processing, and communication. Besides, the ITU-T provides a data handling framework for ML-aware networks [**?**], which defines processes concerning data collection, processing, and output distribution.

Chapter 5

MAIN FINDINGS

[TBD]

Chapter 6

OPEN CHALLENGES AND FUTURE WORK

[TBD]

Bibliography

[1] Boris Bellalta. Ieee 802.11 ax: High-efficiency wlans. *IEEE Wireless Communications*, 23(1):38–46, 2016.

[2] Der-Jiunn Deng, Kwang-Cheng Chen, and Rung-Shiang Cheng. Ieee 802.11 ax: Next generation wireless local area networks. In *10Th international conference on heterogeneous networking for quality, reliability, security and robustness*, pages 77–82. IEEE, 2014.

[3] Evgeny Khorov, Anton Kiryanov, Andrey Lyakhov, and Giuseppe Bianchi. A tutorial on ieee 802.11 ax high efficiency wlans. *IEEE Communications Surveys & Tutorials*, 21(1):197–216, 2018.

[4] S Merlin, G Barriac, H Sampath, L Cariou, T Derham, JP Le Rouzic, R Stacey, M Park, R Porat, N Jindal, et al. TGax simulation scenarios. *doc.: IEEE*, pages 802–11, 2015.

[5] Tae-Suk Kim, Hyuk Lim, and Jennifer C Hou. Improving spatial reuse through tuning transmit power, carrier sense threshold, and data rate in multihop wireless networks. In *Proceedings of the 12th annual international conference on Mobile computing and networking*, pages 366–377. ACM, 2006.

[6] Basel Alawieh, Yongning Zhang, Chadi Assi, and Hussein Mouftah. Improving spatial reuse in multihop wireless networks-a survey. *IEEE Communications Surveys & Tutorials*, 11(3), 2009.

[7] Lin Zhang, Ming Xiao, Gang Wu, Muhammad Alam, Ying-Chang Liang, and Shaoqian Li. A survey of advanced techniques for spectrum sharing in 5g networks. *IEEE Wireless Communications*, 24(5):44–51, 2017.

[8] Christina Thorpe and Liam Murphy. A survey of adaptive carrier sensing mechanisms for ieee 802.11 wireless networks. *IEEE Communications Surveys & Tutorials*, 16(3):1266–1293, 2014.

[9] Yanfeng Zhu, Qian Zhang, Zhisheng Niu, and Jing Zhu. On optimal QoS-aware physical carrier sensing for IEEE 802.11 based WLANs: Theoretical analysis and protocol design. *IEEE transactions on wireless communications*, 7(4):1369–1378, 2008.

[10] Hui Ma, Rajiv Vijayakumar, Sumit Roy, and Jing Zhu. Optimizing 802.11 wireless mesh networks based on physical carrier sensing. *IEEE/ACM Transactions on Networking*, 17(5):1550–1563, 2009.

[11] Jing Deng, Ben Liang, and Pramod K Varshney. Tuning the carrier sensing range of ieee 802.11 mac. In *IEEE Global Telecommunications Conference, 2004. GLOBECOM'04.*, volume 5, pages 2987–2991. IEEE, 2004.

[12] Xue Yang and Nitin Vaidya. On physical carrier sensing in wireless ad hoc networks. In *Proceedings IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies.*, volume 4, pages 2525–2535. IEEE, 2005.

[13] Hui Ma, Hamed MK Alazemi, and Sumit Roy. A stochastic model for optimizing physical carrier sensing and spatial reuse in wireless ad hoc networks. In *IEEE International Conference on Mobile Adhoc and Sensor Systems Conference, 2005.*, pages 8–pp. IEEE, 2005.

[14] Soma Tayamon, Gustav Wikström, Kevin Perez Moreno, Johan Söder, Yu Wang, and Filip Mestanov. Analysis of the potential for increased spectral reuse in wireless lan. In *2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 1963–1967. IEEE, 2015.

[15] Imad Jamil, Laurent Cariou, and Jean-Francois Helard. Improving the capacity of future ieee 802.11 high efficiency wlans. In *2014 21st International Conference on Telecommunications (ICT)*, pages 303–307. IEEE, 2014.

[16] Jing Zhu, Benjamin Metzler, Xingang Guo, and York Liu. Adaptive csma for scalable network capacity in high-density wlan: A hardware prototyping approach. In *Infocom*, 2006.

[17] Ehsan Haghani, Michael N Krishnan, and Avideh Zakhor. Adaptive carrier-sensing for throughput improvement in ieee 802.11 networks. In *2010 IEEE Global Telecommunications Conference GLOBECOM 2010*, pages 1–6. IEEE, 2010.

[18] Christina Thorpe, Sean Murphy, and Liam Murphy. Ieee802. 11k enabled adaptive carrier sense management mechanism (kapcs2). In *12th IFIP/IEEE International Symposium on Integrated Network Management (IM 2011) and Workshops*, pages 509–515. IEEE, 2011.

[19] Liqun Fu, Soung Chang Liew, and Jianwei Huang. Effective carrier sensing in csma networks under cumulative interference. *IEEE Transactions on Mobile Computing*, 12(4):748–760, 2012.

[20] Dong Min Kim and Seong-Lyun Kim. An iterative algorithm for optimal carrier sensing threshold in random csma/ca wireless networks. *IEEE communications letters*, 17(11):2076–2079, 2013.

[21] Bo Yin, Koji Yamamoto, Takayuki Nishio, Masahiro Morikura, and Hirantha Abeysekera. Learning-based spatial reuse for wlans with early identification of interfering transmitters. *IEEE Transactions on Cognitive Communications and Networking*, 6(1):151–164, 2019.

[22] Robert K Schmidt, Achim Brakemeier, Tim Leinmüller, Frank Kargl, and Günter Schäfer. Advanced carrier sensing to resolve local channel congestion. In *Proceedings of the Eighth ACM international workshop on Vehicular inter-networking*, pages 11–20, 2011.

[23] Kyung-Joon Park, Jennifer C Hou, Tamer Basar, and Hwangnam Kim. Noncooperative carrier sense game in wireless networks. *IEEE Transactions on Wireless Communications*, 8(10):5280–5289, 2009.

[24] Kodai Murakami, Tatsuya Ito, and Susumu Ishihara. Improving the spatial reuse of ieee 802.11 wlan by adaptive carrier sense threshold of access points based on node positions. In *2015 Eighth International Conference on Mobile Computing and Ubiquitous Networking (ICMU)*, pages 132–137. IEEE, 2015.

[25] Phillip B Oni and Steven D Blostein. Ap association optimization and cca threshold adjustment in dense wlans. In *2015 IEEE Globecom Workshops (GC Wkshps)*, pages 1–6. IEEE, 2015.

[26] Nakahira, Toshiro and Ishihara, Koichi and Asai, Yusuke and Takatori, Yasushi and Kudo, Riichi and Mizoguchi, Masato. Centralized control of carrier sense threshold and channel bandwidth in high-density WLANs. In *Microwave Conference (APMC), 2014 Asia-Pacific*, pages 570–572. IEEE, 2014.

[27] Wessam Afifi, Enrico-Henrik Rantala, Esa Tuomaala, Sayantan Choudhury, and Marwan Krunz. Throughput-fairness tradeoff evaluation for next-generation wlans with adaptive clear channel assessment. In *2016 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE, 2016.

[28] Yuan Li, Ke Li, Wenwen Li, Yan Zhang, Min Sheng, and Jianxiang Chu. An energy-efficient power control approach for ieee 802.11 n wireless lans. In *2014 IEEE International Conference on Computer and Information Technology*, pages 49–53. IEEE, 2014.

[29] Chevillat, Pierre and Jelitto, Jens and Truong, Hong Linh. Dynamic data rate and transmit power adjustment in IEEE 802.11 wireless LANs. *International Journal of Wireless Information Networks*, 12(3):123–145, 2005.

[30] Jun Fang, Xingjian Li, Wen Cheng, Zhi Chen, and Hongbin Li. Intelligent power control for spectrum sharing: A deep reinforcement learning approach. *CoRR*, 2017.

[31] Md Manowarul Islam, Nobuo Funabiki, Rahardhita Widyatra Sudibyo, Kwenga Ismael Munene, and Wen-Chung Kao. A dynamic access-point transmission power minimization method using pi feedback control in elastic wlan system for iot applications. *Internet of Things*, 8:100089, 2019.

[32] Fabiano S Chaves, André M Cavalcante, Erika PL Almeida, Fuad M Abinader, Robson D Vieira, Sayantan Choudhury, and Klaus Doppler. Adaptive transmit power for wifi dense deployments. In *2014 IEEE 80th vehicular technology conference (VTC2014-Fall)*, pages 1–6. IEEE, 2014.

[33] Carlos Gandarillas, Carlos Martín-Engeños, Héctor López Pombo, and Antonio G Marques. Dynamic transmit-power control for wifi access points based on wireless link occupancy. In *2014 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1093–1098. IEEE, 2014.

[34] Chih-Yung Chang and Hsu-Ruey Chang. Power control and fairness mac mechanisms for 802.11 wlans. *Computer communications*, 30(7):1527–1537, 2007.

[35] Suhua Tang, Akio Hasegawa, Riichiro Nagareda, Akito Kitaura, Tatsuo Shibata, and Sadao Obana. Improving throughput of wireless LANs with transmit power control and slotted channel access. In *Personal Indoor and Mobile Radio Communications (PIMRC), 2011 IEEE 22nd International Symposium on*, pages 834–838. IEEE, 2011.

[36] Minseok Kim, Sungjin Shin, and Jong-Moon Chung. Distributed power control for enhanced spatial reuse in csma/ca based wireless networks. *IEEE Transactions on Wireless Communications*, 13(9):5015–5027, 2014.

[37] Hiroyasu Shimizu, Bo Yin, Koji Yamamoto, Motoki Iwata, Takayuki Nishio, Masahiro Morikura, and Hirantha Abeysekera. Joint channel selection and spatial reuse for starvation mitigation in ieee 802.11 ax wlans. In *2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*, pages 1–6. IEEE, 2019.

[38] Jean-Pierre Ebert, Björn Stremmel, Eckhardt Wiederhold, and Adam Wolisz. An energy-efficient power control approach for wlans. *Journal of Communications and Networks*, 2(3):197–206, 2000.

[39] Xiaoying Lei and Seung Hyong Rhee. Performance enhancement of overlapping bsss via dynamic transmit power control. *EURASIP Journal on Wireless Communications and Networking*, 2015(1):8, 2015.

[40] Wei Li, Yong Cui, Xiuzhen Cheng, Mznah A Al-Rodhaan, and Abdullah Al-Dhelaan. Achieving proportional fairness via AP power control in multi-rate WLANs. *IEEE Transactions on Wireless Communications*, 10(11):3784–3792, 2011.

[41] Oghenekome Oteri, Pengfei Xia, Frank LaSita, and Robert Olesen. Advanced power control techniques for interference mitigation in dense 802.11 networks. In *2013 16th International symposium on wireless personal multimedia communications (WPMC)*, pages 1–7. IEEE, 2013.

[42] Suhua Tang, Hiroyuki Yomo, Akio Hasegawa, Tatsuo Shibata, and Masayoshi Ohashi. Joint transmit power control and rate adaptation for wireless lans. *Wireless personal communications*, 74(2):469–486, 2014.

[43] Roohollah Amiri, Mojtaba Ahmadi Almasi, Jeffrey G Andrews, and Hani Mehrpouyan. Reinforcement learning for self organization and power control of two-tier heterogeneous networks. *IEEE Transactions on Wireless Communications*, 18(8):3933–3947, 2019.

[44] Fei Liang, Cong Shen, Wei Yu, and Feng Wu. Towards optimal power control via ensembling deep neural networks. *IEEE Transactions on Communications*, 2019.

[45] Koji Yamamoto, Xuedan Yang, Takayuki Nishio, Masahiro Morikura, and Hirantha Abeysekera. Analysis of inversely proportional carrier sense threshold and transmission power setting. In *2017 14th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pages 13–18. IEEE, 2017.

[46] Motoki Iwata, Koji Yamamoto, Bo Yin, Takayuki Nishio, Masahiro Morikura, and Hirantha Abeysekera. Analysis of inversely proportional carrier sense threshold and transmission power setting based on received power for ieee 802.11 ax. In *2019 16th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pages 1–6. IEEE, 2019.

[47] Jason A Fuemmeler, Nitin H Vaidya, and Venugopal V Veeravalli. Selecting transmit powers and carrier sense thresholds in csma protocols for wireless ad hoc networks. In *Proceedings of the 2nd annual international workshop on Wireless internet*, pages 15–es, 2006.

[48] Imad Jamil, Laurent Cariou, and Jean-François Hélard. Preserving fairness in super dense wlans. In *2015 IEEE International Conference on Communication Workshop (ICCW)*, pages 2276–2281. IEEE, 2015.

[49] Vivek P Mhatre, Konstantina Papagiannaki, and Francois Baccelli. Interference mitigation through power control in high density 802.11 wlans. In *IEEE INFOCOM 2007-26th IEEE International Conference on Computer Communications*, pages 535–543. IEEE, 2007.

[50] Koki Iwai, Takanobu Ohnuma, Hiroshi Shigeno, and Yusuke Tanaka. Improving of fairness by dynamic sensitivity control and transmission power control with access point cooperation in dense wlan. In *2019 16th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pages 1–4. IEEE, 2019.

[51] Imad Jamil, Laurent Cariou, and Jean-François Hélard. Efficient mac protocols optimization for future high density wlans. In *2015 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1054–1059. IEEE, 2015.

[52] Imad Jamil, Laurent Cariou, and Jean-Fran Hélard. Novel learning-based spatial reuse optimization in dense WLAN deployments.

[53] G Smith. Dynamic sensitivity control-v2. *IEEE*, 802:802–11, 2015.

[54] G Smith. Dsc and obss_pd. *Presentation doc. IEEE*, pages 802–11, 2017.

[55] Masahito Mori et al. Performance analysis of bss color and dsc. *Nov*, 3:11–14, 2014.

[56] Oghenekome Oteri, Frank La Sita, Rui Yang, Monisha Ghosh, and Robert Olesen. Improved spatial reuse for dense 802.11 wlans. In *2015 IEEE Globecom Workshops (GC Wkshps)*, pages 1–6. IEEE, 2015.

[57] Jin Liu, Masahide Hatanaka, and Takao Onoye. A collision mitigation method on spatial reuse for wlan in a dense residential environment.

[58] M Shahwaiz Afaqui, Eduard Garcia-Villegas, Elena Lopez-Aguilera, Graham Smith, and Daniel Camps. Evaluation of dynamic sensitivity control algorithm for IEEE 802.11 ax. In *Wireless Communications and Networking Conference (WCNC), 2015 IEEE*, pages 1060–1065. IEEE, 2015.

[59] M Shahwaiz Afaqui, Eduard Garcia-Villegas, Elena Lopez-Aguilera, and Daniel Camps-Mur. Dynamic sensitivity control of access points for IEEE 802.11 ax. In *Communications (ICC), 2016 IEEE International Conference on*, pages 1–7. IEEE, 2016.

[60] Parag Kulkarni and Fengming Cao. Taming the densification challenge in next generation wireless LANs: An investigation into the use of dynamic sensitivity control. In *Wireless and Mobile Computing, Networking and Communications (WiMob), 2015 IEEE 11th International Conference on*, pages 860–867. IEEE, 2015.

[61] Zhenzhe Zhong, Fengming Cao, Parag Kulkarni, and Zhong Fan. Promise and perils of dynamic sensitivity control in ieee 802.11 ax wlans. In *2016 International Symposium on Wireless Communication Systems (ISWCS)*, pages 439–444. IEEE, 2016.

[62] Kiryanov A. Krotov A. Gallo P. Garlisi D. Khorov, E. and I. Tinnirello. Joint usage of dynamic sensitivity control and time division multiple access in dense 802.11 ax networks. In *In International Workshop on Multiple Access Communications*, pages 57–71. Springer, Cham., 2016.

[63] Ioannis Selinis, Marcin Filo, Seiamak Vahid, Jonathan Rodriguez, and Rahim Tafazolli. Evaluation of the DSC algorithm and the BSS color scheme in dense cellular-like IEEE 802.11 ax deployments. In *Personal, Indoor, and Mobile Radio Communications (PIMRC), 2016 IEEE 27th Annual International Symposium on*, pages 1–7. IEEE, 2016.

[64] Ioannis Selinis, Konstantinos Katsaros, Seiamak Vahid, and Rahim Tafazolli. Exploiting the Capture Effect on DSC and BSS Color in Dense IEEE 802.11 ax Deployments. In *Proceedings of the Workshop on ns-3*, pages 47–54. ACM, 2017.

[65] Yun Wen, Hiroshi Fujita, and Dai Kimura. Throughput-aware dynamic sensitivity control algorithm for next generation wlan system. In *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 1–7. IEEE, 2017.

[66] Tanguy Ropitault and Nada Golmie. Etp algorithm: Increasing spatial reuse in wireless lans dense environment using etx. In *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 1–7. IEEE, 2017.

[67] Ioannis Selinis, Konstantinos Katsaros, Seiamak Vahid, and Rahim Tafazolli. Control OBSS/PD Sensitivity Threshold for IEEE 802.11 ax BSS Color. In *2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, pages 1–7. IEEE, 2018.

[68] Tanguy Ropitault. Evaluation of rtot algorithm: A first implementation of obss_pd-based sr method for ieee 802.11 ax. In *2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC)*, pages 1–7. IEEE, 2018.

[69] Anastasios Valkanis, Athanasios Iossifides, Periklis Chatzimisios, Marios Angelopoulos, and Vasilis Katos. Ieee 802.11 ax spatial reuse improvement: An interference-based channel-access algorithm. *IEEE Vehicular Technology Magazine*, 14(2):78–84, 2019.

[70] Jaha Mvulla and Eun-Chan Park. Enhanced dual carrier sensing with transmission time control for fair spatial reuse in heterogeneous and dense wlans. *IEEE Access*, 6:22140–22155, 2018.

[71] Qiao Qu, Bo Li, Mao Yang, Zhongjiang Yan, Annan Yang, Jian Yu, Ming Gan, Yunbo Li, Xun Yang, Osama Aboul-Magd, et al. Survey and Performance Evaluation of the Upcoming Next Generation WLAN Standard-IEEE 802.11 ax. *arXiv preprint arXiv:1806.05908*, 2018.

[72] Zhao Shen, Bo Li, Mao Yang, Zhongjiang Yan, Xiaobo Li, and Yi Jin. Research and Performance Evaluation of Spatial Reuse Technology for Next Generation WLAN. In *International Wireless Internet Conference*, pages 41–51. Springer, 2018.

[73] Arjun Malhotra, Mukulika Maity, and Avik Dutta. How much can we reuse? an empirical analysis of the performance benefits achieved by spatial-reuse of ieee 802.11 ax. In *2019 11th International Conference on Communication Systems & Networks (COMSNETS)*, pages 432–435. IEEE, 2019.

[74] Lorenzo Galati Giordano Eloise de Carvalho Rodrigues, Adrian Garcia-Rodriguez and Giovanni Geraci. On the latency of ieee 802.11ax wlans with parameterized spatial reuse. 2020.

[75] TGbe. 11-19-0801-00-00be-ap-coordination-in-eht.

[76] TGbe. 11-18-1547-00-0eht-technology-features-for-802-11-eht.

[77] TGbe. 11-18-1926-02-0eht-terminology-for-ap-coordination.

[78] TGbe. 11-19-1779-06-00be-downlink-spatial-reuse-parameter-framework-with-coordinated-beamforming-null-steering-for-802-11be.

[79] Dmitry Bankov, Andre Didenko, Evgeny Khorov, and Andrey Lyakhov. OFDMA Uplink Scheduling in IEEE 802.11 ax Networks. In *2018 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE, 2018.

[80] Konstantinos Dovelos and Boris Bellalta. Optimal Resource Allocation in IEEE 802.11ax Uplink OFDMA with Scheduled Access. *arXiv preprint arXiv:1811.00957*, 2019.

[81] Ruizhi Liao, Boris Bellalta, Miquel Oliver, and Zhisheng Niu. MU-MIMO MAC protocols for wireless local area networks: A survey. *IEEE Communications Surveys & Tutorials*, 18(1):162–183, 2016.

[82] Maddalena Nurchis and Boris Bellalta. Target wake time: scheduled access in IEEE 802.11 ax WLANs. *IEEE Wireless Communications*, 26(2):142–150, 2019.

[83] Paulo Valente Klaine, Muhammad Ali Imran, Oluwakayode Onireti, and Richard Demo Souza. A survey of machine learning techniques applied to self-organizing cellular networks. *IEEE Communications Surveys & Tutorials*, 19(4):2392–2431, 2017.

[84] Mario Bkassiny, Yang Li, and Sudharman K Jayaweera. A survey on machine-learning techniques in cognitive radios. *IEEE Communications Surveys & Tutorials*, 15(3):1136–1159, 2013.

[85] Wenbo Wang, Andres Kwasinski, Dusit Niyato, and Zhu Han. A survey on applications of model-free strategy learning in cognitive wireless networks. *IEEE Communications Surveys & Tutorials*, 18(3):1717–1757, 2016.

[86] Mohammad Abu Alsheikh, Shaowei Lin, Dusit Niyato, and Hwee-Pink Tan. Machine learning in wireless sensor networks: Algorithms, strategies, and applications. *IEEE Communications Surveys & Tutorials*, 16(4):1996–2018, 2014.

[87] Anna Forster. Machine learning techniques applied to wireless ad-hoc networks: Guide and survey. In *Intelligent Sensors, Sensor Networks and Information, 2007. ISSNIP 2007. 3rd International Conference on*, pages 365–370. IEEE, 2007.

[88] Tom M Mitchell et al. "Machine learning". *Burr Ridge, IL: McGraw Hill*, 45(37):870–877, 1997.

[89] Update this. 6G: The Next Frontier. *arXiv preprint arXiv:???*, 2019.

[90] Rubayet Shafin, Lingjia Liu, Vikram Chandrasekhar, Hao Chen, Jeffrey Reed, and Jianzhong Charlie Zhang. Artificial intelligence-enabled cellular networks: A critical path to beyond-5g and 6g. *IEEE Wireless Communications*, 2020.

[91] Ping Yang, Yue Xiao, Ming Xiao, and Shaoqian Li. 6g wireless communications: Vision and potential techniques. *IEEE Network*, 33(4):70–75, 2019.

[92] Chunxiao Jiang *et al.* Machine learning paradigms for next-generation wireless networks. *IEEE Wireless Comm.*, 24(2):98–105, 2016.

[93] Chaoyun Zhang, Paul Patras, and Hamed Haddadi. "Deep learning in mobile and wireless networking: A survey". *IEEE Comm. Surveys & Tutorials*, 2019.

[94] Muhammad Usama *et al.* "Unsupervised machine learning for networking: Techniques, applications and research challenges". *IEEE Access*, 7:65579–65615, 2019.

[95] Manuel Eugenio Morocho Cayamcela and Wansu Lim. Artificial intelligence in 5g technology: A survey. In *2018 International Conference on Information and Communication Technology Convergence (ICTC)*, pages 860–865. IEEE, 2018.

[96] Jessica Moysen and Lorenza Giupponi. From 4g to 5g: Self-organized network management meets machine learning. *Computer Communications*, 129:248–268, 2018.

[97] Chaoyun Zhang and Paul Patras. Long-term mobile traffic forecasting using deep spatio-temporal neural networks. In *Proceedings of the Eighteenth ACM International Symposium on Mobile Ad Hoc Networking and Computing*, pages 231–240, 2018.

[98] Sebastian Troia, Rodolfo Alvizu, Youduo Zhou, Guido Maier, and Achille Pattavina. Deep learning-based traffic prediction for network optimization. In *2018 20th International Conference on Transparent Optical Networks (ICTON)*, pages 1–4. IEEE, 2018.

[99] Udita Paul, Jiamo Liu, Sebastian Troia, Olabisi Falowo, and Guido Maier. Traffic-profile and machine learning based regional data center design and operation for 5g network. *Journal of Communications and Networks*, 21(6):569–583, 2019.

[100] Bilong Shen, Xiaodan Liang, Yufeng Ouyang, Miaofeng Liu, Weimin Zheng, and Kathleen M Carley. Stepdeep: a novel spatial-temporal mobility event prediction framework based on deep neural network. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 724–733, 2018.

[101] Honggang Zhang, Yuxiu Hua, Chujie Wang, Rongpeng Li, and Zhifeng Zhao. Deep learning based traffic and mobility prediction. *Machine Learning for Future Wireless Communications*, pages 119–136, 2020.

[102] Lixin Li, Yang Xu, Jiaying Yin, Wei Liang, Xu Li, Wei Chen, and Zhu Han. Deep reinforcement learning approaches for content caching in cache-enabled d2d networks. *IEEE Internet of Things Journal*, 2019.

[103] Zhiyuan Xu, Yanzhi Wang, Jian Tang, Jing Wang, and Mustafa Cenk Gursoy. A deep reinforcement learning based framework for power-efficient resource allocation in cloud rans. In *2017 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE, 2017.

[104] Ji Li, Hui Gao, Tiejun Lv, and Yueming Lu. Deep reinforcement learning based computation offloading and resource allocation for mec. In *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1–6. IEEE, 2018.

[105] Ying He, F Richard Yu, Nan Zhao, and Hongxi Yin. Secure social networks in 5g systems with mobile edge computing, caching, and device-to-device communications. *IEEE Wireless Communications*, 25(3):103–109, 2018.

[106] Neelakantan Nurani Krishnan, Eric Torkildson, Narayan B Mandayam, Dipankar Raychaudhuri, Enrico-Henrik Rantala, and Klaus Doppler. Optimizing throughput performance in distributed mimo wi-fi networks using deep reinforcement learning. *IEEE Transactions on Cognitive Communications and Networking*, 2019.

[107] Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2009.

[108] Jakub Konečnỳ, H Brendan McMahan, Felix X Yu, Peter Richtárik, Ananda Theertha Suresh, and Dave Bacon. Federated learning: Strategies for improving communication efficiency. *arXiv preprint arXiv:1610.05492*, 2016.

[109] Virginia Smith, Chao-Kai Chiang, Maziar Sanjabi, and Ameet S Talwalkar. Federated multi-task learning. In *Advances in Neural Information Processing Systems*, pages 4424–4434, 2017.

[110] William R Thompson. On the likelihood that one unknown probability exceeds another in view of the evidence of two samples. *Biometrika*, 25(3/4):285–294, 1933.

[111] Robert R Bush and Frederick Mosteller. A stochastic model with applications to learning. *The Annals of Mathematical Statistics*, pages 559–585, 1953.

[112] Peter Auer, Nicolo Cesa-Bianchi, and Paul Fischer. Finite-time analysis of the multi-armed bandit problem. *Machine learning*, 47(2-3):235–256, 2002.

[113] Nicolo Cesa-Bianchi and Gabor Lugosi. *Prediction, learning, and games*. Cambridge university press, 2006.

[114] John Gittins, Kevin Glazebrook, and Richard Weber. *Multi-armed bandit allocation indices*. John Wiley & Sons, 2011.

[115] Sébastien Bubeck, Nicolo Cesa-Bianchi, et al. Regret analysis of stochastic and non-stochastic multi-armed bandit problems. *Foundations and Trends® in Machine Learning*, 5(1):1–122, 2012.

[116] Tor Lattimore and Csaba Szepesvári. Bandit algorithms. *preprint*, 2018.

[117] Aleksandrs Slivkins. Introduction to multi-armed bandits. *arXiv preprint arXiv:1904.07272*, 2019.

[118] Yi Gai, Bhaskar Krishnamachari, and Rahul Jain. Learning multiuser channel allocations in cognitive radio networks: A combinatorial multi-armed bandit formulation. In *New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on*, pages 1–9. IEEE, 2010.

[119] Cem Tekin and Mingyan Liu. Online learning in opportunistic spectrum access: A restless bandit approach. In *2011 Proceedings IEEE INFOCOM*, pages 2462–2470. IEEE, 2011.

[120] Yunxia Chen, Qing Zhao, Vikram Krishnamurthy, and Dejan Djonin. Transmission scheduling for sensor network lifetime maximization: A shortest path bandit formulation. In *2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings*, volume 4, pages IV–IV. IEEE, 2006.

[121] Marc Carrascosa and Boris Bellalta. Decentralized ap selection using multi-armed bandits: Opportunistic {\epsilon}-greedy with stickiness. *arXiv preprint arXiv:1903.00281*, 2019.

[122] Keqin Liu and Qing Zhao. A restless bandit formulation of opportunistic access: Indexablity and index policy. In *2008 5th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks Workshops*, pages 1–5. IEEE, 2008.

[123] Animashree Anandkumar, Nithin Michael, Ao Kevin Tang, and Ananthram Swami. Distributed algorithms for learning and cognitive medium access with logarithmic regret. *IEEE Journal on Selected Areas in Communications*, 29(4):731–745, 2011.

[124] Jonathan Rosenski, Ohad Shamir, and Liran Szlak. Multi-player bandits–a musical chairs approach. In *International Conference on Machine Learning*, pages 155–163, 2016.

[125] Setareh Maghsudi and Sławomir Stańczak. Channel selection for network-assisted d2d communication via no-regret bandit learning with calibrated forecasting. *IEEE Transactions on Wireless Communications*, 14(3):1309–1322, 2015.

[126] Setareh Maghsudi and Sławomir Stańczak. Joint channel selection and power control in infrastructureless wireless networks: A multiplayer multiarmed bandit framework. *IEEE Transactions on Vehicular Technology*, 64(10):4565–4578, 2014.

[127] Setareh Maghsudi and Ekram Hossain. Distributed user association in energy harvesting dense small cell networks: A mean-field multi-armed bandit approach. *IEEE Access*, 5:3513–3523, 2017.

[128] Marc Carrascosa and Boris Bellalta. Multi-armed bandits for decentralized ap selection in enterprise wlans. *arXiv preprint arXiv:2001.00392*, 2020.

[129] Pierre Coucheney, Kinda Khawam, and Johanne Cohen. Multi-armed bandit for distributed inter-cell interference coordination. In *2015 IEEE International Conference on Communications (ICC)*, pages 3323–3328. IEEE, 2015.

[130] Afef Feki and Veronique Capdevielle. Autonomous resource allocation for dense lte networks: A multi armed bandit formulation. In *2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications*, pages 66–70. IEEE, 2011.

[131] Jose A Ayala-Romero, Juan J Alcaraz, Andrea Zanella, and Michele Zorzi. Contextual bandit approach for energy saving and interference coordination in hetnets. In *2018 IEEE International Conference on Communications (ICC)*, pages 1–6. IEEE, 2018.

[132] Tony Daher, Sana Ben Jemaa, and Laurent Decreusefond. Cognitive management of self-organized radio networks based on multi armed bandit. In *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pages 1–5. IEEE, 2017.

[133] Richard Combes and Alexandre Proutiere. Dynamic rate and channel selection in cognitive radio systems. *IEEE Journal on Selected Areas in Communications*, 33(5):910–921, 2014.

[134] Yapeng Zhao, Hua Qian, Kai Kang, and Yanliang Jin. A non-stationary bandit strategy for rate adaptation with delayed feedback. *IEEE Access*, 2020.

[135] Cristina Cano and Gergely Neu. Wireless optimisation via convex bandits: Unlicensed lte/wifi coexistence. In *Proceedings of the 2018 Workshop on Network Meets AI & ML*, pages 41–47, 2018.

[136] Peter Auer, Nicolo Cesa-Bianchi, Yoav Freund, and Robert E Schapire. The nonstochastic multiarmed bandit problem. *SIAM journal on computing*, 32(1):48–77, 2002.

[137] Neha Gupta, Ole-Christoffer Granmo, and Ashok Agrawala. Thompson sampling for dynamic multi-armed bandits. In *2011 10th International Conference on Machine Learning and Applications and Workshops*, volume 1, pages 484–489. IEEE, 2011.

[138] Marco Di Felice, Kaushik Roy Chowdhury, and Luciano Bononi. Learning with the bandit: A cooperative spectrum selection scheme for cognitive radio networks. In *Global Telecommunications Conference (GLOBECOM 2011), 2011 IEEE*, pages 1–6. IEEE, 2011.

[139] Kobi Cohen, Qing Zhao, and Anna Scaglione. Restless multi-armed bandits under time-varying activation constraints for dynamic spectrum access. In *Signals, Systems and Computers, 2014 48th Asilomar Conference on*, pages 1575–1578. IEEE, 2014.

[140] Nadine Abbas, Youssef Nasser, and Karim El Ahmad. Recent advances on artificial intelligence and learning techniques in cognitive radio networks. *EURASIP Journal on Wireless Communications and Networking*, 2015(1):174, 2015.

[141] Setareh Maghsudi and Sławomir Stańczak. Joint channel selection and power control in infrastructureless wireless networks: A multiplayer multiarmed bandit framework. *IEEE Transactions on Vehicular Technology*, 64(10):4565–4578, 2015.

[142] Orly Avner and Shie Mannor. Concurrent bandits and cognitive radio networks. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 66–81. Springer, 2014.

[143] Keqin Liu and Qing Zhao. Distributed learning in multi-armed bandit with multiple players. *IEEE Transactions on Signal Processing*, 58(11):5667–5681, 2010.

[144] Francesc Wilhelmi, Cristina Cano, Gergely Neu, Boris Bellalta, Anders Jonsson, and Sergio Barrachina-Muñoz. Collaborative spatial reuse in wireless networks via selfish multi-armed bandits. *Ad Hoc Networks*, 88:129–141, 2019.

[145] Francesc Wilhelmi, Sergio Barrachina-Muñoz, Boris Bellalta, Cristina Cano, Anders Jonsson, and Gergely Neu. Potential and pitfalls of multi-armed bandits for decentralized spatial reuse in wlans. *Journal of Network and Computer Applications*, 127:26–42, 2019.

[146] Boris Bellalta, Alessandro Zocca, Cristina Cano, Alessandro Checco, Jaume Barcelo, and Alexey Vinel. Throughput analysis in CSMA/CA networks using continuous time Markov networks: a tutorial. In *Wireless Networking for Moving Objects*, pages 115–133. Springer, 2014.

[147] Boris Bellalta. Throughput Analysis in High Density WLANs. *IEEE Communications Letters*, 21(3):592–595, 2017.

[148] Sergio Barrachina-Muñoz, Francesc Wilhelmi, and Boris Bellalta. Dynamic channel bonding in spatially distributed high-density wlans. *IEEE Transactions on Mobile Computing*, 19(4):821–835, 2019.

[149] ITU-T Rec. Y.3172, “Architectural framework for machine learning in future networks including IMT-2020”, 2019.

[150] 3GPP TR 23.791 V16.2.0 (2019-06). "Study of Enablers for Network Automation for 5G". 2019.

[151] ETSI GS ZSM 002 V0.13.5 (2019-07). Draft "Zero-touch network and Service Management (ZSM); Reference Architecture". 2019.

[152] Suzhi Bi *et al.* "Wireless communications in the era of big data". *IEEE Comm. Magazine*, 53(10):190–199, 2015.

[153] I Chih-Lin *et al.* "The Big-Data-Driven Intelligent Wireless Network: Architecture, Use Cases, Solutions, and Future Trends". *IEEE Vehic. Tech. Magazine*, 12(4):20–29, 2017.

[154] Mowei Wang *et al.* "Machine learning for networking: Workflow, advances and opportunities". *IEEE Network*, 32(2):92–99, 2018.

Chapter 7

PUBLICATIONS

7.1 Spatial Reuse in IEEE 802.11 ax WLANs

7.2 On the Performance of the Spatial Reuse Operation in IEEE 802.11 ax WLANs

7.3 Implications of decentralized Q-learning resource allocation in wireless networks

7.4 Collaborative spatial reuse in wireless networks via selfish multi-armed bandits

7.5 Potential and pitfalls of multi-armed bandits for decentralized spatial reuse in WLANs

7.6 A Flexible Machine-Learning-Aware Architecture for Future WLANs. IEEE Communications Magazine

7.7 Komondor: a wireless network simulator for next-generation high-density WLANs

7.8 Usage of Network Simulators in Machine-Learning-Assisted 5G/6G Networks