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THESIS

«A study of IEEE 802.11ax Performance in Highly Dense Wireless Local Area Networks »

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Βεβαιώνω ότι είμαι ο συγγραφέας αυτής της εργασίας και ότι κάθε βοήθεια την οποία είχα για την προετοιμασία της είναι πλήρως αναγνωρισμένη και αναφέρεται στην εργασία. Επίσης, έχω καταγράψει τις όποιες πηγές από τις οποίες έκανα χρήση δεδομένων, ιδεών, εικόνων και κειμένου, είτε αυτές αναφέρονται ακριβώς είτε παραφρασμένες. Επιπλέον, βεβαιώνω ότι αυτή η εργασία προετοιμάστηκε από εμένα προσωπικά, ειδικά ως πτυχιακή εργασία, στο Τμήμα Μηχανικών Πληροφορικής και Ηλεκτρονικών Συστημάτων του ΔΙ.ΠΑ.Ε.

To my grandpa who is watching us from above.

Abstract

The main target of the current thesis is to research and study the performance of the IEEE 802.11ax amendment in high density wireless local area networks. For that purpose we inspect and evaluate the application of machine learning algorithms by considering various deployments on both normal and high dense scenarios. The normal scenarios provide a first view on how wireless networks operate and the performance due to the variation of certain parameters. We then consider more dense scenarios recreating potential real world problems leading us to discover if machine learning algorithms are efficient and applicable to next generation networks.

Nowadays where telecommunications make huge step forward evolution steps combined with the ever increasing number of users, the need for higher and higher data rates and the 5th and 6th generation networks, already on the way, wireless connections gathered the interest of the technological community. For that reason with our research, we dive as deep as we could on the nature of wireless networks and reinforcement learning. Initially the thesis provides an introduction on the history of wireless networks and how they reached the point they are in our days. We also dig out the features and the optimization IEEE 802.11ax amendment is going to bring in compare with its ancestors.

In the first chapter we study the evolution of the IEEE 802.11 standards and applications that have introduced through the years. We focus on the first high throughput amendments IEEE 802.11n/ac and we then consider the IEEE 802.11ax amendment which is the main point of interest in our research. The second chapter introduces networking simulators a crucial tool for both network designers and researchers, by particularly focusing on Komondor an IEEE 802.11ax wireless network simulator.

In the next chapter we execute various scenarios in simple topologies in order to assess the performance due to the variation of parameters like transmission power and sensitivity, trying to understand their importance and influence to the overall performance. In chapters 5 and 6 consider reinforcement learning by introducing the learning method of Multi Arm Bandits and learning strategies. We then apply and study different action selection strategies. Furthermore, Chapter 6 re-creates a real deployment by applying again Reinforcement Learning (RL) technologies in order to investigate their impact to more dense scenarios.

Finally, Chapter 7 concludes the thesis by presenting our findings on the performance of the IEEE 802.11ax amendment in high dense scenarios and illustrates how reinforcement learning improves performance. Finally, we propose what can be done as future work about the feasibility of smart algorithms by especially mentioning the drawbacks of RL algorithms that have to overcome in order to be effectively applied in high dense scenarios.

Περίληψη

Κατά την διάρκεια εκπόνησης της πτυχιακής εργασίας, βασικό μέλημα και κύριος στόχος ήταν η μελέτη του πρωτοκόλλου IEEE 802.11ax, αξιολογώντας την απόδοσή του σε πολύ πυκνά ασύρματα δίκτυα. Στη διάρκεια της μελέτης καταφέραμε να χρησιμοποιήσουμε μια σημαντική τεχνολογία, την μηχανική μάθηση, που μπορεί να αποτελέσει βασικό χαρακτηριστικό των δικτύων στο μέλλον. Δημιουργήσαμε τόσο σενάρια με πυκνά ασύρματα δίκτυα όσο και απλές παραστάσεις δικτύων οι οποίες μας βοήθησαν να καταλάβουμε εκτενέστερα την φύση των παραμέτρων που τις αποτελούν καθώς και των επιπτώσεων που μπορεί να υπάρχουν σε κάποια αλλαγή. Επίσης στα σενάριά μας, όπου υπήρχαν πυκνές συστιχίες δικτύων, καταφέραμε να ρίξουμε μια πρώτη ματιά στις δυνατότητες των αλγορίθμων μηχανική μάθησης.

Ο τομέας των τηλεπικοινωνιών και των ασύρματων δικτύων έχει εξελιχθεί ραγδαία τα τελευταία χρόνια, προσπαθώντας να καλύψει τις ανάγκες της όλο και αυξανόμενης ζήτησης για υψηλότερες ταχύτητες και περισσότερες δυνατότητες από τους χρήστες. Οι επερχόμενες γενιές ασύρματων δικτύων 5G και 6G έχουν τραβήξει την προσοχή της ερευνητικής κοινότητας. Ως εκ τούτου η φύση της έρευνάς μας αποτελεί μια προσπάθεια για ανάδειξη της πορείας των ασύρματων δικτύων, από την αρχή τους μέχρι την εποχή μας, εστιάζοντας στο πρωτόκολλο που θα έχει πρωταγωνιστικό ρόλο στην συνέχεια της έρευνάς μας, το IEEE 802.11ax. Παράλληλα κάνουμε μια εκτενέστερη ανάλυση στις δυνατότητες των αλγορίθμων μηχανικής μάθησης, επικεντρώνοντας το ενδιαφέρον μας στην ενισχυμένη μάθηση η οποία θα χρησοποιηθεί εκτενέστερα στα πειράματά μας.

Στο πρώτο κεφάλαιο παρουσιάζουμε την ιστορία εξέλιξης του πρωτοκόλλου IEEE 802.11, μαζί με επεκτάσεις και αναβαθμίσεις που έφεραν επιπλέον δυνατότητες στα ασύρματα δίκτυα στο πέρασμα των χρόνων. Ιδιαίτερη μνεία γίνεται στα πρώτα πρωτόκολλα υψηλής απόδοσης IEEE 802.11n/ac που αποτέλεσαν τους πυλώνες δημιουργίας του πρωτοκόλλου IEEE 802.11ax τονίζοντας τις πρωτοπορίες που έφερε σε αντίθεση με τους προγόνους του. Στην συνέχεια στο δεύτερο κεφάλαιο βρίσκουμε ένα πολύ σημαντικό εργαλείο για την μελέτη και την εξέλιξη των ασύρματων δικτύων, του προσωμοιωτές δικτύων. Σε αυτό το κεφάλαιο θα συναντήσουμε και τον Komondor, τον προσομοιωτή ο οποίος χρησιμοποιήθηκε κατά την εκτέλεση των πειραμάτων και μας βοήθησε στην συλλογή στοιχείων.

Το ακόλουθο κεφάλαιο 4, θα μπορούσαμε να το χαρακτηρίσουμε σαν μια εισαγωγή στον κόσμο των ασύρματων δικτύων καθώς παρουσιάζοντας απλές τοπολογίες, μέσα από προσομοιώσεις καταφέραμε να δούμε την επίδραση διάφορων παραμέτρων στην συνολική απόδοση των δικτύων. Συνεχίζοντας την έρευνά μας, τα επόμενα δυο κεφάλαια 5 και 6 πραγματεύονται την ενισχυμένη μάθηση, την μέθοδο εκμάθησης Multi Arm Bandit καθώς και την εφαρμογή τους σε αναπαραστάσεις προβλημάτων τις καθημερινότητάς μας.

Την έρευνά μας κλείνει το κεφάλαιο 7 όπου παραθέτουμε όλα μας στα συμπεράσματα περί της αποτελεσματικότητας του πρωτοκόλλου IEEE 802.11ax σε πυκνά δίκτυα παραθέτοντας παράλληλα την δυνατότητα της ενισχυμένης μάθησης να βοηθήσει έμπρακτα την εξέλιξη των ασύρματων δικτύων στο μέλλον. Κλείνοντας παρουσιάζονται κάποιες προτάσεις για εκτενέστη έρευνα στο μέλλον αναφορικά με την βιωσιμότητα έξυπνων αλγορίθμων στο τομέα των δικτύων καθώς υπάρχουν πολλά εμπόδια που πρέπει να αντιμετωπιστούν για να μπορέσουν οι εν λόγω αλγόριθμοι να χρησιμοποιηθούν. Ιδιαίτερα σε πυκνά ασύρματα δίκτυα.

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Notations

AP	Access Points
AI	Artificial Intelligence
BSS	Basic Service Set
CTS	Clear to Send
DCB	Dynamic Channel Bonding
DRL	Deep Reinforcement Learning
ESS	Extended Service Set
IHU	International Hellenic University
MAB	Multi Arm Bandits
MAC	Medium Access Control
MCS	Modulation Coding Scheme
MU-MIMO	Multi User Multiple Input-Output
NAV	Network Allocation Vector
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
RL	Reinforcement Learning
RTS	Ready to Send
RU	Resource Units
SCB	Static Channel Bonding
SINR	Signal plus Interference to Noise Ration
STA	Stations
WN	Wireless Network
WLAN	Wireless Local Area Network

Chapter 1: Introduction

At the dawn of the 21st century where the Mobile Internet came, new technologies and applications appeared that immediately redefined aspects of our lives, work and even entertainment, that we could not even imagine before. The increasing number of wireless connected objects, from computers, laptops and smart watches to tiny sensors for industrial, and not only use, triggered a surge in mobile data traffic.

Wireless networks have faced a breathtaking evolution through the years. Since the beginning of their existence with the packet radio based ALOHANET, which was developed at the University of Hawaii in 1971 and connected seven campuses spread out of four islands and achieved data rates on the order of 20 Kbps, did not stand still but evolved dramatically. From the "legacy" 2 Mbit/s IEEE 802.11 (1997), to the 11 Mbit/s of IEEE 802.11b (1999), the 54 Mbit/s of IEEE 802.11a/g (1999,2003), the 600 Mbit/s of IEEE 802.11n (2009) and the above Gbit/s rates of the IEEE 802.11ac (2013), now almost five decades after ALOHANET, the main focus of the next generation wireless networks (e.g., the fourth generation or 4G and the beginning of 5G) is to introduce the feature of heterogeneity.

As different wireless access technologies are integrated to co-operate with each other in terms of coverage area, support, bandwidth and price, dynamic network selection scheme is required to support quality of service (QoS) but also loading balance. The already extreme traffic load wireless networks accommodate, forced the IEEE 802.11 community to create the IEEE 802.11ax Task Group to develop a new set of physical layer and medium access control layer specifications in order to keep the pace with the ever increasing number of users, offering a sustained multi-Gb/s throughput in high density scenarios.

However, an emerging tool that can effectively address a variety of problems and challenges wireless networks are called to cope with, especially in dense scenarios, is reinforcement learning. Reinforcement learning is one of the most important sections of machine learning which had a significant impact on the development of Artificial Intelligence the past 20 years. Reinforcement learning (RL), is based on an agent whose job is to optimize an objective in long terms while interacting with the environment, structured on trial and error. There are plenty of reinforcement learning algorithms applied in surveyed studies like Q-Learning, Deep Reinforcement Learning and Multi Arm Bandits (MAB). Although, in this study we are going to focus on the last mentioned.

In the MAB model, a single applied agent, sequentially takes actions and receives a random reward generated by a corresponding distribution while the main objective is to maximize the aggregated reward. The MAB framework allows us to properly approach the exploration-exploitation trade-off in face of uncertainty. In contrast with classic RL algorithms, MAB is a stateless fact that allows it to construct a policy which should be followed in future situations. Despite that MAB has been very popular in wireless communication, the application of reinforcement learning in order to improve next-generation wireless deployments efficiency is disputed.

In the current research we are going to investigate the benefits that IEEE 802.11ax brought to wireless local area and the hurdles it has to face alongside with the side effect todays WLANs and next generation networks are going to get by applying reinforcement algorithms. The remaining of this research is constructed as it follows: In Chapter 2 we are taking a close look to the evolution of the IEEE 802.11 standards from the first version in 1999 till the last revision released IEEE 802.11-2016. We take a snick picture of the enhancements the extension amendments brought focusing on legacy IEEE 802.11a/b/g and their features. Extended presentation will be made for the first high throughput IEEE

802.11n/ac amendments focusing on the most notable features they brought on wireless networking. This chapter ends with the comprehensive research on IEEE 802.11ax, its features, obstacles that has to face and application that have made in our literature for further extension of its capabilities.

In Chapter 3 we see wireless network simulators, a very handful tool in wireless networking. The rest of the chapter that will follow is a small tutorial on Komondor, a high density wireless network simulator designed for the IEEE 802.11ax and next generation networks. We are going to present the features that makes him stands out in comparison with other well-known simulating tools. Continuing in Chapter 4, with the help of Komondor we are going to investigate the nature of wireless networks and the variables that have direct impact to its performance in order to try to understand the hierarchy, if existed, of them that might affect more than others.

Then, in Chapter 5 we introduce Multi Arm Bandits algorithms into wireless networking and how this algorithms work. We are going to mention the important parts that we have to focus on during the setup of this smart algorithm. For the rest of the chapter which also extends and in Chapter 6 we are going to investigate through various simulations even in highly density scenarios the effectiveness of such technologies. Finally in Chapter 7 we export our overall results of the feasibility of technologies on wireless networking proposing the same time what should be investigated in a bigger scale in order to have a greater view about this issue.

Chapter 2: The IEEE 802.11 family at a glance

2.1 Introduction to WLANs and its applications

The field of wireless networking (WN) is a rapidly emerging technology developed to provide high bandwidth access to users in a specific area without tethered on a wired network. Wireless local area networks faced huge evolution steps since the current time where the next generation wireless networks are even ready to fully replace the wired connection. The difference between wired and wireless technology occurs to the fact that wireless prioritize the needs of the users of each system as it is developed, like that to provide the mobility where needed, like rental car check in or conventions where wired connection is not possible.

Wireless networking technology, even when it first came out, had many early adopters due to the "premium mobility" as it was characterized feature this systems brought. From stores and warehouse for inventory control, WN usage increasingly used in hospitals, university campus and other wide area facilities where most users are on the go and their bandwidth needs are not so high. In addition to the breakthrough feature of mobility, WN found application in environments where the cable installation was either not possible due to its manufacturing like historic buildings or expensive and impractical such as in trading floors.

The IEEE committee begun working on wireless local area networks since 1990 and the first standard IEEE 802.11a (legacy) was released in 1997 and approved in 1999. The general architecture provided by the IEEE committee introduced two primary topologies. In the first topology, we meet basic service set (BSS), a fundamental building block similar to cells in cellular networking, which constituted a group of stations operating in a specific geographical area known as basic service area as shown in Figure 2.1, under the control of a single coordination function. The application of this topology was designed to provide complete coverage in big facilities by deploying multiple access points.

The second topology supported by the IEEE 802.11 standard is ad hoc network also known as independent BSS (IBSS). Ad hoc network applications was in first focused in applications such as file sharing in conference room and extend the range of the current network. In our days Ad hoc networks involved in more even crucial applications such as in heath sector by monitoring patients, in military application creating a network among all soldiers, environmental application for weather forecasting even in crisis condition where it can be used for emergency signals. Both of these topologies are developed that way that they can co-exist in the same environment.

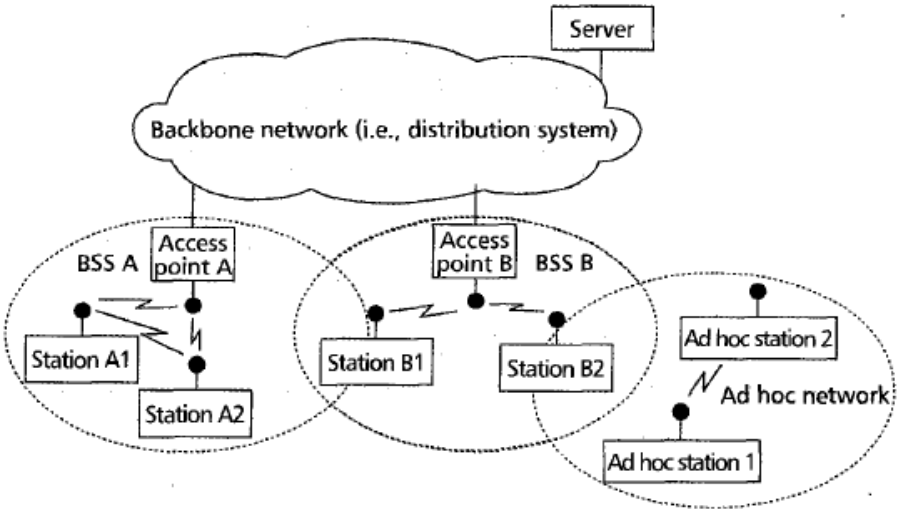


Figure 2. 1 Wireless architecture [27]

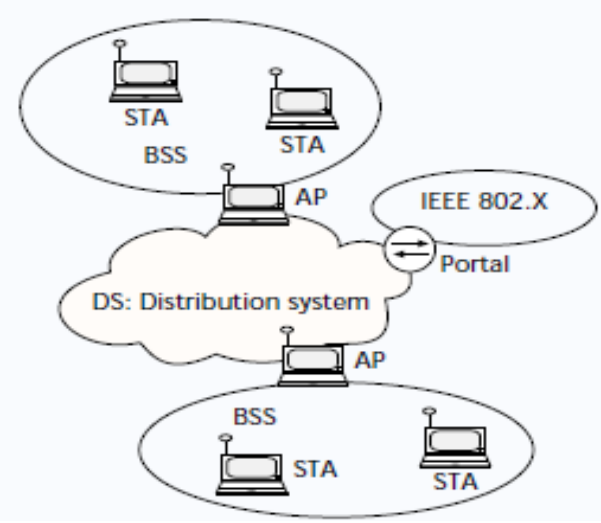


Figure 2. 2 An infrastructure network [7]

Those infrastructure networks are established by using Access Points (AP). Access Points are similar to base stations in cellular network and their responsibility occurs to range extension by providing the necessary integration points to connect multiple BSSs. The connection of multiple BSSs forms an extended service set (ESS). The including BSSs of the larger ESS are using a common distribution system which is considered as the main responsible for Medium Access Control (MAC) level transports which can be either wired IEEE 802.3 Ethernet or another IEEE 802.11 wireless medium.

In order to achieve all of these features, wireless networks had to overcome many challenges and constraints that their counterparts do not have to deal with. Starting point is the frequency allocation. In addition with the cellular networks that operate in unlicensed bands, on WN is required for all users to operate on a common band. Each one of this bands must be approved and licensed from every single one country respectively which is time consuming procedure.

Another major challenge is the limitation of the interference between networks and their reliability. With the dramatic increase WLANs in shopping malls, offices, airports etc. the overlapping effect between the coverage area of each networks and the collisions occurred when simultaneous transmission have been made is a daily problem in wireless networking. A more in depth response to the problem came with the IEEE 802.11n amendment which began the transition to Multiple Input Multiple Output technologies providing crucial improvements in MAC layer allowing multiple transmissions up to 4 spatial streams.

In early years there was a huge luck of trust from the users about the security that can be provided in wireless networking communications. In addition with their counterpart where in wired networks the transmission medium can be physically secured and controlled, in WN is more difficult to secure the transmission as the transmission medium is the atmosphere. Despite that fact, through the years the medium encryptions have been dramatically evolved and the cost needed to be achieved also drop down. In our days that challenge is almost disappeared as the users are pretty convinced for the protection they have been offered.

With the dramatic evolution of Wi-Fi technologies, the number of the devices that, in the current time this research is made, are connected daily from phones, computers to tiny sensors to industrial areas even released in the nature is calculated near 5.000 million, 5 times more than it was in 2004 and they predict that this number is going to be increased even more. As the most of this devices consist of wireless devices, the challenge of power consumption is real even in our days where low power SoCs and processors are applied to these devices. Therefore we see especially in amendments like IEEE 802.11ax are very power efficiency and with “sleeps” mode focused

Last, but not least, another major challenge which is the main reason of all those new technologies, is the performance. The physical limitation alongside with the extra problems combinations of previously mentioned challenges like the interference or the power consumption made it really hard for network developers and researchers to create a capable amendment to fully exploit the capabilities of wireless networking. Evidence of that is itself the history of the progressive evolution of the WN where from IEEE 802.11a with throughput 11Mbit/s we finally arrived into today's amendments IEEE 802.11ax where the possible throughput reaches 7 Gbit/s.

2.2 The first phases of IEEE 802.11 family

In the last 20 years, a number of amendments, that later in years constructed the family of IEEE 802.11 standards, has been proposed in order to make wireless connectivity for fixed and portable devices feasible. The start of the IEEE 802.11 standard [4] was in June 1997 where the IEEE finalized published the first standard and provided three main solutions, a frequency hopping, a direct sequence spread spectrum in the 2.4 GHz band alongside with an infrared Physical Layer (PHY) at 316-353 THz. It provided two modes for the given data rate where the basic was 1 Mb/s and the optional was around 2 Mb/s and it implemented a carrier sense multiple access with collision avoidance (CSMA/CA) in addition with the collision detection IEEE 802.3 had. The launch of a standard like this had a tremendous success in the market creating a basis for future improvements and extensions. As we will see continuing the journey through the history of the IEEE 802.11 amendments the letter next to the IEEE 802.11 standard most of the times refer to a feature the current amendment includes.

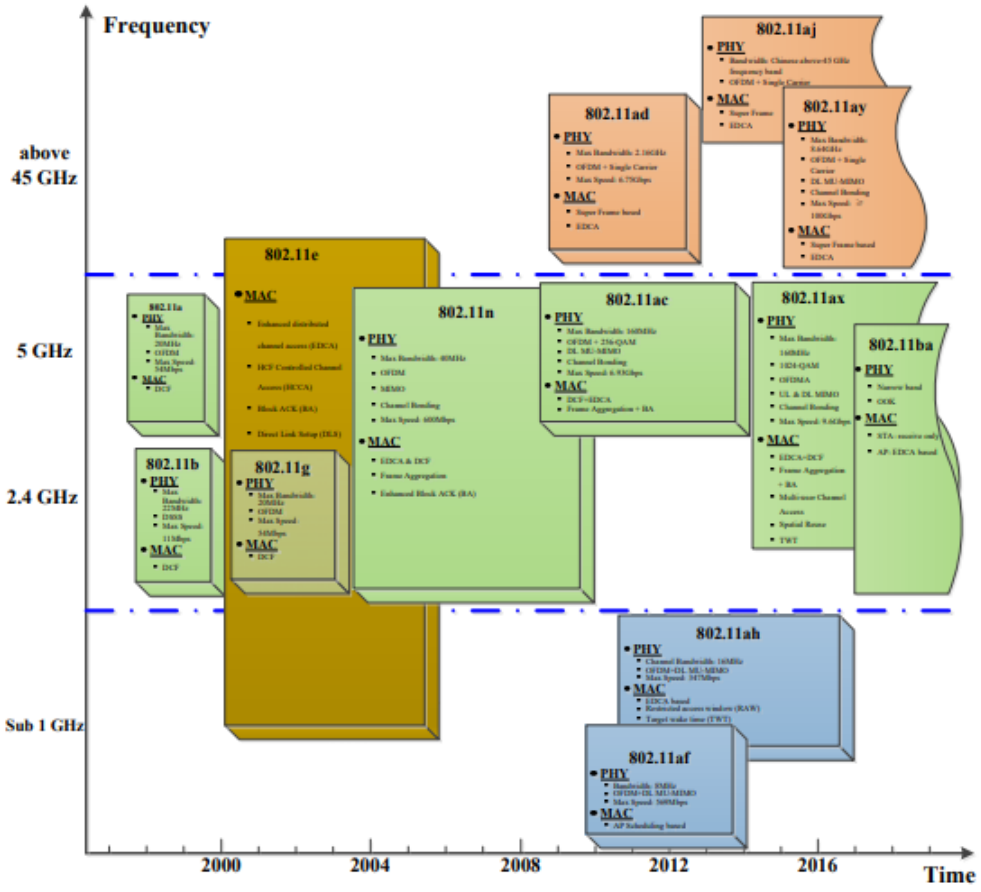


Figure 2. 3 The evolution of IEEE 802.11 standards [25]

The first extensions of the IEEE 802.11 standard did not take long to come out as in September and December of the same year IEEE 802.11a/b had already been started. From the beginning IEEE 802.11a achieved a huge step forward regarding data rate in compare with the previous version reaching the range of 54 Mb/s with the addition of the orthogonal frequency division multiplexing PHY. Although the operation of the specific extension in the 5GHz band and the lack of interoperability with the devices did not go well. In contrast the IEEE 802.11b project operating in 2.4 GHz achieved to boost the data rate of the DSSS PHY to 11 Mb/s surpassing the preferred at this moment FHSS PHY due to its voice and data services. Both of the fore mentioned amendments where finally approved in September of 1999. For literature reasons in June of 1999 started IEEE 802.11d that added support for additional regulatory domains and if approved in June of 2001.

The lack of IEEE 802.11a to be used, led in September of 2000 the start of IEEE 802.11g amendment. Except of the introducing the OFDM to the 2.4 GHz band allowing data rates around 54Mb/s, IEEE 802.11g amendment extended the DSSS signaling allowing the devices to move from the IEEE 802.11 standard to IEEE 802.11-2007 standard [1]. Main purpose of the revision of the IEEE 802.11 standard was to define one MAC and several PHY specifications for wireless connectivity for either fixed or mobile stations within a local area. The same time IEEE 802.11h started in order to meet the needs of European regulatory for the band of 5 GHz and introduced at the end of 2003 while one year later in 2004 IEEE 802.11j introduced for the same reasons for 4.9-5 GHz operations in Japan. With the IEEE 802.11h amendment dynamic frequency selection and transmit power control mechanisms in MAC as the operation of 5GHz band in each country is subject of different legislation. Again for literature reasons two more amendments introduced during the IEEE 802.11-2007 standard IEEE 802.11e and IEEE 802.11i. Both of them they were MAC enhancements extensions for support of Quality of Service and Security respectively.

In February 2012 a new revision of the IEEE 802.11 standard [2]approved focusing on specific technical correction and clarifications the previous revision was missing in terms of WLANs and provided enhancements on the existing MAC and PHY functions. Trying to provide the user experience of the Fast Ethernet performance a new project where the targeted data rate was on top of the MAC layer. So that in September of 2009 IEEE 802.11n was introduced, delivering up to 600 Mb/s and for that reason they called it “high throughput”. Further information for this amendment such as IEEE 802.11ac we will see in Chapter 2.2 as their features where breaking through and they made a huge lip on wireless networking technology. The IEEE 802.11ac amendment characterized also as “very high throughput” was developed under the International Telecommunication Unions requirements as an IMT Advanced standard. Main target of developing such amendments was to achieve data rate more than 1 Gb/s in frequencies lower than 6GHz.

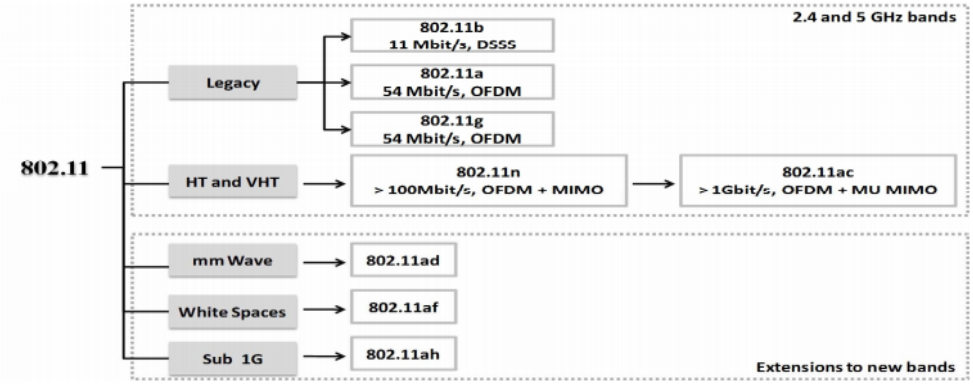


Figure 2. 4 IEEE 802.11 major amendmends [9]

Despite all of these major updates, many amendments came through all this time enhancing the functionality of the previous standards. Approved in September of 2004 IEEE 802.11p created targeting at car to car communications. Operating in 5.85-5.95 GHz Intelligent Transportation Systems (ITS) application band in USA and the 5.855-5.905GHz band allocated in Europe it was focused on limiting the feature of latency and longer distance communications. The final approval came in June of 2010. Other amendments such as IEEE 802.11y/k/r/s/u/v/w/z where created for either WN management, new operations setup or security enhancements. Following the same pattern in the revision of IEEE 802.11-2016 standard [3], except of the IEEE 802.11ad amendment which was introduced in December of 2012, where similar to IEEE 802.11ac included enhancements targeting the above 1 Gb/s throughput but now it the 60GHz band, new amendments such as IEEE 802.11aa/ae/af where introduced too featuring enhancements for audio video streams, new network security standards at the MAC layer and new operation space spectrum in the VHF and UHF bands between 54-790 MHz known as White-Wi-Fi or Super Wi-Fi respectively.

2.3 The breaking through IEEE 802.11n and IEEE 802.11ac amendments

2.3.1 IEEE 802.11n

The rapid increase of the user demand for faster connections created the interest for gigabit wireless LANs. To reach closer to high throughput revision of the WLAN standard, the IEEE committee formed TGn task group in late of 2003 in order to start the development of the IEEE 802.11n amendment (For literature the “n” represent next generation). At the start of the development of this amendment the main goal was to achieve throughput at least double as fast as its ancestor IEEE 802.11a/g performed and surpass the border of 100 Mb/s and also include backwards compatibility to legacy devices. To this research many known companies such as Atheros Communications, Broadcom, Motorola, Intel etc. contributed by depositing suggestions for this new amendment. Till February there were two drafts selected from the IEEE where they approached the enhanced the development of this amendment from different perspectives. The first one suggested to use the bandwidth used at the IEEE 802.11b/g networks and with the application of MIMO technology the achievable throughput could be around 135 Mb/s.

The counterpart proposed that even by the doubling of the available bandwidth from 20MHz to 40 MHz the main goal of the essential doubling of the throughput was achievable. Although with the addition of other, more sophisticated processing techniques TGn devices where able to transmit up to 315Mb/s. Both proposals as the time passed by where evolved by offering both MIMO communication and optional 40 MHz bandwidth. Due to the division into two opposite camps neither was able to obtain the majority vote needed to be approved. So in July of 2005 members of each groups agreed to create a joint proposal which was submitted in TGn in January of 2006. Finally in September of 2009 IEEE 802.11n amendment was introduced even higher throughput at the rate of 600 MB/s.

In order to achieve that significant step forward in terms of throughput a combinations of enhancement techniques bot in MAC and PHY layer have been made. The first enhancement that we already mentioned was the exploit of the channels width of 40MHz which was twice larger than in previous IEEE 802.11 PHY’s. Following we have the increase of the coding rate where from 3/4 we moved to 5/6 which lead to the reduction of the redundancy bits inserted during the coding process. Despite all this new techniques included, the most notable feature was the transition to MIMO technologies. The use of multiple antennas allowed to exploit the multipath phenomena leading to throughput and range increasing alongside with the reduction of the bit error rate.

The same time MAC layer received crucial improvements in terms of reducing the overhead both in interframe spaces, preambles and control frames. A new Reduced Interframe Space (RIFS) was introduced of 2μs in contrast of the 10 and 16μs of the Short Interframe Space (SIFS) in order to separate each transmission of the same station. Also the IEEE 802.11n added two frame aggregation methods,

Aggregated MAC Service Data Unit (A-MSDU) and Aggregated MAC Protocol Data Unit (A-MPDU) improving the overall transmission reliability and a reverse direction protocol allowing the transmitting stations to efficiently transfer to another stations who want to transmit without initiating a data transfer.

Other secondary features included on the IEEE 802.11n amendment was the Quality of Service for delay sensitive applications and power saving feature in order to increase battery life in mobile devices. The same time an extended channel switch announcement was added so each access point could select between the supported 20MHz and 40 MHz channel while improved the radio recourse management efficiency of multiple APs in a network. Last but not least another feature that was also included was the support of fast roaming.

2.3.2 IEEE 802.11ac

The continuous effort in pursuit after the IEEE 802.11n devices achieved to reach data rates in amount of 600 Mb/s, in September of 2008 a new Task Group started working on a new amendment IEEE 802.11ac. Main target of the current amendment was to achieve throughputs beyond 1 Gb/s in the band of 5GHz. The IEEE 802.11ac maintained most of the features of its ancestor such as the binary convolutional coding for forward error correction, the basics of the MIMO technologies, the modulation coding schemes and the regular guard interval. Although in order to achieve the wanted increase of its throughput IEEE 802.11ac introduced new mechanisms like Multi user multiple input multiple output (MU-MIMO), larger channel bandwidths and a new a new amplitude modulation of 256 quadrature.

To cope with the problem that many terminals were not deployed with more than 1 or 2 antennas due to manufacturing reasons leading to lower data rates than the new amendment could achieve, IEEE 802.11ac introduced MU-MIMO. Besides increasing the number of spatial streams up to eight the IEEE 802.11ac was the first to introduce the Downlink (DL) MU-MIMO, allowing the simultaneously transmission to four clients at a data rate in amount of 866 Mb/s which concludes in 3.46 Gb/s overall. The Uplink MU-MIMO in contrast was postponed for future amendments because due to the tight synchronization required, a complete amendment redesign needed.

Continuing into the newly introduced features, the IEEE 802.11ac amendment kept the channel bandwidths of 20 and 40 MHz introduced in IEEE 802.11n and added to more bandwidths of 80 and 160 MHz. The 80MHz channel mode uses two individuals 40MHz channels, likewise in 160MHz where is constructed by two individuals 80MHz channels, but with some extra subcarriers to fill the unused tones. That was the main reason this amendment was developed to operate in the 5 GHz band as there was no room for 80 and 160 MHz channels in the 2.4GHz band. In addition two new MCSs are introduced on 256-QAM with 3/4 and 5/6 coding rates having as results 20-30% improvement performance. With the maximum number of spatial stream the use of 160MHz channel, for a single spatial stream using 256-QAM the possible data rates of this amendment was up to 7 Gb/s increasing the data rate of a 10x factor in comparison with IEEE 802.11n.

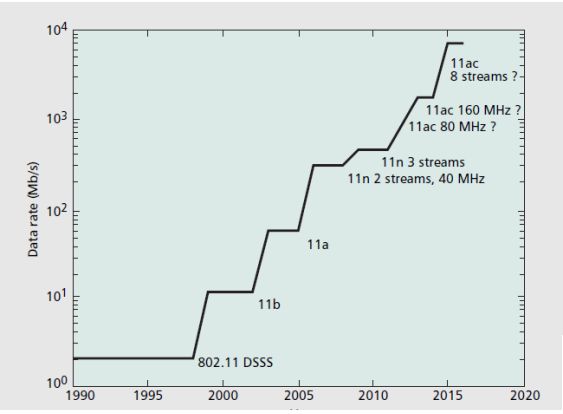


Figure 2. 5 Growth of IEEE 802.11 data rate [28]

Last but not least, the MAC layer faced many enhancements mostly focused on the multi channels operations. In order to increase its efficiency despite the support of both A-MSDU and A-MPDU which have although been enhanced by the increasing their size from 7935 to 11406 bytes and 65535 to 1048575 bytes respectively a new hybrid type of aggregation is available by the combination of these two. Closing this section, the IEEE 802.11ac provided support of Very High Throughput capabilities by transmitting beamforming control with sounding protocol and compressed beamforming feedback, DL MU-MIMO and transmission opportunity power save through the field of management frame. For literature reasons it is important to mention that this was the first time that an amendment focused on improving the total network performance instead of a single link.

2.4 IEEE 802.11ax and next generation wireless networking

Recent years the popularity of the IEEE 802.11 WLAN for indoor solutions combined with the huge global traffic which reached 24.3 Exabyte per month in 2019 , 10 times more than it was in 2014, created the issue of the overlapping basic service set (OBSS) leading to performance degradation. Trying to design an extension of IEEE 802.11ac, the IEEE standards committee created a High Efficiency Wireless LAN Study Group (HEW WLAN SG) which later is already known as Task Group AX. Main target of this task group was to develop an amendment which will improve the efficiency of wireless networks in high density scenarios. This amendment was IEEE 802.11ax.

The specification framework documents of IEEE 802.11ax started in 2014 but finally released at the end of 2016. Like the first draft which created in December 1 and balloted in January 2017 such as the second draft which created one year later, did not reached the required threshold to be officially released. Only the third version accomplished to pass through the ballot, although it was planned to be finalized by 2019 there are many open issues that need to be addressed

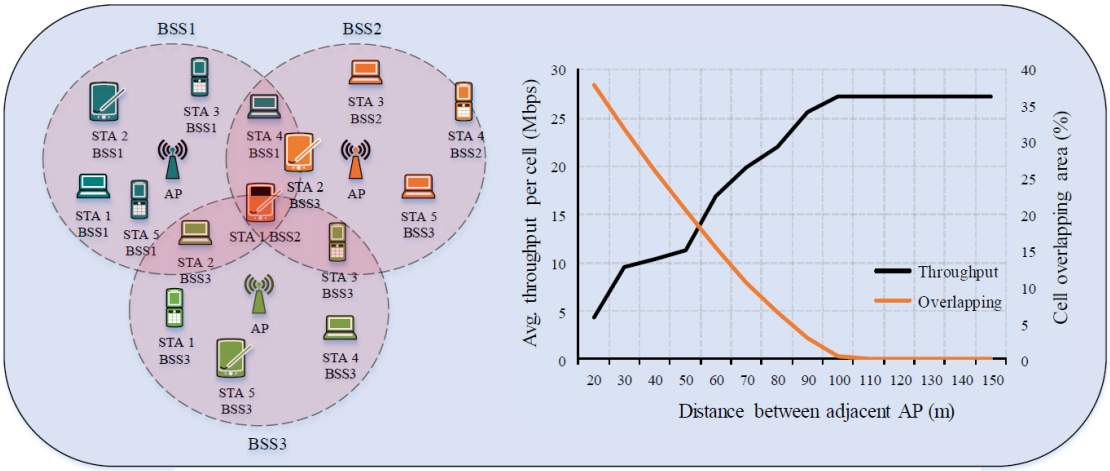


Figure 2. 6 High density scenario with overlapping BSS's [22]

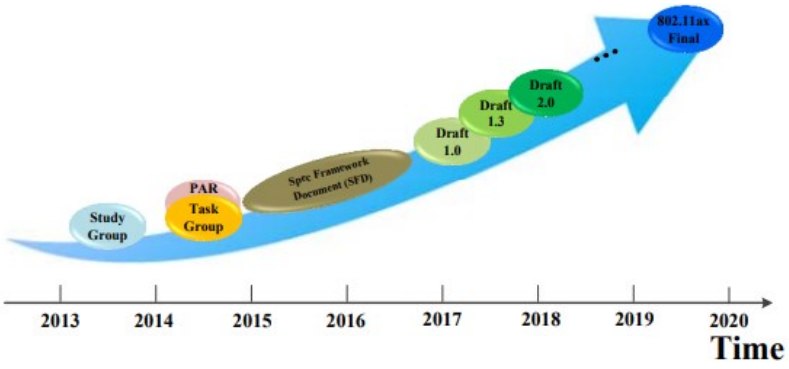


Figure 2. 7 The journey of IEEE 802.11ax [25]

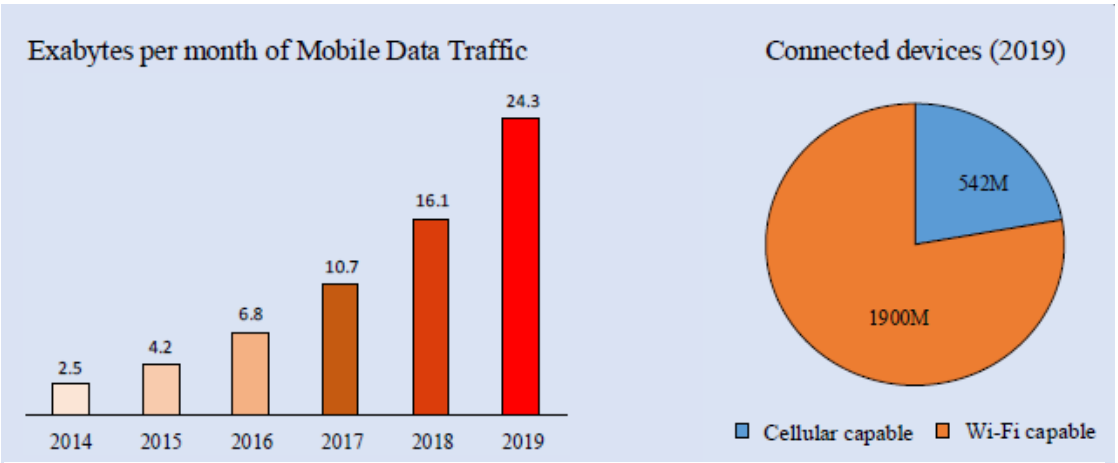


Figure 2. 8 Global data traffic and Wi-Fi position [22]

	Legacy feature	New 802.11ax features
PHY		
Spectrum	up to 40 MHz at 2.4 (11n), up to 160 MHz at 5 GHz (11ac), or up to 16 MHz at 0.9 GHz (11ah)	up to 40 MHz at 2.4, up to 160 MHz at 5 GHz
OFDM Constellation Order	256-QAM (11ac)	1024-QAM
OFDM Symbol duration	3.2μs	12.8μs
OFDM Guard Interval	0.4 or 0.8μs (10 or 20% overhead)	0.8, 1.6 or 3.2μs (5, 10 or 20% overhead)
MIMO Order	4 (11n), 8 (11ac)	8
Maximal Data Rate	≈ 7 Gbps	≈ 9.6 Gbps
Channel Access		
Basic channel access	CSMA/CA	OFDMA on top of CSMA/CA
Random Channel Access	DCF, EDCA	UL OFDMA Random Access on top of CSMA/CA
Contention-free Access	PCF, HCCA (not implemented in real devices), RAW (11ah)	Trigger-based UL OFDMA
MU Technology	MU-MIMO (11ac)	MU-MIMO, OFDMA
MU transmission direction	DL (11ac)	DL and UL
Fragmentation	Static	Flexible
Aggregation	A-MSDU, A-MPDU (11n) without fragmentation	A-MPDU, A-MSDU with Fragmentation
HE/Legacy Fairness		2 EDCA Parameter Sets
OBSS Management		
Interference Mitigation	NAV, RTC/CTS, HCCA TXOP Negotiation	Two NAVs, Quiet Period
Spatial Reuse	Sectorization (11ah)	Adaptive Power and Sensitivity Thresholds, Color
Power Management		
Power Management	Many	Enhanced TWT, Enhanced Microsleep

Table 2. 1 Main features of IEEE 802.11ax compared with legacies [13]

The main scope of this amendment was to improve the user experience in dense deployments either in residential environments where OBSS are created by the deployment of a large number of WLAN access points in a small geographical area or in Outdoors and Stadium scenarios. Also IEEE 802.11ax had to improve the spectrum reusability alongside with the interference created in OBSS's scenarios. In addition major issue was to maintain and improve the power efficiency, as the most used devices are mobile and battery dependent, which did by introducing several new PHY's and MAC features allowing multi user access. Continuing the IEEE 802.11ax extended the support of parallel transmission in frequency domain enabling both UL and DL MU parallel access. Finally the task group worked for a backwards compatible amendment and focused on both indoor and outdoor operations on the band between 1 and 6 GHz.

Key feature of IEEE 802.11ax in contrast with the previous amendments, was the use of the Orthogonal Frequency-Division Multiple Access (OFDMA). This addition of OFDMA in WiFi was a step towards the cellular networks where it is widely used. The application of the OFDMA achieved 6 times higher throughput than the legacy according to the TGax investigations. With OFDMA, neighbor subcarriers are grouped into resource units (RU) with different sizes, allowing its sender to choose the best RU for each particular receiver. There are seven types of RU's in IEEE 802.11ax amendment. We

have 26-tone RU, 52-tone RU, 106-tone RU, 242-tone RU, 484-tone RU which is used only in 40/80/160MHz bandwidths, 996-tone RU available in 80/160 MHz bandwidth and finally 2*996-tone RU seen only in 160 (80+80) MHz bandwidth. It is notable that IEEE 802.11ax was the first IEEE 802.11 standard amendment to introduce OFDMA.

As its ancestor IEEE 802.11ac which was the first to introduce MU-MIMO including only DL transmissions, IEEE 802.11ax came to establish both DL and UL simultaneous transmission. When grouped stations transmit simultaneously, their signals can be distinguished through spatial streams. Due to the fact that for both complexity and cost reasons AP's are usually equipped with multiple antennas in contrast with STA's where fewer antennas are installed, MU-MIMO can take full advantage of this multi-antenna deployment allowing simultaneous both UL and DL transmissions improving spectrum utilization alongside with transmission rate improvement. With IEEE 802.11ac the maximum number of STA's that could simultaneously transmit was 4 when with the IEEE 802.11ax amendment, this number increased up to 8.

In IEEE 802.11ax the PHY layer faced many enhancements to meet the needs of the main scope of the amendment. The first change concerned the physical coding decision. Despite the fact that Binary Convolutional Coding (BCC) was mandatory while Low Density Parity Check (LDPC) was only optional for traditional IEEE 802.11, IEEE 802.11ax requires both of them. As it was proposed when the transmission bandwidth is above 20 MHz LDPC should be preferred instead of the BCC which is otherwise selected for transmission in lower bandwidths lower or equal to 20 MHz. LDPC was used in previous IEEE 802.11n/ac amendments for Forward Error Correction (FEC). With LDPC the computational cost would be lower than in BCC but it is strictly in distinguished application scenarios.

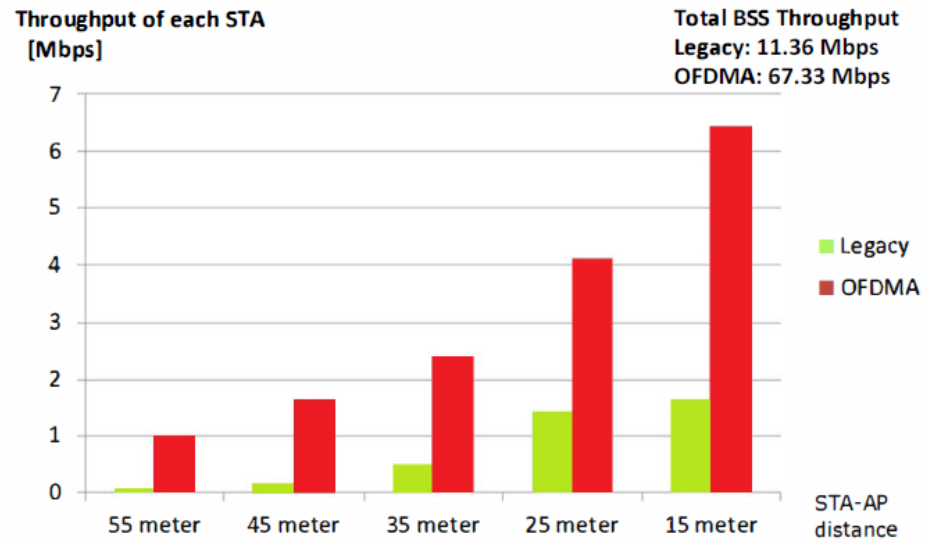


Figure 2. 9 OFDMA throughput against Legacy distributed coordination function [13]

There was also introduced a new optional modulation technique enriching the legacy BPSK, 16-QAM, 64-QAM and 256-QAM. This technique was 1024-QAM where it could be used in indoor scenarios where the channel conditions are very good achieving 25% gain in compare to IEEE 802.11ac. It was measured that combined with the FEC, in addition with a more fine-grained subcarrier division and a new designed guard interval, IEEE 802.11ax could achieve the maximum throughput of 9.6 Gb/s in a 160MHz spectrum.

The same time in order to improve the spectral efficiency both for indoors and outdoors communications the TGax decided to increase the Fast Fourier Transform four times than that was used in IEEE 802.11ac. For that purpose it defined four High Efficiency PHY layer convergence Protocol data Unit (HE-PPDU) formats in order to support different technologies and scenarios. The first one was HE-SU-PPDU referring to connection between an AP and a single STA or between two STA's. In that format compared to the previous IEEE 802.11ac amendment we see Repeat L-SIG, an enhancement of the previous L-SIG, which is used to confirm when a PPDU is HE format through automatic detection. Also a packet extension is included extending the time for the receiver to process data.

Afterwards we see HE-MU-PPDU and HE-TB-PPDU format. The first mentioned allowed the simultaneous transmission through OFDMA and MU-MIMO and it was based to the single user format. In contrast the trigger-based format was in charge for the UL MU transmission. Last but not least we have HE-ER-SU-PPDU format. This format was created in order to improve the transmission coverage of the outdoor scenarios through DCM narrowband RU transmission.

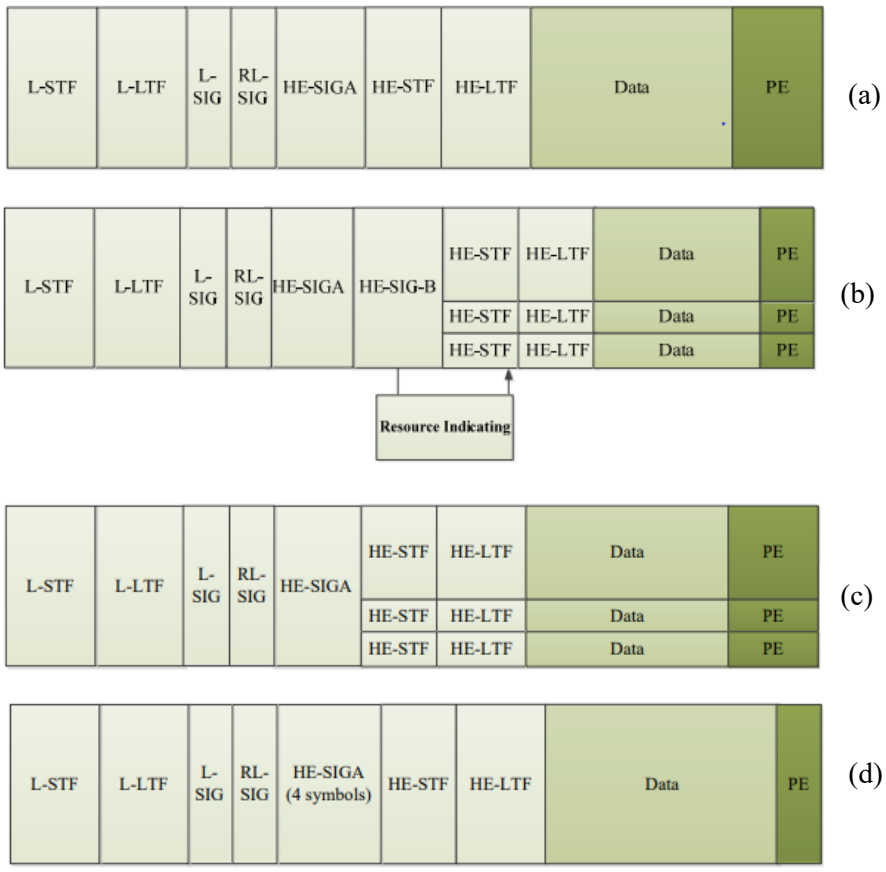


Figure 2. 10 HE-PPUD: a) SU format b) MU format c) TB format d) ER SU format

The last PHY layer enhancement considered to be the frequency selective scheduling. This feature is extra beneficial for OFDMA systems in terms of frequency diversity. Main mission of this feature is to increase throughput gains for stations located far away from the transmission point. That happens by allocating physical resource blocks with the minimum possible fading. Overall the IEEE 802.11ax amendment tends to adapt a Dual Sub-Carrier in order to improve the performance and the robustness in either narrow band interference or high dense deployments.

At the MAC level enhancements, the IEEE 802.11ax amendment introduce dynamic PHYCCA modifications allowing multiple transmission to coexist. Even in high density deployments the application of the Dynamic Sensitivity Control algorithm could optimize the existing deployments with the proper tuning. This idea was transferred also to the transmit power mechanisms. The goal of the dynamically tuning of the transmission power was to reach a target Signal to Interference plus Noise Ratio. Both of this techniques focused on increasing the spectral reuse.

Continuing features like BSS coloring where each BSS was marked with a specific “color” allowing each station to abandon receiving frames from neighboring BSSs has been added alongside with the utilization of two NAV timers for each station. An Intra-BSS NAV was added except from a regular NAV in order to handle its timer only when frames of the assigned BSS allowing the stations to ignore RTS/CTS in overlapping cases. Both of these features lead to remarkable when used in IEEE 802.11ax targeting use cases. Other notable features of the IEEE 802.11ax amendment was the power saving techniques in order to utilize energy which could either extend the sleep time or allow the awake time to be reduced.

As the IEEE 802.11ax amendment is moving towards Long Term Evolutions (LTE) technologies the challenges that it has to face are about its viability as a communication network such as its support to the Internet of Things paradigm. Starting with, in contrast with the LTE networks, Wi-Fi networks do not operate in licensed bands where interference level is not guaranteed. Also the LTE network channel is divided in blocks, for the DL channel the base station selects an arbitrary subset of resource blocks in order to transmit data to the user and the UL the resource blocks need to be continued. Those restrictions in Wi-Fi makes the development of an optimal scheduler very complicated. Despite its limitations, IEEE WLANs can be the connecting bridge with IoT paradigms because the huge data exchange from mobile devices can be handled by cellular technologies.

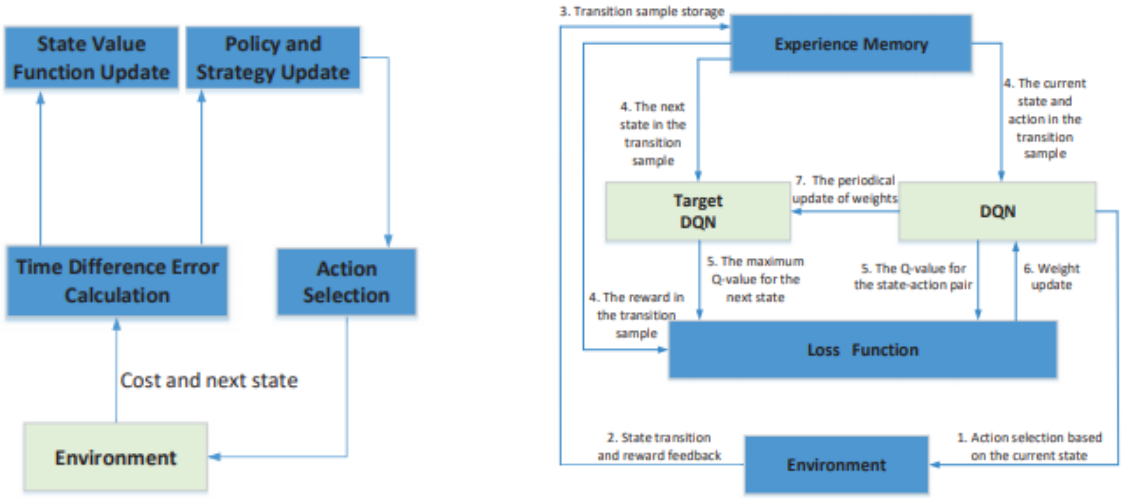
Parameter	IEEE 802.11ax	LTE-U and LAA-LTE
Design architecture	Distributive	Centralized
Channel bandwidth (MHz)	20, 40, 80, 160	1.25, 2.5, 5, 10, 15, 20
Highest order Modulation scheme	1024 QAM	256 QAM
Access technology	CSMA/CA	TDD based OFDMA
Handover	Client-driven, network-assisted	Network-driven, client assisted
Interference problems	Collisions, hidden and exposed node problem, partially overlapping channels	Co-channel co-tier, cross tier interference, For LAA-LTE (additional interference due to collisions)
Scheduling	Contention based de-centralized, EDCA	For LTE-U (Base Station controlled without contention), For LAA-LTE (Contention based de-centralized, EDCA)
Range	Possible methods under consideration to improve range	Better range characterization as compared to legacy IEEE 802.11
Rate control	Vendor specific algorithms (implicit and explicit feedback based on probing, lack of acknowledgments, etc.)	Constant channel feedback
MAC and PHY layer protocol overheads	In-band signaling (e.g. RTS/CTS, sounding, Null data, etc.), headers, Pilot symbols, etc.	Control channel signaling, LBT (non-adaptive backoff range), CSAT (channel oblivious duty cycle), Pilot symbol, transmission scheduling etc.
Integration with current 4G networks	Requires Mobile Core Integration (MCI) for mobile offload	No requirements
Coexistence with other technologies	Based on LBT	For LTE-U (CSAT and optional LBT), For LAA-LTE (Based on LBT)
Potential market	Belongs to IEEE 802.11 family and is a natural evolution	Motivation for operators to enable/extend services to unlicensed spectrum without the need to integrate with a non-LTE technology

Table 2. 2 Comparison of IEEE 802.11ax amendment with LTE in unlicensed spectrum [22]

2.5 Literature research

From another perspective, except from the already including features of the existing amendments a key technique capable to solve complex problems in wireless networks is machine learning (ML). In their survey on the applications of ML in wireless networking [32],the authors mentioned that the continuous expansion of the network scale, the diversification of services alongside with the difficulty of algorithms to proper adapt to dynamic network environment and the infeasibility of traditional centralized to handle such number of nodes make the idea of machine learning very popular. The main idea behind the implementation of such algorithms in wireless networks is due to its ability to “learn” useful information from either input data or the environment leading to performance improvements.

It is very important to also underline that machine learning helped us to realize that ultimately our goal was self-organized networks. Machine learning can divided into three classes, supervised, unsupervised and reinforcement learning. In supervised learning a learning tries to learn a general rule by providing them a set of inputs and their desired outputs. In unsupervised learning, data are not labeled and the agents have to create a structure from the given inputs. Last but not least is reinforcement learning, one of the most important part of machine learning because of its huge impact to the Artificial Intelligence (AI). In reinforcement learning an agents continuously interacts with its environments and a policy according to a reward-cost feedback.



(a) (b)

Figure 2. 11 The main process and components of a) actor-critic & b) deep reinforcement learning [32]

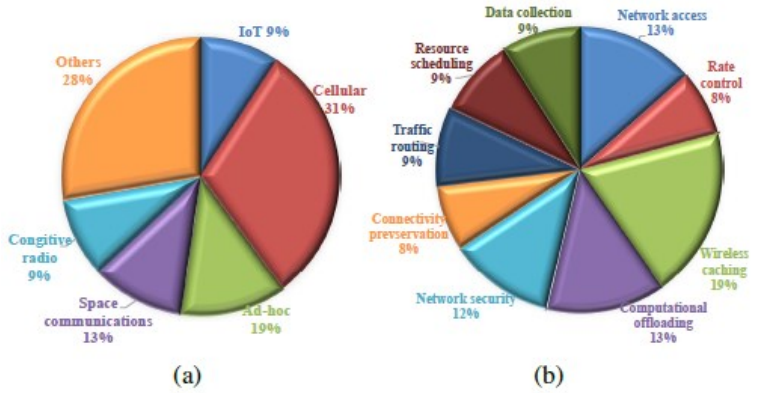


Figure 2. 12Application of DRL in a) different networks and b) issues has been assigned to handle [24]

Concluding from their researches in [24] & [32], we see that machine learning has already stepped up and has many application in our days. As we can see in Figure 2.12, despite the open issues there are, deep reinforcement learning has been applied in various networks taking care serious objectives such as network security, data collection network access, etc. Although as the authors mentioned there are a lot of unresolved challenges machine learning techniques can outline, there are many open issues to solve in the future. While the ML based techniques are capable of selecting the suitable backhaul/fronthaul solution, the cost of large delays and pre-processing of asynchronous information can be harmful. So a balance between the information and the learning performance agent consume.

The positive outcomes that machine learning algorithms do not stop there. During the survey we see that in deep reinforcement learning approaches, it is possible for users to get achieve the

maximum possible throughput. Although to reach that point users must report continuously their local state which will might be difficult in future networks. With the next generation of IoT and the large volume of data traffic, with features such as distributed caching are able to achieve a more cost-efficient solution. Overall what they conclude is that enabling wireless networks to operate intelligently is not fully feasible yet as we are already in primary stages and there are a quite a number of issues that have to be addressed and need further investigation.

Multi Arm Bandits framework although, which has a main role in our research, has been very popular the past years into wireless communication problems. In Multi Arm Bandits learning model a learning agent obtains information from the environment and reacts according to what actions are performed. In this model exists a tradeoff in face of uncertainty between taking the current best action and gathering information in order to achieve larger rewards in future. In their research [18], the authors wanted to address the Spatial Reuse problem in uncoordinated WLANs through Multi Arm Bandits as these networks are performance limited due decentralized channel access mechanisms. So the authors decide to set the MABs to apply adjustments on Transmit Power Control and the Carrier Sense Threshold trying to find the best possible combination in term of the frequency channel alongside with the transmit power and the sensitivity of the WLANs in scenarios as we can see if Figure 2.14 below.

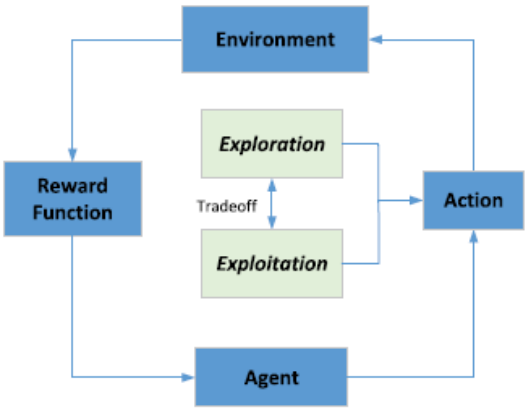


Figure 2. 13 The MAB main process [32]

Figure 2. 14 A scenario of two overlapping WLANs and the agents learning procedure [18]

Although as it is highlighted interactions such like these, especially in next gen deployments set to be extremely complex. As we already mentioned before MAB unlike other Reinforcement Learning algorithms, does not consider a specific state. A state might refers to a specific moment where the agent was involved allowing the agent to construct a policy which follows in future situations and keeps building by requiring new knowledge in each new interaction. As the author mention, the learning through states in unknown environment increase even more the complexity. The main contributions of their work except to showcase how the modification of parameters affect the network performance, were to give an insight of using learning in decentralized and adversarial wireless networks such as evaluate the performance of self-adapting networks in Dense scenarios.

The reward given to the agent after each action is defined in two different ways, as selfish reward and as environmental reward. Through comprehensive research they conclude that despite the first strategy the action of the agents is granted according only to its own throughput in addition with the second which judge how good its actions were based on the mix-max throughput of the whole network, the potential of applying uncoordinated MABs in dense WLANs are capable to achieve the hope for decentralized deployments. Albeit that they emphasize that there is a lot of future work must be done as other important challenges must be over-come yet such inter-WLAN communication in order to get to that point.

Chapter 3: Komondor a high density IEEE 802.11ax simulator

3.1 Introduction

A useful tool that we widely used during our experiment, was Komondor, an IEEE 802.11 high density for next generation wireless networks simulator created by the wireless networking research group of Universitat Pompeu Fabra in Barcelona. According to the authors of an insight of the Komondor [31], Komondor is an open source tool having as main purpose to serve either as an academic or education tool and simulate the behavior of IEEE 802.11ax amendment designed to boost spectral efficiency. Komondor is an event driven based simulator based on the CompC++ COST library with simplified physical layer dependencies and high event processing rate, which occurs due to the simplification of the core operation, resulting in the outperformance compared to other well-known wireless network simulators. Other advantages of the aforementioned simulator is that some of the rest simulators are either no open source or they have some inherent limitations such as high complexity. The motivation for creating a tool like Komondor, as the authors mention, were the lack of next-gen Wlan simulator in combination with the lack of analytical model techniques, the high complexity and the large execution time of the other existing simulators. Another serious motivation was the need for application of Machine Learning based agents in the simulation tools.

3.2 WLAN Simulators

In our days where large scale wireless networks researches, new untested protocols and architectures are created, a simulation tool for the verification of their functionality and their performance and accuracy, is absolutely necessary as the cost of launching a system like this again and again until we reach the optimal version is not possible. Computer-based simulations, like the ones we are going to see during the past of this research with the help of such a network simulator, Komondor, are very important for researching groups, designers etc. as the networks simulators are capable to provide realistic results and help them understand how the networks and its protocols behave through their performance. As the authors mentioned in [5], the basic steps in order to run a proper simulation are four as they follow.

The first one is to develop a model which in our case the new “model” developed is the IEEE 802.11ax amendment and the features it brought to wireless technology which was and the main reason of the creation of our current using simulator. The second and the third step are to create various simulation scenarios and collecting statistics from the output of simulators. With these two steps we dealt extensively during our research as we created and simulated a various numbers of different scenarios and extracted our results from the logs provided of our simulating tool which we visualized an analyzed for the sake of our research. The visualization of those results constitutes the fourth of our basic steps to run a simulation.

Simulator	Open-source	Source lang.	Complexity	GUI	11ax features	ML/based module
ns-3	Yes	C++	High	No[1]	Partial	No[2]
ns-2	Yes	C++/OTcl	Low	No[1]	No	No
OMNET++	No	C/C++	Medium	Yes	No	No
OPNET	No	C++	Medium	Yes	No	No
NetSim	No	Java	Low	Yes	No	No
Komondor	**Yes**	**C/C++**	**Low**	**No**	**Partial**	**Yes**

Table 3. 1 Networking simulators comparison [31]

The available wireless networks can be divided into two categorize, continuous-time and discrete-event. Continuous time simulators divide the simulation time into small pieces which keeps track of them all the time. In addition discrete event simulator are faster than continuous time as the events are only used to mention system changes. The family of the most popular wireless simulators consist of the ns-3 which is a high complexity open-source simulator based in C++ library, ns-2 also an open source simulator with great accuracy and low complexity. Other simulators, are OMNET++, OPNET and NetSim, which are not open-source simulators which Medium complexity. Although we have to mention that except our simulator, Komondor, which we extensively present and ns-3 all the fore mentioned does not support features of the IEEE 802.11ax amendments that we study in the current research. The lack of next generation wireless technology capable simulating tool as we conclude combined with the limitations that ns-3 suffers from, makes Komondor a very promising tool for next-gen networks.

Closing this section we must emphasize that it is not proper to characterize simulators as “bad” or “good”, its one is selected by the researchers requirements. Although the optimal features that a network simulator has to establish is to keep a good balance between efficiency, accuracy and how much user friendly is.

3.3 Usage tutorial

As we mentioned, Komondor is an event-based simulator strictly depended on the CompC++ library. The simulator is operating in particular Linux Environment while a 64-bit system is highly recommended. Its execution mode is performed by the console with the input files and arguments provided. Komondor uses a set of inputs which includes information about the nodes, system configurations, and simulation times, machine learning methods etc. After the insert of the input files, Komondor initializes the main module “Komondor.cc” which authority is to process the input given, initialize each one node separately and generate the network and within the simulation time given it gathers information about the network it is each time generated, exporting the results into logs for the user.

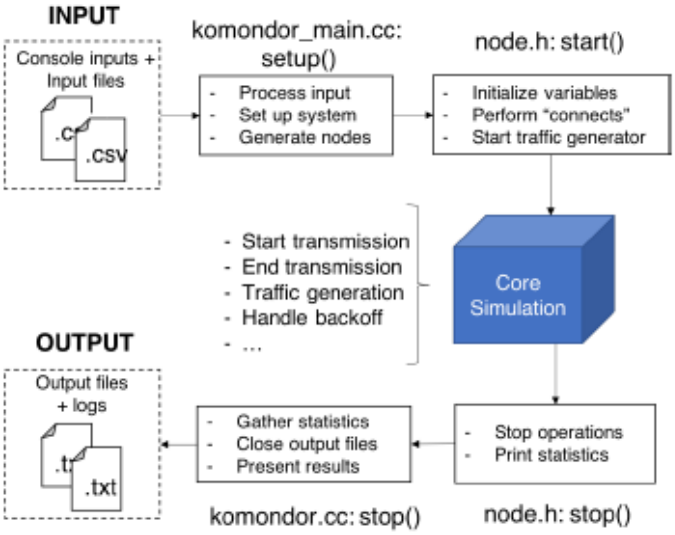


Figure 3. 1 Komondor’s execution flowchart [31]

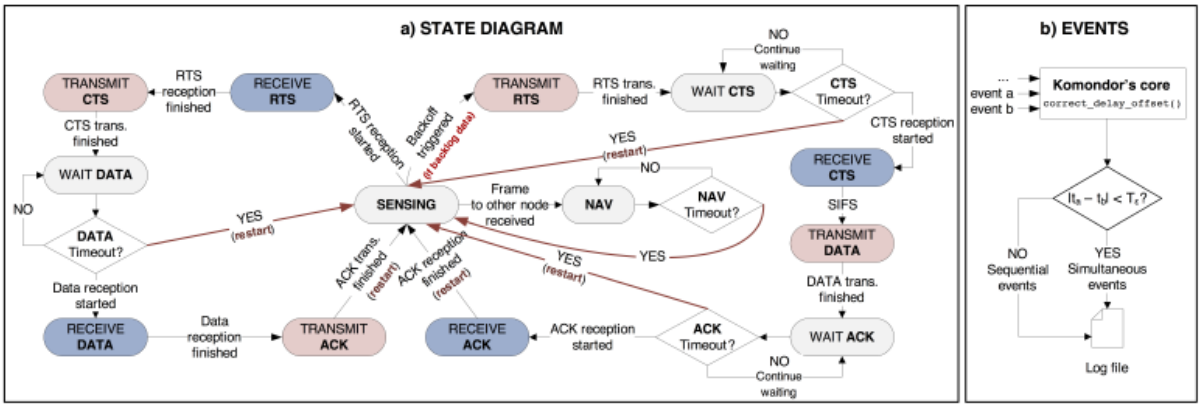


Figure 3. 2 Komondor's state and event diagram

In order to achieve that stage our simulation has to go through some states that represent each time which nodes is involved and how it behave when new events occur. The first state is the sensing state which has two existing purposes. First one is that our node following the CSMA/CA operation it senses the given channel, after its backoff counter has ended, for any traffic load in order to take access of the medium. If the channel is occupied the backoff of the node freezes till the medium is free. Except from the medium access purposes, the node senses the channel when it waits a responding transmission.

Continuing we have transmit and receive state. Both of them are after the sensing state and they are the states responsible for either transmitting or receiving and decoding incoming packets. It is important to mention that when a transmission is occurred the receiving capabilities of the node are cut out during the end of the current transmission. In addition when a node tries to receive an incoming packet and a new event is occurred by another node, if the interference is high enough, the incoming packet could be discarded leading us to the packet loss effect.

Between all the before mentioned states, there is the waiting state. Main mission of this state is to detect packet losses when there are interruption in the network. More specifically when a node transmits either one Request-to-Send or Clear-to-Send or even a data packet, then it awaits a corresponding message similar to Clear-to-Send, a data package or an Acknowledgment/Block Acknowledgement packet. If that respond does not happen in the given time, the timeout mechanism is triggered resets to sensing state and assumes that the given packet is lost.

Last but not least we have the NAV state. When a node is entering NAV is due to the fact that it successfully received a frame addressed to a different destination, leading to set at NAV timer which sensing the primary channel addressed to the node. Every time a new frame is received successfully before the NAV timer expires, it updates the timer. All of the events that trigger the previously mentioned states are lined up on the time axis and handled by the core itself. In order to overcome the obstacle that when two events are scheduled simultaneously cannot really be executed the same time leading to inconsistencies, Komondor creates to temporary variables. This variables handle the timestamp its event was generated making our simulator behave like it is in a real world situation.

There are four modes of execution available in Komondor. First and foremost we have the "Basic execution" where all the parameters for the operation of a basic wireless network are indicated. In this mode 9 arguments are required for the execution. Then we have the "Quick execution" where a basic execution can be performed with only the mandatory arguments are required, as we are going to see in table 3.2. Third execution mode is the "Script based" where our execution is handled by a bash script.

Last but most important is the “Execution with agents”. In this case as we include smart agents, we must add corresponding parameters in order to inform about the creation of the agents. In this case all of the arguments are needed to be specified at the console.

During the simulation nodes interact with each other by sending packets until the simulation time is over when a set of output files is generated where they include network performance information. Mandatory inputs except the simulation time and the seed, which refer to a random seed for the experiment, are the nodes files and the configuration model, then we can select if we want to apply machine learning agents into our simulations and decide which information we want to be logs we want to be saved.

When we presented the execution modes we talked about mandatory and “optional” arguments on the input at the console. In table 3.2 below there is a detailed presentation of all the arguments which can be used as input to our simulator highlighting the ones that mandatory for the basic execution scenario.

Table 3. 2 Arguments passed through console

Mandatory	Nodes input	Contains information about the current nodes (channel used, transmission power etc.)
Optional	Agents input	Contains information about the applied agents
Optional	Output filename	Path to the output file
Optional	Simulation Code	Code for the specific simulation
Optional	Save System Logs	Flag indicating the ability to save the system logs
Optional	Save node Logs	Flag indicating the ability to save the node logs
Optional	Save agent Logs	Flag indicating the ability to save the agent logs
Optional	Print system Logs	Flag indicating to print system logs
Optional	Print node Logs	Flag indicating to print node logs
Optional	Print agent Logs	Flag indicating to print agent logs
Mandatory	Sim time	The Simulation time (seconds)
Mandatory	Seed	Random seed for the experiment

In older versions of Komondor the simulation environment was also an input file but in the current version this research is written, configuration model file is a default editable file which is not imported as input at the console and contains global parameters which replicate the whole environment of our experiment such as the pathloss model, co-channel interference etc. input parameters can be seen in table 3.3 below.

Table 3. 3 Configuration model file

Path-loss model	Path-loss model: (0: LFS, 1: Hata, 2-3: Indoor (1-2), 4-8: TGax(1-5), 9: Indoor 5Ghz, 10: In-room Loss 5.25GHz, 11: Room-Corridor 5.25GHz, 12: TMB)
Adjacent channel model	Co-channel interference
Collision model	Collision model
Backoff type	Type of backoff: slotted or continuous
pdf backoff	Pdf for generating the backoff: deterministic or exponential
Simulation_ix_output_script	Simulation index for the scripts output

As we see in table 3.2 there are two input file types that allow Komondor to actually generate the desired simulation file. The creation of each WLAN is depend on the node input files which is the first input file type and defines the location including also the characteristics of both Access Points and Stations. Except from the input files that divide in two types, there are two ways to generate nodes where they are separated according to the file name. When the keyword of the file is “node” both Access Points and Stations are described. Elsewhere when the keyword is “aps” only Access Points are defines as the set of Stations is randomly generated. We can notice the node input parameters in the table 3.4.

Table 3. 4 Nodes file description

Parameters	Description
Node code	A code assigned to a specific node
Node type	Type of the node, either AP or STA
Wlan code	A code assigned to a specific WLAN
X(m)	Coordinates on axis X (meters)
Y(m)	Coordinates on axis Y (meters)
Z(m)	Coordinates on axis Z (meters)
Central frequency (GHz)	Defines the frequency band used either 5 or 2.4 GHz
Channel bonding model	Channel bonding model: (0: Primary channel, 1: SCB, 2: SCB Log2, 3: Always Max, 4: Always Max Log 2, 5: Always Max Log 2 MCS, 6: Uniform Probability Log2)
Primary channel	Defines the channel which is used as primary
Min channel allowed	Left channel in range
Max channel allowed	Right channel in range
TX power	Defines the transmission power (dBm)

Sensitivity	Defines the sensitivity of our APs and STAs (dBm)
Traffic model	Traffic Models: (0: Full buffer, 1:Poisson, 2: Deterministic, 3: Poisson Burst, 99: Full Buffer No Differentiation)
Traffic load (pkts/s)	Traffic load (packets per second)
Packet length	The length of each packet
Num packets aggregated	The number of packets aggregated to be transmitted
Capture effect thr	Minimum capture effect threshold
Capture effect thr	Maximum capture effect threshold
Constant PER	Defines a constant Packet Error Rate
Pifs activated	For activating PIFS
CW adaption	For activating channel window adaption
CW	Fixed Channel Window
CW stage	Initial Channel Window stage

Last but not least except from the nodes input as we mentioned, our simulator is capable of using machine learning models when a given user may need them in order to apply them in the already created WLANs. So long the second input file type is the agent input file which includes crucial information about the agent characteristics such as the available learning methods, the WLAN it is applied etc. In the current stage agents can only work on their own and not as a part of a centralized system. Alongside the only available learning method is Multi-Arm Bandits which we are going to see a lot through this research with other Reinforcement Learning techniques such as Q-learning and Neural Networks are on the way for future releases. In below we describe more detailed the input parameters of the agent files.

Table 3. 5 Agent input file

Parameters	Description
Wlan code	Defines the code of that WLAN that agent is applied to
Centralized	Flag that indicates whether the node is attached to a centralized system
Time Between Requests (seconds)	Time between request by the agent to AP
Action channels	A list of channels that are available by the agent.
Action cca (dBm)	A list of CCA values that are available by the agent
Action tx_power (dBm)	A list of transmission power values that are available by the agent
Max_bw	Max bandwidth

Reward	Type of reward used by the agent
Learning Mechanism	Type of the learning mechanism used by the agent
Selected strategy	Selected strategies: (1: E-greedy, 2: Thompson Sampling, 3: Sequential)

Till the moment this research is conducted, various features have been tested and implemented on the current version of Komondor. Such features are the Distributed coordination, Buffering and packet aggregation, Modulation coding scheme selection, RTOT algorithm for Spatial Reuse and Ready to Send (RTS)/Clear to Send (CTS) and Network Allocation Vector. Future plans include orthogonal frequency division multiple access (OFDMA), multi-user multiple input/output (MU-MIMO) transmission, beam-forming and other ML-Based configurations as Q-learning and Neural Networks which we already mentioned before

3.4 Applications

In addition with other simulating tools, Komondor is designed that way so it will support the usage of machine learning based configurations in the future. In Multi Arm Bandits which is the only available learning method at the current time, smart agents are deployed to wireless networks in order to either monitor their performance or even use action selection strategies so they can be able to propose new configurations to the WLAN in search for better performance. In Komondor they have been implemented three different action selection strategies for MAB's. As we can easily see in the table 1.4 previously the available selection strategies are E-greedy, Thompson Sampling and Sequential. In the current research E-greedy and Thompson sampling were used extensively in our experiments as we took a deeper view of their performance in chapter 3. Except to find out the impact of Machine Learning in wireless networking by using both of these strategies in our scenarios was a great opportunity to make a comparison of them through their results and even see how they cooperate when they have to coexist with the other.

Komondor has been used in various lists of projects as a simulation tool which we are going to see even further. As we fore mentioned, the biggest advantage of Komondor instead of other simulation tools, is its capability of using machine learning and the handling of high dense scenarios for next generation wireless networks. Bright example for that is the research on [7], whereas the authors claim that the connection link between machine learning and communication systems can be networks simulators. That was proved by showcasing the potential benefits of ML models implemented in 5G and 6G Wi-Fi networks.

Continuing Komondor was used to prove that the Machine is the key feature for the next generation wireless networks. As the authors mention in [17], due to the fact that ML can handle the large volume of data of the ever-increasing complexity networking, the current networks are not ready yet to support similar applications. The article's target is to present the requirements needed for the future wireless networks, focusing on 5G and beyond, to include ML.

3.5 Epilogue

Concluding from this chapter what we can conclude is that Komondor is a reliable wireless network simulator is validated in a big amount of scenarios against various similar tools like the ns-3 simulator and two analytical tools based on Continuous Time Markov Networks and Bianchi's Distributed coordination function model. At the same time due to its very user friendly usage alongside with the low complexity operation and the new features that supports or is going to support in next versions like Machine Learning, OFDMA, MU-MIMO, we can say that it is ready fill the gap for the upcoming next generation networks. Accordingly to the creators of the simulator the support for more previous IEEE 802.11 amendments such IEEE 802.11n/ac/ad/ay is possible.

Chapter 4: Understanding WLAN performance

4.1 Introduction

Before we investigate the application of RL in wireless networks we have to fully understand first the factors that immediately affect the performance of our networks. For that reason, at the beginning of this experiment we created a number of low complexity scenarios where we investigate how "low complexity" parameters like the distance, transmission power or the sensitivity can affect the overall performance. Afterwards, the next step was to introduce reinforcement learning and the learning strategies that we widely used for the simulation of our scenarios. This chapter is going to create the base reference by learning the basic concept of IEEE 802.11ax wlans and reinforcement learning. Having that in mind in chapter 3 we are going to continue the experiment even further and investigate more real life applications with high density scenarios which is the main issue of this thesis.

At this stage of our experiment, as we have already mentioned, our main focus was to fully understand how a variation change of network parameters can fully affect the behavior of the whole system. In order to achieve our target, we created a two networks scenario, where we included 2 Access Points with 1 Station each. The parameters that have been used on the specific scenario can be seen in table 4.1 below.

Table 4. 1 Experiment setup

Parameters	Values
Central frequency	5.25 GHz
Basic channel bandwidth	20 MHz
Data packet size	12000 bits
No. of aggregated packets	64
Min. contention window	16
CCA threshold	{-82,-76,-70,-62} dBm
Path loss model	TMB
Capture effect threshold	10
Simulation duration	10 s

The pathloss model used in our experiment is TMB, an empirical model that according to [33], combines available data and without requiring any previous computation of traversed obstacles, providing a selected MCS and number of spatial streams on a specific distance. TMB is more or less the most suitable pathloss model for indoor environments as it has been tested in a typical office with multiple partition walls, from the authors that are also the "creators" of the specific model. As we used the TMB pathloss model, the average distance for overlapping networks is 21 meters. Having that in mind we applied 5 distance use cases between AP-AP and 2 adjusting the distance between AP-STA, to our topology as we can see in Figure 4.1

4.2 Transmission Power (tx_power) use cases

As a starting point on our research, we wanted to create a number of scenarios, where our main focus will be on the transmission power of our network, as it is easy to foresee the possible outcome of our actions. So we create a number of cases where we adjust different values of transmission power on our networks. We assume that as we increase the value of transmission power on our AP's, the strength of the signal received from the STA is equally increased. We have to mention on this part of the experiment that on our topology both networks select by default the same channel, which is also their primary channel, to transmit in order to also observe if the phenomenon of overlapping networks appears. We achieved that by creating three transmission power use cases: i) 8 dBm ii) 15dBm iii) 20 dBm where we indicated them as low, medium and high tx_power respectively. Those tx_power cases have been applied t on 5 different locations where the distance between AP's increases. The results of our simulations are represented at the Figure 4.2 below.

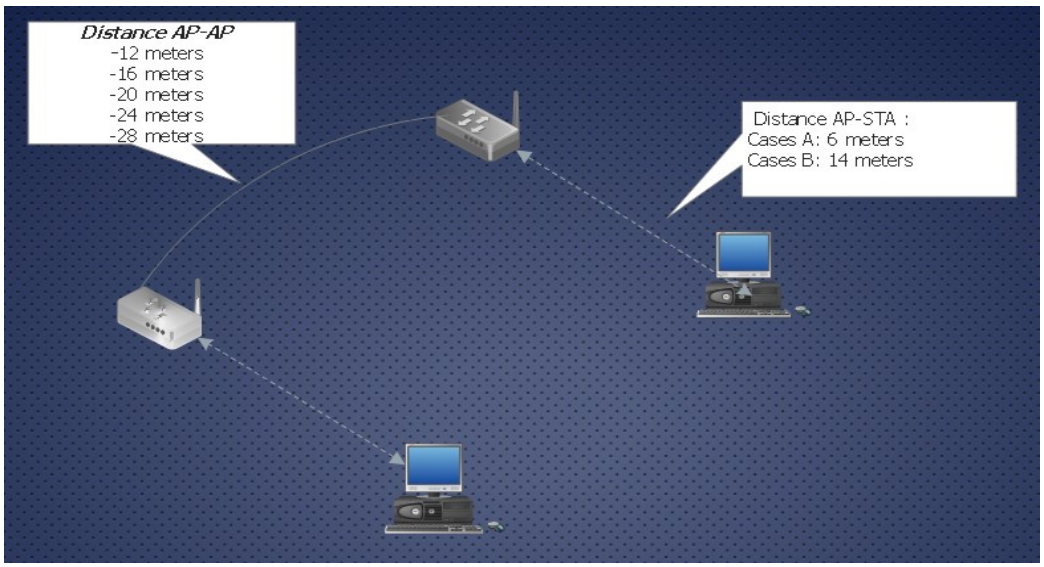


Figure 4. 1 Current scenario topology. Including "distance use cases" information

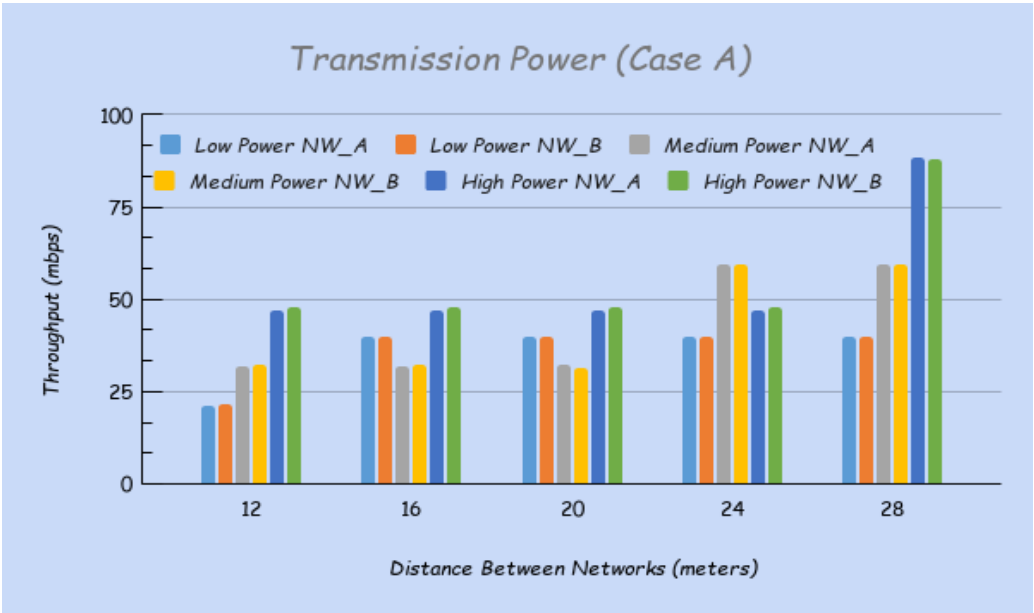


Figure 4. 2 Average throughput (mbps) per transmission power use case for 5 distances

It is easy for someone not expert in networking to say that as we increase the power someone is transmitting the performance is also increased. Taking a look on the previous figure (figure 4.2), we can say that the results are indeed as obvious as everyone could think but it is not as simple as the scenario is a simple representation mostly created for educational reasons. As we see in fig.2 our power cases are not increasing equally in each change of the distance between our networks but it is not something that cannot be explained. Starting from the low power case, we see that from the first transition from 12 to 16 meters, it reaches its maximum possible performance and stays the same at all the other states.

In addition with low power, all the other cases require a bigger distance between our networks and we can say that it is also scalable. We mention that our cases reach their maximum throughput in line from the lower to the high power, as the low power changed immediately, the medium power needed to reach 24 meters between networks in order to reach a high data rate as the high power case we see is directly opposite to the low power case. It is in mostly all cases the same and only in the last one where the distance between networks is the biggest then it reaches its highest data rate.

So we decided to divide the explanation of our current test in two sub-sections. In the first section we are going to take a look at overlapping areas, explaining what they actually are, how they are created and what is their affection on our wireless networks. Then in the second section we are going to represent the data rate. As in the first section we are going to what the data rate is and how we can associate it with the performance we get from our networks.

4.2.1 Overlapping areas

The increased number of devices accessing the internet wirelessly made the need for higher data rates necessary. For that reason channel bonding, one very promising technique, was recruited in order to create wider channels by letting two separate channels combine into one, resulting in higher spectrum efficiency. Although the data rate was increased, the possibility for co-channel interference was increased making our nodes vulnerable in hidden nodes effect cause as the authors say, as we widening the channel, the value of Watt per Hertz is reducing which refers to vulnerability of our nodes to interference. Main target of this section is to make clear the definition of the term “overlapping area” and what their contribution is to the whole networking system. Since we are also going to face them during the past of our experiments at the following sections, we will see according to (Barrachina-Muñoz, Sergio, et al., 2019) if the widening of the channels is indeed the better choice in order to succeed at higher network performance.

During their research, the authors examined Channel Bonding policies like Dynamic Channel Bonding and Static Channel Bonding through random allocated high density deployments. As it came out SCB was viable only in scenarios where the traffic load of our networks was really small. On the other hand DCB when spectrum adopting policies are applied, can be significantly better compared with the traditional single channel approaches, especially in high density scenarios. Nonetheless, concluding the authors emphasize the risk of unfair scenarios where hidden nodes appear and the harmness can be done in low traffic situations is still real. That fact leaves a headroom for even further work to be done while machine learning based DCB policies can be the key factor for even further improvement.

4.2.2 Data rate

As we wanted to have a clear view about the parameters that have immediate performance impact, we decided to examine the outcome of a single network and how it reacts when we change the positions of grouped stations. Our tx_power in all tests was set at 15 dBm and our CCA was at -82 dBm.

Figure 4. 3 *Distance vs. throughput on a single network*

During our simulations, we noticed that as we increased the distance between AP and the STA, the value of modulation code schematic (MCS), which is directly linked with the data rate and the signal to interference plus noise ratio (SINR) was decreased causing performance issues. As we can see in Figure 4.3 in high transmission power scenarios we reached almost the maximum possible MCS values, therefore the maximum data rate and throughput available. In addition in low transmission power scenarios we reached 0 throughput from our network.

Having that in mind, combined with the fact when two networks share a single channel, they also have to split in half the available transmission time. We found that data rate on our AP's was not only affected due to the overlap between them, but also because the increased distance between our AP and STA which can justify the degradation of performance in a case on fore-mentioned Figure 4.2.

From the results exported from this scenario, we saw that the performance determination curve of the high power use case is steeper than both of the other cases. Although the low power use cases follow the same pattern as it is also steeper than that case with the medium use power case. The descent angle in our graphs corresponds to the rate that our network's performance decreases as the MCS and the SINR is getting lower and lower. Except from the angle of our performance curve that can be seen from the first sight, we notice that in low power cases, our networks even at the case where the distance between station and access power was the lower one, it did not achieve the max possible modulation coding scheme.

Continuing in the second case of our experiment, where we also increased the distance between AP and the STA and set it to 14 meters. The difference between these two cases can be noticed immediately. In Figure 4.4 we can see that the performance is even more reduced because the distance our signal had to cover in order to reach our receiving station and due to a possible interference with neighboring networks.

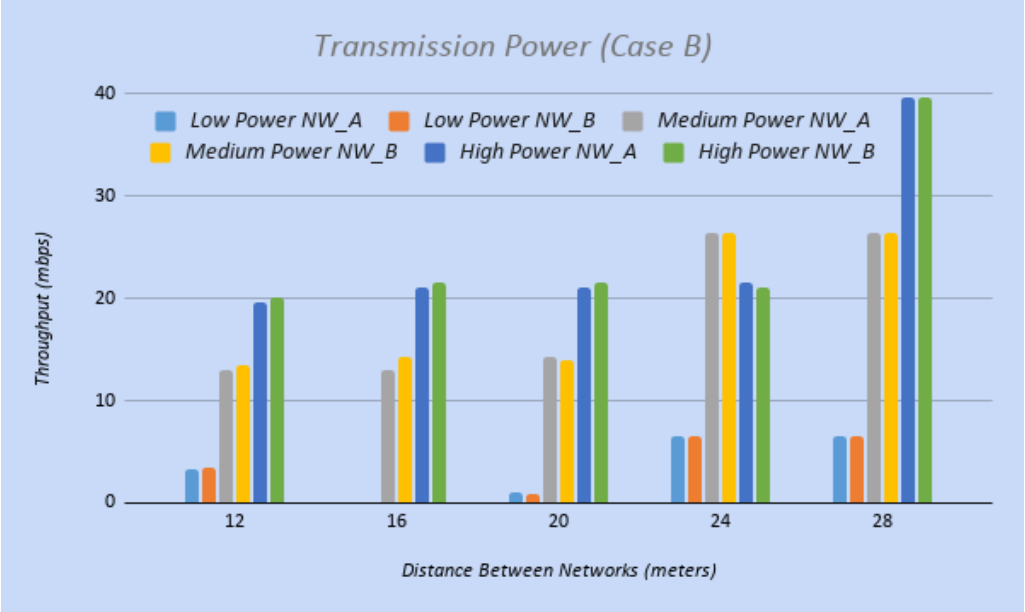


Figure 4. 4 Transmission power use cases in increased AP-STA distance.

In addition with our main topology, seen in Figure 4.2, the results of our current scenarios were not so simple to explain. Although we only changed the distance between access point and station, the consequence was that our experiment got unstable. Except that in case B the overall performance was decreased as we expected, we notice that the results during the progress of our experiment were not linear as in case A.

This instability starts from the low power use case, where the overall performance, instead of getting better as we increase the distance between networks, it either reaches zero throughput (16 meters between AP's) or has smaller performance than the starting point in 20 meters between AP's. From that point and then, the behavior we see is normal as we see our network reach maximum performance. Then in the rest use power cases, the only difference we have to notice is that we see that in some distance cases the network A has better performance and in other cases the opposite, something that has minor significance in comparison with the one we first mentioned.

The above results confess, that despite the common knowledge that high transmission power implies good data rate performance, we must take in mind also the distance between our AP-STA too.

4.3 Sensitivity (CCA) use cases

Moving further in our research, the next step was to add the parameter of CCA. The value of CCA determines how sensitive our network is to the interference of the surrounding networks and decides if our transmitters will transmit or not. As we increase the value of CCA, our network has more chances to transmit, although the danger of hidden nodes lurks around. It is easy to understand that with these capabilities, combined with the distance and transmission power, CCA is tightly connected to the expected throughput.

In order to investigate further CCA, we created 3 cases where we applied 3 different CCA values to our experiment. So, except for our by default value (-82 dBm) we added: i) -76 dBm, ii) -70 dBm and iii) -62 dBm. Observing our results in Figure 4.5, we notice that even from the current phase of our

experiment, our networks reached their maximum performance much earlier compared to the outcome we have with the original state scenario. It is interesting to highlight that in high power cases the fact that by increasing the value of CCA, we did not observe to cause any performance degradation even in small distance between networks scenario.

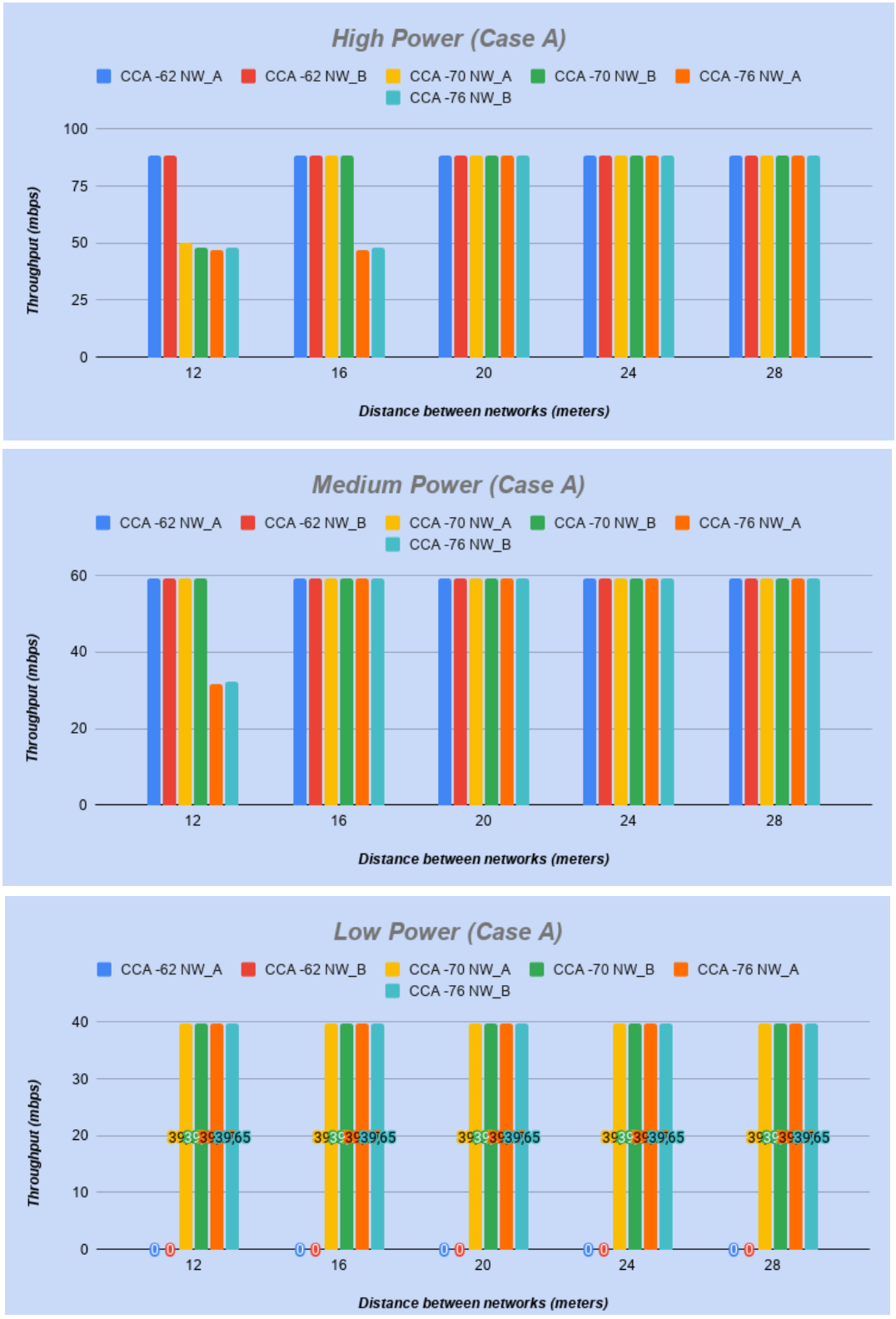
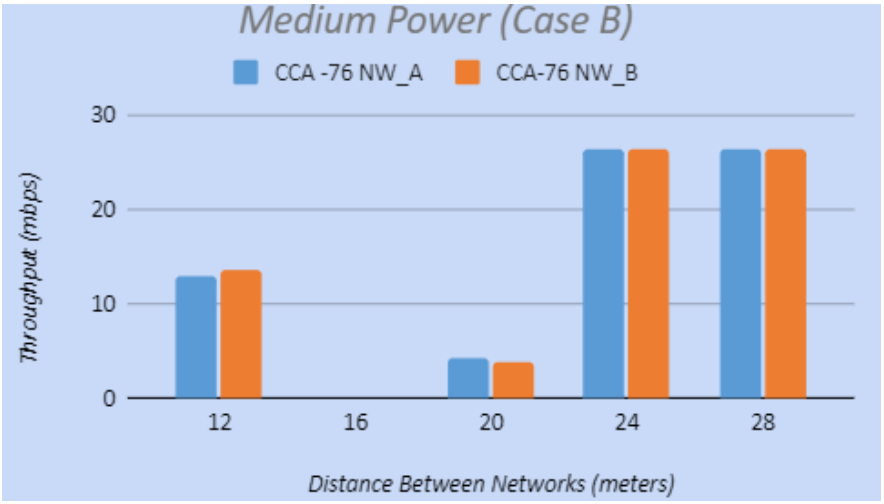


Figure 4. 5 Variant sensitivity use cases

Proceeding to the Case B, were we increased again the distance between our AP-STA location, consulted by the data logs of our simulator, the increased distance between our Access Point and our Station, combined with increased value of CCA, resulted the reduction of Signal plus Interference to Noise Ratio (SINR). Although in some cases the hidden node effect appeared, our AP throughput was 0 mbps as the SINR during the transmission was below our capture effect threshold. In Figure 4.6 we chose to select specific distances between AP's in order to cover the low, medium and high distance cases. As we mentioned earlier the low transmission power is missing from this chart as some CCA cases from Medium and High power are missing too. That is due to a combination of the high sensitivity and distance that causes that big performance loss.



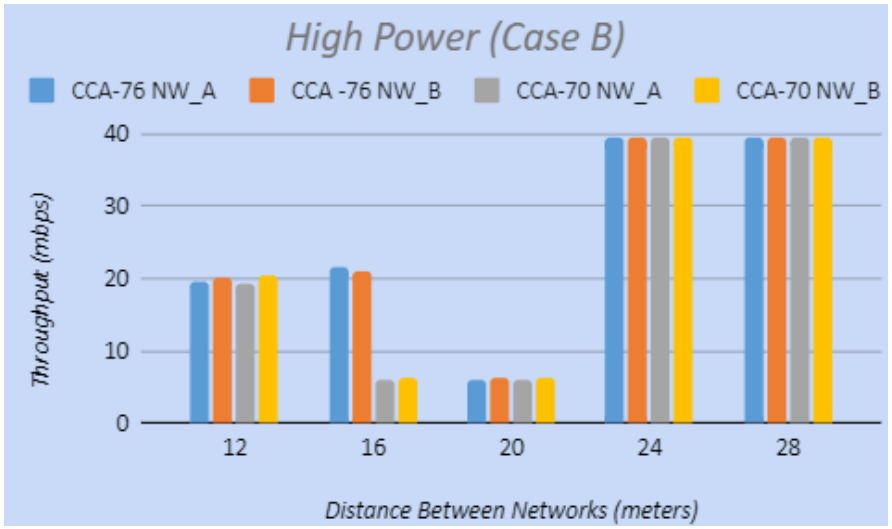


Figure 4. 6 Sensitivity use cases on increased AP-STA distance.

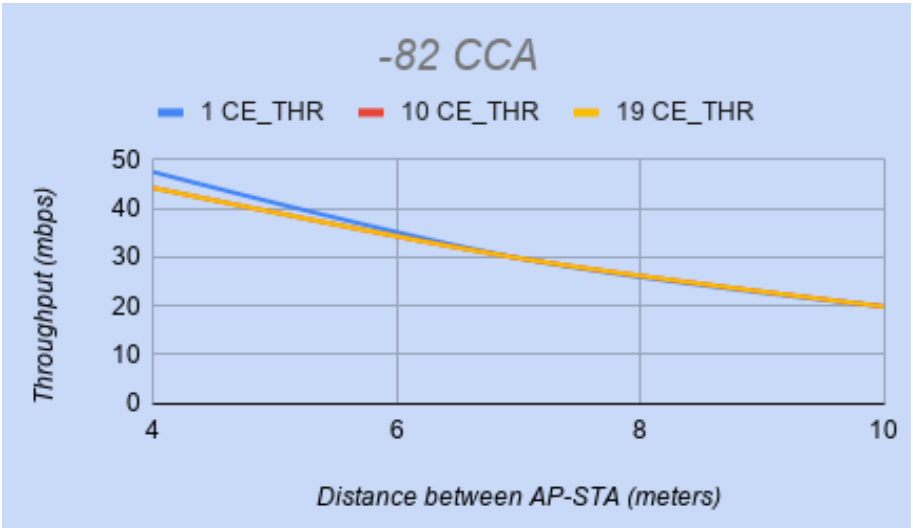
Figure 4. 7 Forcing hidden nodes topology

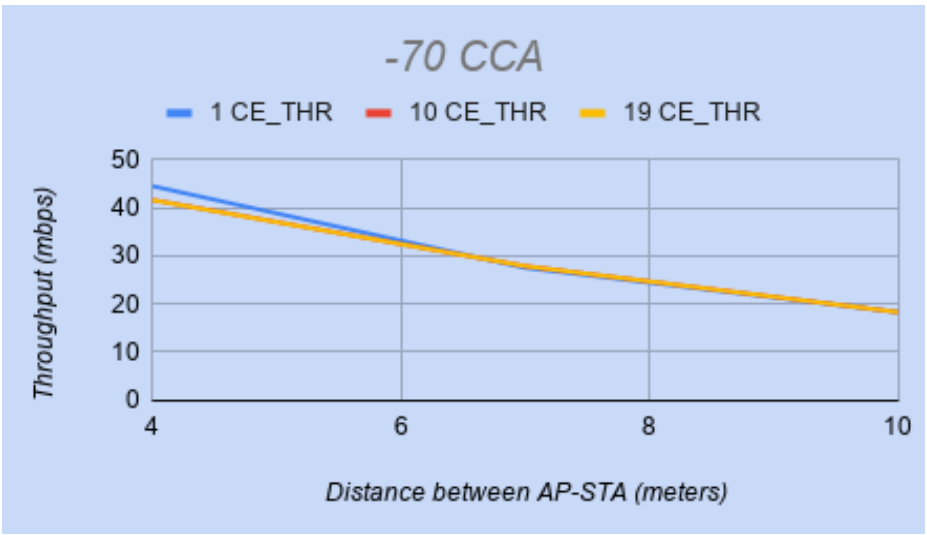
In order to make clear the effect of hidden nodes, we decided to create a new topology, which can be said to be more "efficient" to notice that effect. In this case we will focus on the effectiveness of the topology, sensitivity and we will introduce one new variable, capture effect threshold. So as we see in Figure 4.7, by changing the topology of our networks we executed our scenarios, similar to the previous cases to observe the behavior of our networks.

As we noticed in our data logs, during our experiments, when the sensitivity was set at the default value the interference between our networks was none and the only thing affected our performance was either the transmission power or the distance between AP and the STA.

Although it was interesting to apply different CCA values in the specific topology as we mentioned earlier, by increasing the CCA, our networks will have more chances to transmit but the cost can be great if the hidden node effect appears. The crucial parameter in this point is the capture effect threshold. This parameter, determines how strict our network reacts to interference taken by neighbor networks and transmitters. Taking that in mind, we saw that by putting the stations at gradually increasing distance, the SINR value, in some cases, dropped even below our threshold causing both of our networks unable to transmit successfully.

The next step was to try changing that threshold. First we put the lowest possible value but having in mind that our networks do not transmit without checking if our channel is in use, the result that we got from our simulations were really close as it can be seen in Figure 4.8. Although by increasing the capture effect threshold, our networks have been stricter in order to transmit, we noticed that we did not have any performance impact. That situation exists because our networks do not transmit simultaneously most of the time.





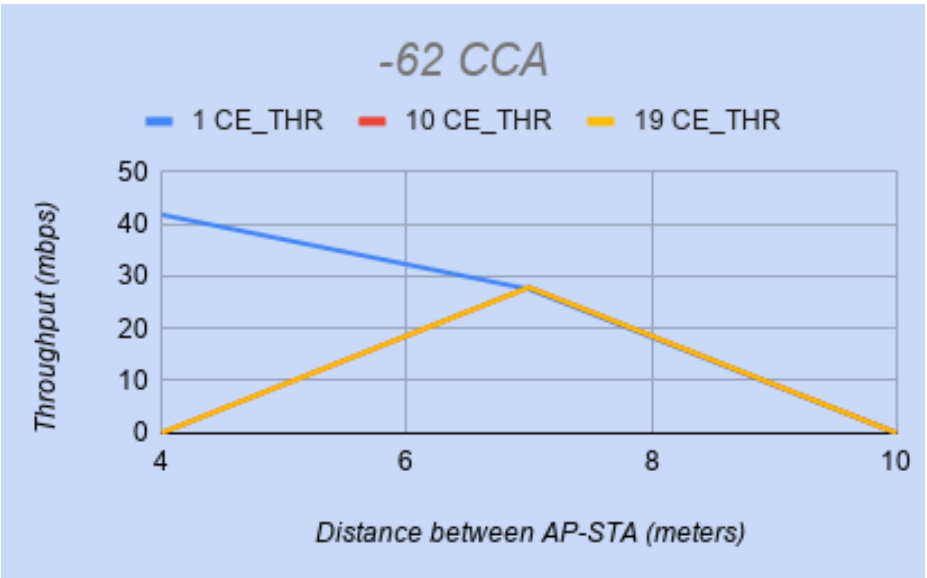


Figure 4. 8 Capture effect and CCA use cases at different topology

Trying to interpret the above figure, we can see excluding the cases with -70 and -82 CCA which are similar and we are going to comment continuation of the chapter, we see that -62 sensitivity case, is a straight to the bottom scenario as the results are pretty low in terms of performance and in some cases even zero.

Now coming to the next two cases, we can notice that they are pretty the same, although there is something really serious to talk about. The curve -82 CCA case is bigger than that in -70, that means that in all capture effect cases in -70 dBm sensitivity, our scenarios hold higher performance much more that all the other scenarios.

4.4 Epilogue

In this chapter we studied about some basic and simple parameters used in wireless networking and we tried different applications of them in order to see their influence. Concluding from this chapter we can understand that the possible combinations we could try in order to create the optimal performance, are a lot as the numbers of the available parameters, that affect our performance, to configure is huge. Specifically in random allocated Wireless local area networks, which can be found in our daily life, doing the configuration by hand is impossible. There is where machine learning can make their entrance something that we will investigate in the next chapter.

Chapter 5: Network self-adaption by learning

5.1 Introduction

At this stage we are going to apply machine learning and more specifically Reinforcement Learning. A classic reinforcement learning problem model that we are also going to use during our experiments, is Multi Arm bandits. Our target in the current phase of our research, is to introduce MABs and explain how they work. Afterwards we are going to present two types of the learning strategies that are used in our scenarios (E-greedy and Thompson Sampling) more detailed, stating the pros and cons and finally we are going to try to prove if smart algorithms like MABs can be the feature needed to make the technological leap in to the next generation wireless networks.

5.2 Multi Arm Bandits

The MAB's problem is indeed a one-state Markov decision process. In MABs a smart agent, that simultaneously trying to retrieve knowledge from each environment, while optimizing its decision based on the existing knowledge, applies a configuration on the wireless network of its competence. Regarding the performance its configuration achieves, our agents enriched his knowledge with information, leading him to propose a new configuration. The configuration that is chosen most of the time as our experiment comes at its end of the test is proposed as the optimal one, regarding the learning strategy used. In order to get step by step deeper into the multi arm bandits problem and gradually increase the complexity of our research, we decided to apply in the beginning, only one agent in one of our networks so to evaluate its performance and observe how it reacts to its environment. After that we will apply agents on both of our networks in order to investigate how they cooperate and their effect on our networks as a whole.

The privileges our agents will have for start, will be limited allowing them to control only a specific parameters on our networks which in our case, this parameter will be the transmission power. As the experiment goes on we will promote the agent's authority by increasing their responsibilities of our agents by allowing him to handle the control of the sensitivity of our networks too. This chapter will end with the application of a second agent both having restricted responsibilities and a more loose case, while we will be observing the impact of the coexistence of our agents in the environment of our networks. Although there is a controversial choice we have to take and this is about the learning strategy that we set for our smart agents to use. Facing that dilemma of learning strategies, we decided to try two of them, e-greedy and Thompson Sampling. So we thought that we should take advantage of this opportunity and make a small comparison of the outcome and extend our research even further. The parameters that will be used on our agents file are presented at the table 5.1 below.

Table 5. 1 Agents setup

Time between requests	1 second
Actions cca (dBm)	{-82,-76,-70,-62} dBm
Actions tx_power (dBm)	{8,10,15,20} dBm
Learning mechanism	1 (Multi Arm Bandits)
Selected strategy	1 (E-greedy) | 2 (Thompson Sampling)

5.3 Learning Strategies

Learning strategy is in general an individual way of organizing and using a particular set of "skills" in order to accomplish tasks more effectively. In our case, this task is the performance of our networks. Before we continue to the experimental part of our research, it will be useful to mention some important information about what learning strategies are and how they operate. Also we are going to notify the exploration-exploitation dilemma that occurs and has a direct impact to our network environment. Two learning strategies that we are going to focus on this chapter are E-greedy and Thompson Sampling, as those are the learning strategies we use widely in our scenarios.

5.3.1 E-greedy vs. Thompson Sampling & Exploration-Exploitation dilemma

The first learning strategy we are going to see as we mentioned before, is E-greedy. E-greedy is a simple selection method that tries to keep a balance between exploration and exploitation by choosing randomly one of them where the epsilon seen on its name refers to the probability of choosing to explore. It can be categorized as a semi-uniform strategy due to its greedy behavior where most of the time exploitation is preferred than exploration.

Exploration and Exploitation are two terms widely used in learning strategies as we already saw during the small presentation of E-greedy and we will also meet them as we move through with the presentation of Thompson Sampling. With exploration, a smart agent is allowed to extend his current knowledge, by choosing different actions without taking in mind only the performance. This knowledge based thinking leads to long term benefits while improving the possible accuracy of the estimated values.

Exploitation on the other hand, is a greedy minded model choosing action in order to get the best reward by exploiting the current estimated action-value. This happens against exploration as when an agent explores, the estimated actions-values are more precise but when it exploits the reward might be bigger. Those two prospects cannot be chosen simultaneously and that is what is called the exploration-exploitation dilemma.

Thompson Sampling is a randomized algorithm where exploration is being achieved by choosing the arm with the "best" sampled mean. The basic idea assumes there is a prior distribution on the underlying parameters of the reward distribution of every arm and at each time step an arm is selected based on its posterior probability of being the optimal. The algorithm continues to sample all actions that could be optimal, shifting those arms that are considered to underperform while finding finally the optimal one.

5.4 One agent application

As we already mentioned, the first step on understanding reinforcement learning and multi arm bandit model while applying smart agents at the same time on our networks was by deploying a single one agent only in one of our networks. The instructions the agent was given, where to find the ideal transmission power for the best possible throughput. In table 5.1 where the agent setup is mentioned, we see that in the CCA parameter is a list with a various number of possible values, although in this stage we will use the by default value of -82 dBm.

It is important to emphasize that in contrast to our experiments in the first phase, we had to significantly increase the simulation time from 10 to 300 seconds, so our reinforcement learning algorithm would have the proper time needed to provide us accurate results. This decision was made as during the simulation test it has been seen that during our runs at 10 seconds some "levers" have not been chosen at all from our agents. Despite that, the upcoming results will be isolated from the last 10 seconds of our simulations so the comparison with the origin scenarios will be fairer.

As our experiment went on, the results seen in Figure 5.1 were mostly confusing, despite the fact that in some cases (i.e at 16 and 20 meters distance between networks) that even our "simple" agents had better results than that we had in our origin performance but not as we have expected, we could say that in overall the results when we applied the smart agents had worse performance driving us to question the ability of RL algorithms to properly configure wireless networks. However it is interesting to mention that when we deployed "enhanced" agents with higher privileges in the cases where the simpler agents outperformed the original state, now we see a huge increase of performance and the overall results are closer to those ones where no agents were applied.

Comparing the two different action learning strategies, we see that as we use the simple agent the Thompson Sampling has better overall results than E-greedy but as more parameters come in the hands of the agents we see that it is the other way round. Another point that we must highlight is that in some cases the simpler choice the better one as we can see complex agents are outperformed from simpler ones.

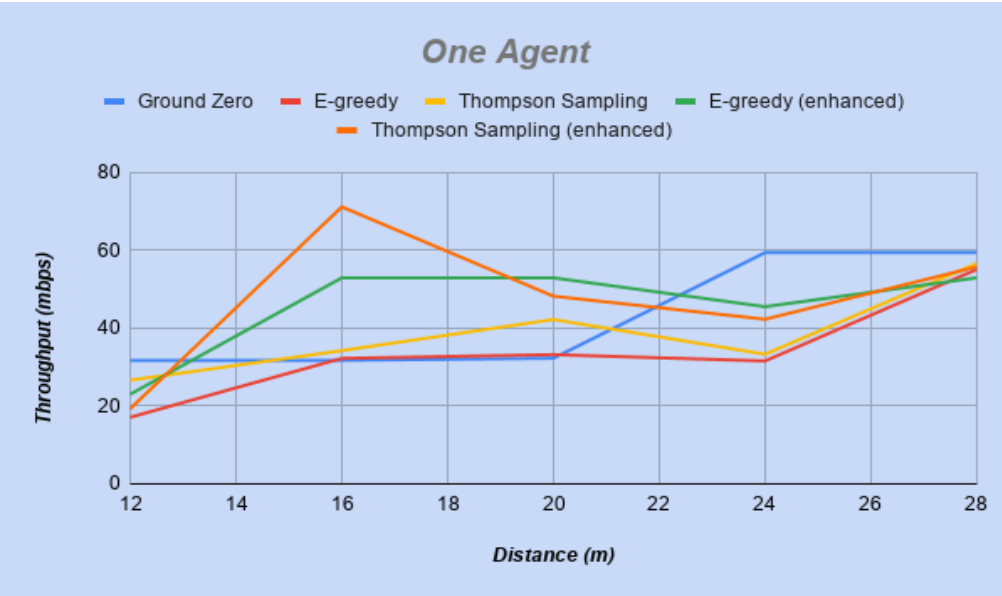


Figure 5. 1 One agent application with simple (tx) and "enhanced" (tx,cca) agents

Summing up we see that the smart agents and the reinforcement learning algorithms did not perform as we were thinking but it may be more complex than we thought the usage of features like that. For that reason we wanted to investigate a little bit further on why that happens, so we wanted to try a different approach topology to check if the location of our networks is indeed the main factor that pre-decides the max throughput.

5.4.1 A different approach topology

The result we exported in the previous scenarios made us wonder as we mentioned if the topology of our networks is the main factor that has the biggest effect on the maximum throughput of our wlans. In order to answer this question we created a new scenario with a different topology as it appears in Figure 4.7 so we can either confirm or contradict our theory. The configuration used in this case was the same with the previous ones scenarios on both our AP's, STA's and agents.

Looking at the outcome of this experiment as we can see in Figure 5.2 below, we see that the impact of the agents was more noticeable when we gave the agents the highest authority in our cases compared to our outcome in the previous case. From the starting point we see that our agents achieve much higher performance except one specific case (when the difference between networks is at 16 meters) where there may be a bunch of reasons for that performance dip might be. The specific topology made the learning process difficult enough as consulted by the simulation logs we see that its "lever" had been chosen less times than in previous cases. So as more time was added to the execution time of the scenario, we got better and better results each time. Despite that we see that in the scenarios when we applied smart agents which handle only the transmission power, our networks are still outperformed in most of the cases from the original scenario where no agent was applied. That fact made us think about the tier those parameters that we gave to our agents to handle are in the chase for optimal configured networks, as in the majority of our cases agents handling only one parameter like transmission power did not have the impact expected.

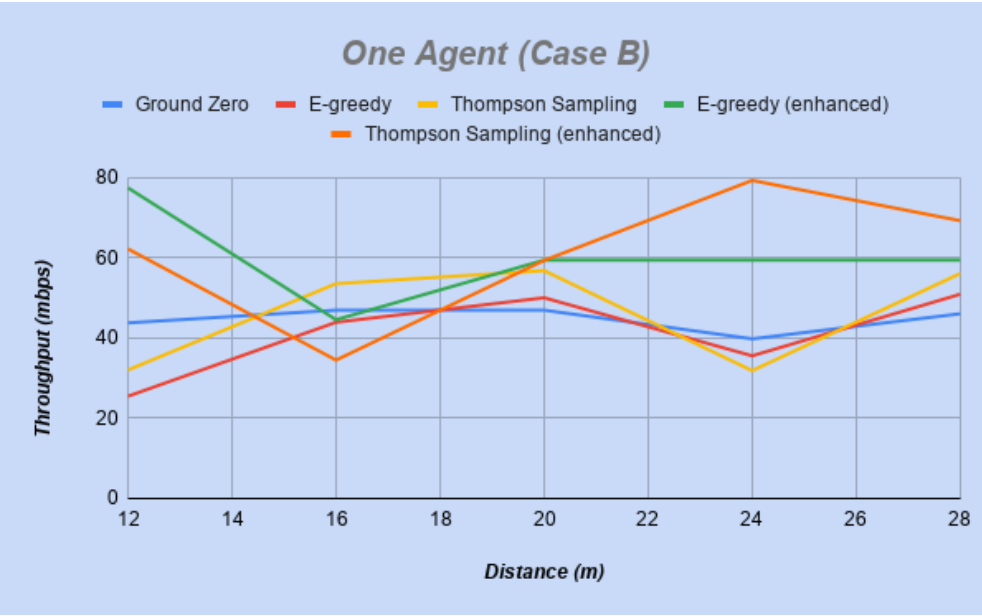


Figure 5. 2 One agent application on a different topology

5.4.2 E-greedy vs. Thompson Sampling

The selection of the proper "action selection strategy" to be applied in a multi arm bandit problem is not trivial. Both e-greedy and Thompson Sampling have been tested as objects of research and we have seen that both give great results. The exploration-exploitation dilemma is the trigger point that makes it difficult to choose most of them.

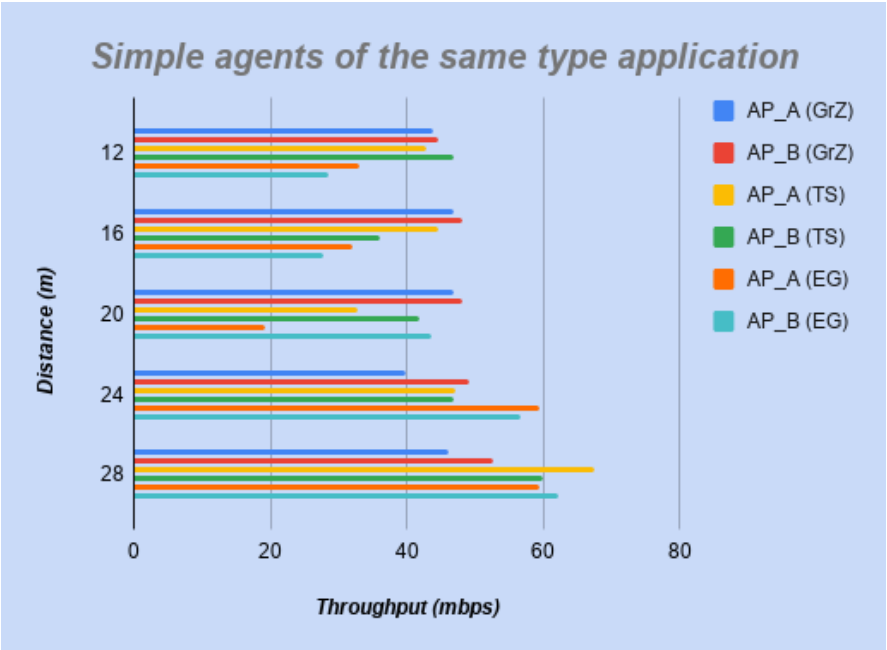
During the simulations, we see that e-greedy was not so fair in terms of choosing all the available arms, something that we have been expecting as the chances of exploring are really small. So the result of this is that some available arms are not even used in some cases. Although as we can obviously see in table.3&4 the performance compared to Thompson Sampling is pretty much the same. In addition while we used the Thompson Sampling strategy, we saw that the chances on each arm were fairly distributed.

5.5 Coexisting agents

The next level of our research, after investigating the influence of RL algorithms in WLANs in a simple scenario, was to apply agents in all of our networks. Main target of this step is to observe how a set of similar agents interact with each other and of course we will focus on the performance of outcome. In the first part of this section we will see how similar learning type agents coexist in the same environment and we will continue in the next one, where we will investigate how different learning type agents react to each other and of course how this heterogeneity affects neighboring networks.

5.5.1 Similar agents

The topology preferred for this case, was the one seen in Figure 4.7 as we wanted to put our agents in a more intense environment. As we applied a second agent with the same action learning strategy, we executed the same "distance cases" between our Access points and Stations, as in the previous scenarios and the results we got were very interesting. In this part it is important to highlight that we used both E-greedy and Thompson Sampling so we can extend their comparison part more detailed.



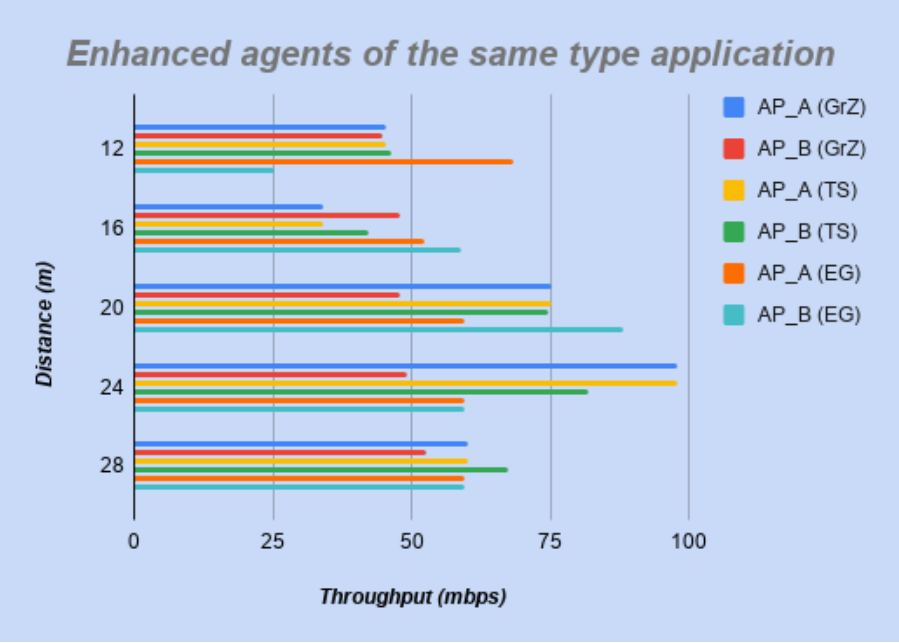
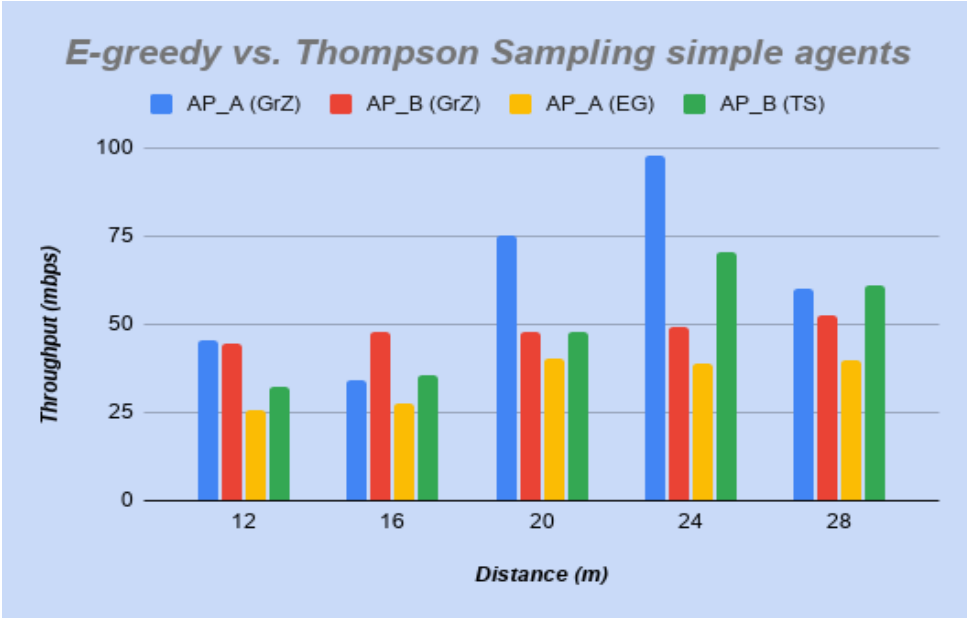


Figure 5. 3 Two agents of the same type application in simple (tx) and enhanced (tx,cca) version

At Figure 5.3, we represent the overall results of our networks at 5 different distances between Access Points and Stations. For one more time we see that the major upscale in performance is given when the "complex" agents are deployed. More specifically we notice that either in one of our networks or even in both of our networks, our performance is much better than in the original case. It is interesting to highlight that using E-greedy we get better performance earlier than Thompson Sampling exceeding of course the performance of the cases without agents although reaching lower values than Thompson Sampling. Compared with the previous results when only transmission power is used, we will assume that there is something wrong and that our agents did not accomplish their obligations but it is not that simple. While we checked the logs from and the statistics the simulator provided us during the simulation execution, we noticed that even though when we set our agents having in mind the optimal throughput, they both decreased the transmission power of their networks in most cases. Although that happened because our agents wanted to increase the transmission time of our networks which indeed achieved around 10-20%.

5.5.2 E-greedy & Thompson Sampling coexistence

Despite the answer of the upcoming question, if we could have better performance if we use two opposite directed learning strategies, can be easily predicted, we wanted to investigate how a set of networks using agents with different action learning strategies will perform. For this one we picked the topology seen in Figure 2.1 and the results can be seen on the Figure 5.4 below.



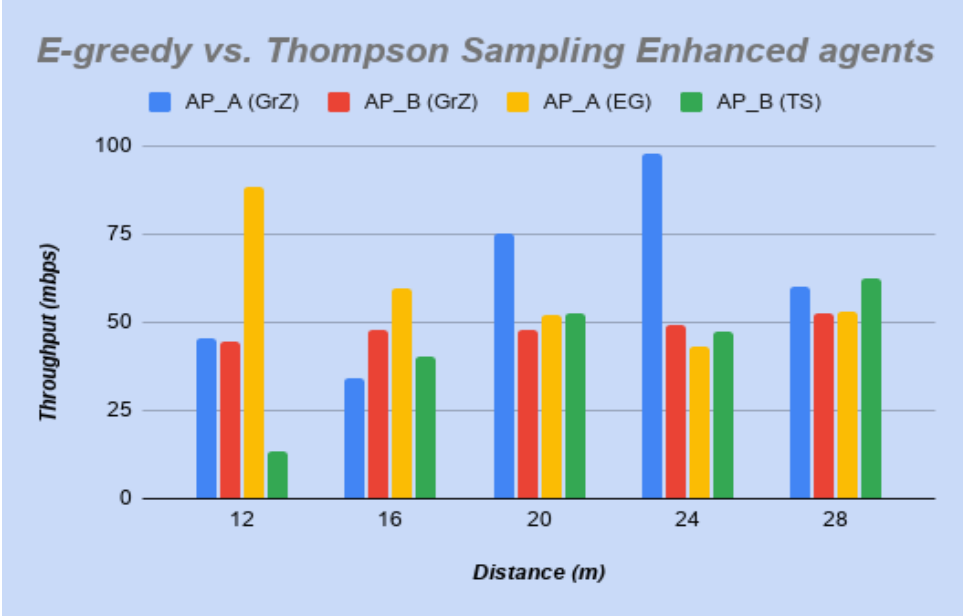


Figure 5. 4 Overall throughput (mbps) using both action learning strategies the same type.

Trying to interpret the results, we had mixed feelings about the outcome. The results are mostly one sided in our cases. We noticed from our logs that in the first case when our agent only handled the transmission power the Thompson Sampling overcame E-greedy keeping it at low throughput exceeding also by a lot the original scenario without agents. Although, when we proceeded and authorized our agents to handle both transmission power and CCA, we noticed that the Wireless Networks were one sided from the opposite side now. The network where E-greedy applied tried to take advantage of the decision of TS agent to decrease its own transmission power and increased his own according to our simulating logs achieving high performance. Interesting here is to highlight that despite that Thompson Sampling was in lower priority, achieved better performance than that in our starting case. Overall we

observed that in most cases the wlan with the TS agent had access to the transmission channel less than the other one where e-greedy was applied.

5.6 Epilogue

During this chapter we presented reinforcement learning algorithms and different learning strategies while we applied our knowledge in various simulating scenarios to export our conclusion about how effective they can be. From our extensive tests, we noticed that as more parameters are handled by a smart agent the better performance we can get but everything comes with a cost. Having more complex agents, the time needed for our smart agents to be properly trained is increased accordingly.

Chapter 6: Multi-agent High Density Networks

6.1 Introduction

After our current work, we understand that when we refer to the performance of a network, it is not only the throughput of it, but a wide range of variables we have to take in mind. For sure, we saw that the application of RL algorithms like MABs can be very helpful in the hunt of the optimal setting in our networks.

Now we decided to level up and move to a bigger scale scenario, something which can occur in our daily life. So in order to avoid possibly ideal scenarios, using a Random Node generator by specifying the restriction we want to set for our nodes, we created 2 new scenarios. The restrictions that have been set on the generator can be found in the table 6.1 below.

Table 6. 1 Node generator

Scenario Map Width: 100 m
Scenario Map Width: 100 m
Number of desired Wlans: {3,5}
Minimum Number of STA's
Maximum Number of STA's
Minimum distance between AP's: 10 m
Minimum distance between AP's-STA's : 3m

In this part of our research we are going to test how our agents perform, when the number of either the wlans or the station included are highly increased. We are going to execute two different scenarios were the number both of station and AP's is the same as it follows:

i. Wlans with 3 STA's each
ii. 5 Wlans with 3 STA's each

The setup of the rest of the scenarios, will be the same as it has been with all of the previous phases of our research. The outcome of this phase is not only to see how variables like transmission power and sensitivity affect but also to notice how agents work and their viability in more dense scenarios.

The series that followed for the integration of this phase was similar to the other phases despite the bigger data volume. We executed our scenarios for 10 seconds with no agents applied, in order to have a starting point on our test so we can have a baseline of comparison with the upcoming scenarios where agents will be applied. The scenarios where agents of all kinds will be applied, the simulation time will be set at 300 seconds, in order to give our smart agents the proper time to extend their knowledge

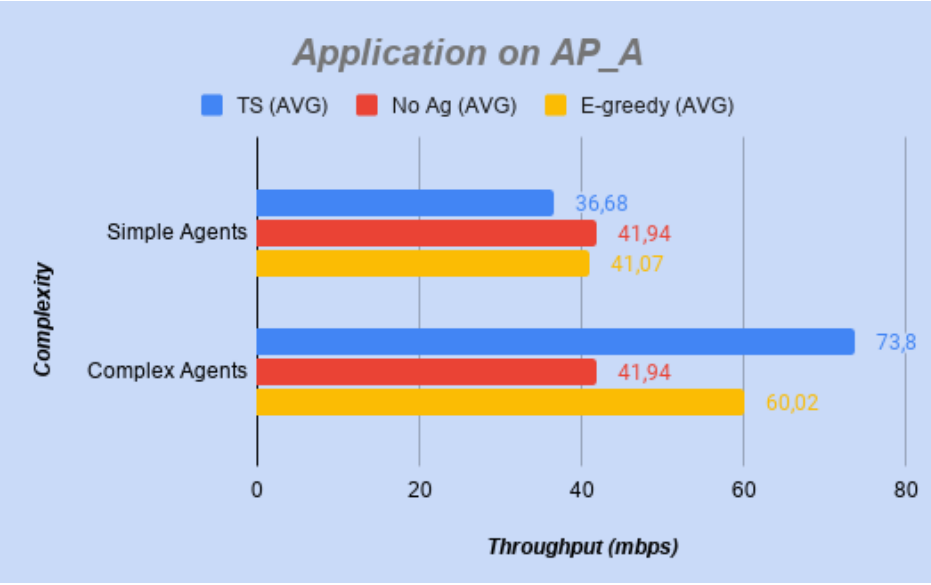
6.2 3 WLAN – 3 Stations

In the first phase of the current experiment we are going to test 3 different wireless networks, where each one will have 3 stations. In order to have acceptable results the deployment of our access points and stations has been randomly with the use of our generator. Now during the simulations, we parted the cases into sub cases. One is called “simple agents” where the agents handled only the transmission power and the other called “complex agents” where the agents handled both transmission power and CCA. (We decided in this current thesis not to add channel selection as one of the parameters that agents can allocate and set it as a target for future work). The results were pretty interesting for both cases can be seen at the Figure 6.1 below.

During our research we saw that using agents which handle more than one parameter of our networks had a perceived performance advantage compared with cases where our agent configured only one parameter where in our case was transmission power. Although we agreed we that hypothesis, in this case things got complicated. As we see in mentioned results we can make an overall conclusion that by applying a “simple” agent as we call them. Despite the fact that only in one case and more specifically in Access Point A, our smart agent’s scenarios had lower performance than the “original” case, the degradation was really small when in the rest of our networks we had more than 20% increase of performance.

Contrary to the simpler scenario, when more complex agents applied the situation was twisted. We noticed a greedier behavior from our networks whatever the learning strategy was and the performance was not as balanced as we had in the previous results. In this case only one wireless network got full advantage of the capabilities of more complex agents reaching above 43% performance increase compared to the other two which performance gradually collapsed. Our second network got a small performance degradation, which could be understandable if its surrounding networks upgraded, but instead of that we reach to our third network almost stop transmitting cause as we can see in table.11 when Thompson Sampling was applied the performance degradation was around 35% and in the worst case when E-greedy was applied our Access point could not transmit.

The outcome on this stage of our research was only the start of our try to see how smart agents work when they are applied in more density scenarios than we have already faced till the start of our experiments. Continuing our research in the next chapter, we are going even further by inserting more wireless networks on our scenarios creating a high density case.



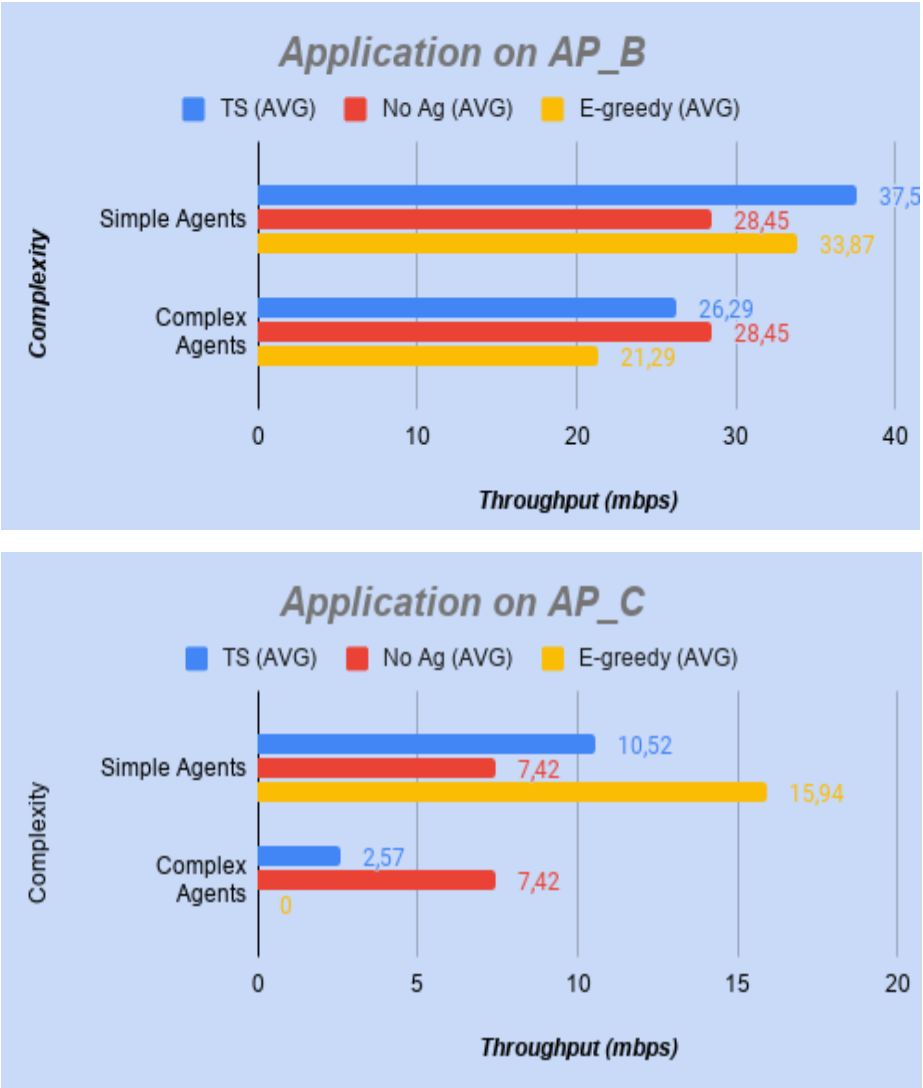


Figure 6. 1 Simple & complex agent's application

6.3 5 WLANS – 3 Stations

In addition to the previous case where 3 wlans had only applied, in this case the addition of two more wireless networks made things a lot different. From the first moment when we executed the original scenario where no agents have been applied as we saw in Figure 6.2 the effect of the high density cases networks appears immediately. The overall performance on our networks can be calculated lower than we faced in previous cases which is an event that we regularly encounter in our daily life which is also the main reason we decided to prepare this thesis. A major factor that we already knew that we will face due to the complexity of our scenario, was the time that the learning procedure of our agent would be needed in order to extract proper results, making things messier in the end.

We can say that in this specific scenario the power and the capabilities of reinforcement learning and smart agents can be seen. Through the results we can testify that almost in almost cases using either one or the other learning strategy our major target which is the performance increase is achieved. This positive effect of our smart agents can be also noticed in our "complex" scenarios as either one or both learning strategies achieve huge performance increase that in the simpler performance or either the

strategy that in “simple” scenario did not have the expected performance, now it can be near to what we expected.

A major note that we can make by looking at the table 6.1, is that between the two learning strategies e-greedy because of its nature to choose grindingly the action with the best performance, had almost in every case better results than Thompson Sampling. Either way, this experiment is the most important outcome of this current report that is capable of handling high density situations and that is what we should focus on in the future.

6.4 Epilogue

With this chapter we close our research on the wireless networks and the effect of application of reinforcement learning on them in more dense scenarios closer to what we encounter in our daily lives. During the scenarios we executed in this part of our research we faced different behavior from our agents. What we can overall conclude is that indeed the application of algorithms like this are viable for next generation networks.

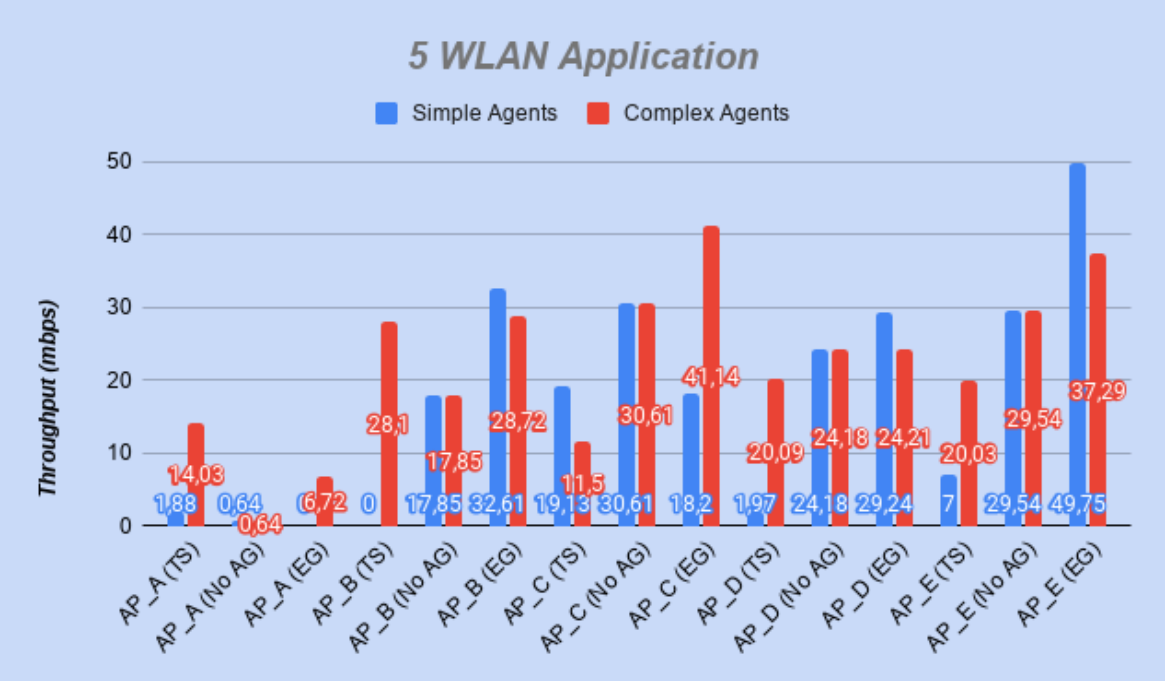


Figure 6. 2 Simple and complex application 5wlans edition

Chapter 7: Conclusions and future work

In this work, we aimed to study the feasibility of applying reinforcement learning on dense wireless local area networks such as react to the impact of the IEEE 802.11ax amendments feature to overcome these issues. To that purpose, we made an historical reference on the evolution of the IEEE 802.11 family, analyzing the legacy versions with its continuously increasing features alongside with their extensions. We made a more comprehensive presentation on IEEE 802.11n/ac, the first high and very high throughput amendments which tried to overcome the threshold of 1 Gbps on the band of both 2.4GHz and 5 GHz. In addition with the massive increase of the performance with a combination of other MAC and PHY's enhancements, those two amendments where the ones that introduced the MU-MIMO technologies to the wireless networking community. Finally we reached to the IEEE 802.11ax amendment that came to continue the work of its ancestor and produce new features that will overcome the most common obstacle of our days, the high density between networks.

As the reinforcement learning has been widely used the last years in order to overcome the current amendment could not come through. For that reason we selected Komondor, a wireless networking simulator to handle and supervise our scenarios validated against both other Simulators and two analytical tools based on Continuous Time Markov Networks and Bianchi's Distributed coordination function model. In contrast with other well-known simulators such as NS-3, OPNET etc., Komondor was developed that way focusing for next generation wireless networks implementing new features like machine learning algorithms. Its low complexity, alongside with the high event processing rate, OFDMA and MU-MIMO (which is not implemented till this research has been made) makes it capable to fill the gap for the upcoming generations.

The first step of our research was focused on understanding the function of a network and how the variation of one of its parameters could affect its performance. For that purpose we created two difference simple topology scenarios with two only networks in order to also force phenomena's such as hidden nodes. Although the center of our attention were on the handling of the transmission power and the sensitivity of our networks which where the parameters that we chose to be the main actors through all the current work. By creating three different use cases for each of them for low, medium and high values, with the help of Komondor we executed our scenarios in our topologies. Each topology had too different use cases were the distance between our networks was varied. From this first phase we conclude that each change may have a huge impact to the overall performance and even though sometimes we can predict that change, most of the times it is unknown what is going to finally happen. For sure the combinations in order to find the optimal setup are a lot in number and doing that by hand is an impossible task for current time deployments.

The next step was to apply machine learning and more specific in our case reinforcement learning in our already done scenarios. Due to the limitation of Komondor as the only RL learning mechanism implemented the current time this research has been done, we selected Multi Arm Bandits learning mechanism to apply in our scenarios. The same time in order to face the exploration & exploitation dilemma two different strategies were selected to be used (E-greedy & Thompson Sampling) taking the chance to make a starting comparison between them. Our plan was to apply one agent at a time on one of our networks and then step by step add a second one of the same strategy learning type, handling only one the two available parameters. Finally we allowed both of them to be in charge of allocating the proper value for both of our available parameters and even applied different strategy learning type agents so we could observe their co-existence. Our conclusions on this part was that for better performance

more complex agents needed handling more parameters where that could be harmful as more time will be needed for our agent to be “trained”.

The final part of our work was focused in the main question of our research, if machine learning algorithms are capable to help wireless networking overcome the issues created in high density deployments. For that reason we created random allocated topologies of 3 and 5 networks respectively with a specific number of 3 stations per network. The pattern we followed in this part of our experiment was not the same with the previous ones. In this part we applied smart agents to all of our networks creating two use cases where they stood out in the number of parameters each smart agent was in charge of. The outcome of this part of our research was the most important because it is visible through our metrics that the advantages smart agents and machine learning algorithms are existing even in a small range scenario where only two parameters are handled by such technologies.

As a final conclusion we can reassure that machine learning algorithms will be for sure a new feature for the next generation wireless networks because their capabilities are huge and when the implementation of more machine learning in wireless networking will be done there is going to be a huge step forward in terms of performance. Future will also consider the application of more complex agents allocating more and more parameters but it is important to overcome the hurdle of the time needed for our agents to be trained and the performance gain of current and future networks.

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